The Cost of Air Pollution for Workers and Firms

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Abstract

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

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1 Introduction

It is widely acknowledged that air pollution has detrimental effects on human health.[1] Air pollution exposure causes higher emergency admissions and mortality (Schlenker and Walker, 2016; Deryugina et al., 2019), higher medical expenditures (Barwick et al., 2024), and a higher number of work loss days (Holub et al., 2021). Cognitive functions and intellectual performance may also be impaired (Aguilar-Gomez et al., 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 $\mu g/m^3$ 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. Taking the average value added ratio of 27% from French firms' accounting data in 2015, this gives 7.3 billion euros of foregone value added in the short-term, ignoring 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 7.7 billion euros annually in France. This comparison between average costs and benefits does not account for their distribution across firms and regions. Still, tightening air pollution regulation to align it with WHO standards is likely to generate economic benefits of the same order of magnitude as the cost of regulation on average. This is ignoring the wider morbidity and mortality benefits from improved air quality.

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 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 high-income countries. 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

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

[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.

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 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. Finally, we add to a handful of papers that study how consumption behaviors change with temperature shocks (Lee and Zheng, 2024) or salient air pollution shocks (Barwick et al., 2024) and also show a negative impact.

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 formalizes how pollution exposure 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 several 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

[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.

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 (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. (2024) find a statistically significant negative impact of $PM_{2.5}$ exposure on necessities and supermarket spending within two weeks, but not in the long run, which can be rationalized with avoidance behaviors.

Unlike in previous studies, air pollution remains a low-salience issue in France 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 past decades (Champalaune, 2020; Sicard et al., 2021; Currie et al., 2023). However, pollution levels still exceed 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] Despite this, local and national authorities have demonstrated limited commitment to addressing air pollution. France's persistent non-compliance with EU air quality standards has led to the European Commission referring the country 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

[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).

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 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 behavioral changes from local consumers.

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 $0 < \rho_i < 1$.

[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. In France, most private sector employees (88% in 2017) also benefit from an employment contract ensuring job security.

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

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 $u'_{fit}(c)$ 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:

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

where p_{fit} is the price of variety f at time t and P_{it} corresponds to the CES price index for industry i, 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]

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

[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).

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, $a_{fit}(c)$, 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 adjust to short-term fluctuations in air pollution, it varies with 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

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

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 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. One of our main objective is thus to evaluate the reduced-form effect of air pollution on firms' sales.

Second, equation (6) reveals that 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.

The last 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 anticipate the behavioral response from consumers. Few studies have explored how air pollution shocks influence purchasing behaviors over a wide range of products, especially in a context with low-salience air pollution shocks. In our study, we explore this channel not through consumers' bank card transactions and spending data (as in Barwick et al. 2024; Lee and Zheng 2024), but through firms' sales data in consumer-oriented retail and services sectors.

3 Data

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

[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 $\eta - \theta = -0.26$.

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.

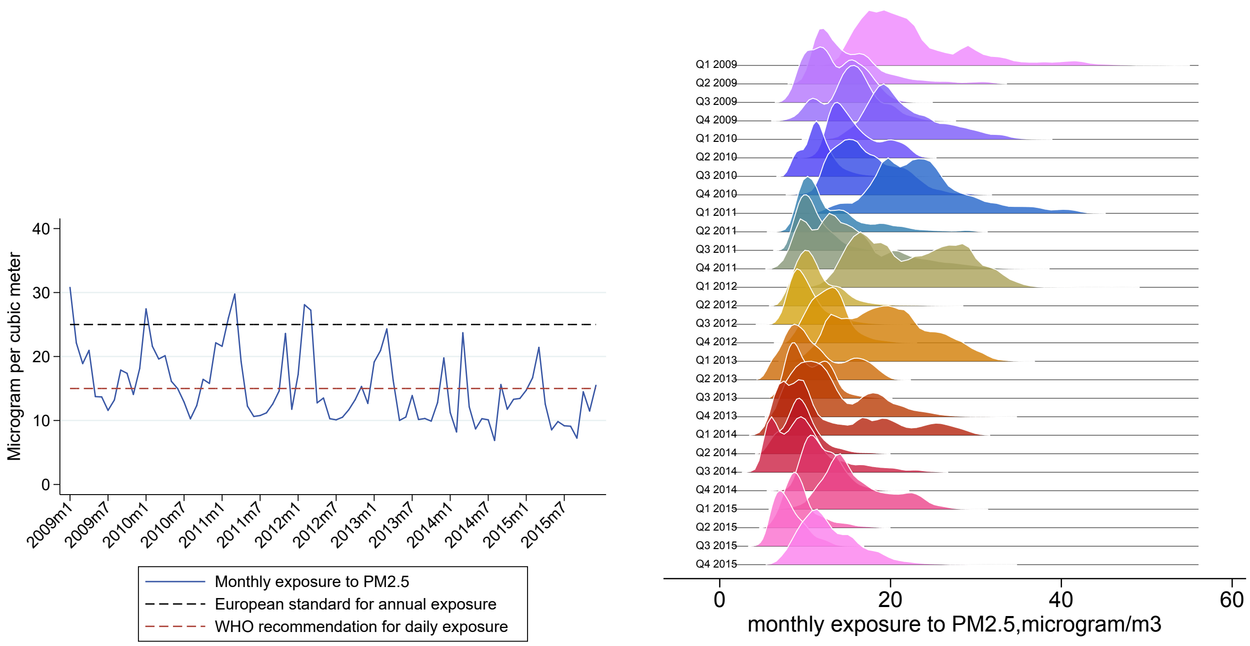
Gridded reanalysis pollution data are in principle better suited to capture the average pollution exposure of local residents than pollution-monitor readings. Monitors are sparse and sometimes strategically placed, so their readings may not take into account all polluting sources. By contrast, reanalysis data combine monitor readings with a chemistry-transport model that uses emission inventory as an input and takes into 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 that includes PM_{10} readings—for which the number of monitoring stations is larger—in the prediction of $PM_{2.5}$ concentration.[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 and the significant reduction in average $PM_{2.5}$ concentration over the period. Similarly, panel (a) in Figure 1 shows the average monthly exposure over the period. Although pollution is quite seasonal, there is substantial variation in monthly exposure within a quarter-year, as illustrated by panel (b) in Figure 1.

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 cardinal directions: North (below 45° or above 315°), East (between 45° and 135°), South (between 135° and 225°) and West (between 225° and 315°).

[14]Over the study period, there are between 62 and 105 background monitoring stations for $PM_{2.5}$, between 173 and 251 for PM_{10}, between 318 and 385 for ozone, and between 282 and 337 for NO_2.

[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



(a) Monthly average exposure to $PM_{2.5}$ ($\mu g/m^3$) (b) Distribution from Q1 2009 to Q4 2015

Figure 1: Monthly exposure to $PM_{2.5}$ ($\mu g/m^3$)

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 $PM_{2.5}$.

Firm-level sales. We use monthly sales data at the firm level from Value Added Tax (VAT) records collected by the French administration. The tax administration imposes monthly declarations to firms with annual sales above certain industry-specific thresholds, while small-sized firms are allowed to report either monthly or quarterly to the tax authorities.[16] We restrict our sample to firms that declare their VAT every month, that have at least one employee observed in the sick leave dataset, and that belong to four broad economic sectors: manufacturing (including manufacturing industries, mining, and utilities), construction, business-to-business trade and services sector (including communication and IT services, wholesale trade, professional services, and cleaning services), and business-to-consumer retail and services sector (including groceries and supermarkets, restaurants, hairdressers, clothing stores, furniture stores, and car sales and repair). The final sample includes 158,223 firms totalling €1.9 sales in 2013, which represents 52% of all French firms' sales (excluding agriculture and financial sectors).

In our data, sales are reported at the firm level. Sixty-four percent of the firms in our sample own a single establishment. In this case, we assign them pollution and weather exposure using previously described reanalysis data based on the municipality where the establishment is located.[17] The remaining thirty-six percent of firms own more than one establishment. These are large firms as they jointly represent 75% of total sales in our sample. To build firm-level pollution and weather exposure for them, we leverage exhaustive matched employer-employee data (DADS-postes) that provide 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 weighted-average firm-level exposure to pollution and weather characteristics, where the weights are the annual number of workers in each establishment owned by the firm.

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).[18] 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. Our main measure of absenteeism is an indicator for an individual starting a SLE in a given month, but we also observe the count of sick days and the total sickness

[16] The French tax administration imposes monthly declarations to firms with annual sales above €818,000 for manufacturing and hospitality industries, and above €247,000 for 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] Specifically, $PM_{2.5}$ exposure levels for each municipality are assigned based on the values from the nearest CHIMERE model grid cell, while weather variables are derived from the nearest Copernicus grid cell.

[18] 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).

leave spending associated with SLEs that started in a given month. In the main analysis, we only consider SLEs that last less than three months, which represents 93% of the spells.[19]

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 to both air pollution and weather data and firm-level information. We aggregate sick leave data at the establishment-month level. Furthermore, 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.[20]

Descriptive statistics. Panel a of table 1 shows that the average firm in our sample employs 59 workers and reports an average monthly sales of €1,316,300, whereas the median monthly sales only amount to €145,372. Firms are almost evenly distributed across sectors: manufacturing represents 20% of firms,, construction 16%, business-to-business trade and services 31%, and business-to-consumer trade and services 33%.

Panel b of table 1 shows descriptive statistics for the sample of workers for which we observe social security information and that are employed by a firm with monthly VAT records. We obtain a panel dataset for around 400,000 individuals working in 353,155 private sector establishments over the period 2009-2015. These employees are 40 years old on average. They earn an average annual gross wage of €28,542 and spend on average €442 in annual medical expenditures. Additionally, each month, 23 per 1,000 of these workers, on average, enter sick leave for less than three months.

Appendix Table A.1 compares this sample of workers to the representative sample of workers before conditioning on being employed by a firm with monthly VAT records. Because firms with monthly VAT records tend to be larger, we observe that workers in our sample of analysis 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.

[19]In our data, the average sickness leave episode lasts 29 days whereas the median duration is only 9 days. Figure C.17 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.

[20]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)

Table 1: Summary Statistics, 2009-2015

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

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

4 Empirical Strategy

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

4.1 Firm-level econometric specification

We model the relationship between firms' sales and pollution exposure using the following equation:

$$Y_{fiyt} = \beta PM_{2.5fyt-1} + W'_{fyt-1}\gamma_1 + W'_{fyt}\gamma_2 + W'_{fyt+1}\gamma_3 + \nu_{fy} + \theta_{iyt} + \delta_{dq} + \epsilon_{fiyt}, \tag{7}$$

where the unit of observation is firm f producing in industry i in month t in year y. The outcome Y_{fiyt} 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 (in particular, for services or for exports).[21] The parameter of interest is β, the coefficient on lagged monthly $PM_{2.5}$ exposure for firm f. When firm f owns a single establishement, exposure is measured at the municipality where that establishment is located. When firms own multiple establishments, firm f's air pollution exposure is a weighted average of $PM_{2.5}$ levels at the different establishment locations, using labor shares as weights.

Our preferred specification includes firm-by-year (ν_{fy}), industry-by-month-by-year (θ_{iyt}), and quarter-by-county (δ_{dq}) fixed effects.[22] 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_{iyt} 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 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. It captures for instance the seasonal demand variation in ski or sea resort areas.

The vectors W_{fyt-1}, W_{fyt}, and W_{fyt+1} include two types of time-varying firm-specific controls. To account for the joint influence of weather conditions on air pollution (different climatic conditions can lead to different air pollution levels) and sales (for instance, hot days may result in

[21] The rules defining the business month when the firm must declare sales and 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 when 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. Additionally, 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.

[22] We use the terminology "county" to denote a French *département*. There are 96 French *départements* in mainland France, and it corresponds to the second smallest administrative subdivision before municipality.

a decrease in activity) within firm-years, we generate indicators for monthly averages of daily maximum temperatures, wind speed and precipitation in each location, and include in W_{fyt} the set of indicators for all possible interactions of these weather parameters.[23] When firms own multiple establishments, we build these weather controls as weighted averages of the values taken at each establishment. 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 location.[24] Since we want to isolate the effect of a lagged monthly air pollution exposure on outcomes observed at t and t+1, our OLS regressions also include monthly $PM_{2.5}$ exposure 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). Another potential source of biases arises from unobserved local shocks that may influence pollution concentration while also affecting firms' sales and workers' absenteeism (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 exposure with a combination of the share of hours in a month where wind blows from each of the four cardinal 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

[23] 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.

[24] 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.

as follows:

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

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 term B 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 direction j, and N and T are the total number and set of days over the period of analysis.

Figure A.4 shows how the deviation from mean pollution (term B) varies for a given wind direction across municipalities in France. Winds blowing from the East and the 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). By contrast, winds blowing from the North and the South have heterogeneous effects on pollution across regions: North (South) winds increase (decrease) pollution in the Northern half of the country, while having moderate effects in the Southern half of the country.

The specification of our first stage is:

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

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 direction j, where these intensity increases arise both from higher frequency of wind direction j and from how much wind direction 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 location 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.[25] 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.5 and A.7 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 the analysis at the establishment or municipality level, we cluster standard er-

[25]Note that in a sample of single-establishment firms, each firm is located in a unique municipality, thereby allowing us to control for firm-year fixed effects.

rors at the Copernicus grid cell level, which is the scale at which the component A of the wind instrument varies. For multi-establishment firms, we generate a plausibly exogenous predicted pollution exposure using the first stage results from equation (9). We save the vector of estimated $\widehat{\beta}_j$ and compute the predicted pollution exposure in each location as $\widehat{PM_{2.5gyt}} = \sum_{j=1}^{4} \widehat{\beta}_j \mathrm{Z}_{jgyt}$. We then compute the firm-level predicted pollution exposure, $\widehat{PM_{2.5fyt}}$, as the weighted average of $\widehat{PM_{2.5gyt}}$ across locations g where firm f owns establishments in year y using labor shares as weights. We use $\widehat{PM_{2.5fyt}}$ as an instrument for $PM_{2.5fyt}$ in equation (7).[26] In firm-level analysis, we cluster the standard errors at the firm level, which is the scale at which the instrument varies.

4.3 Identification assumptions

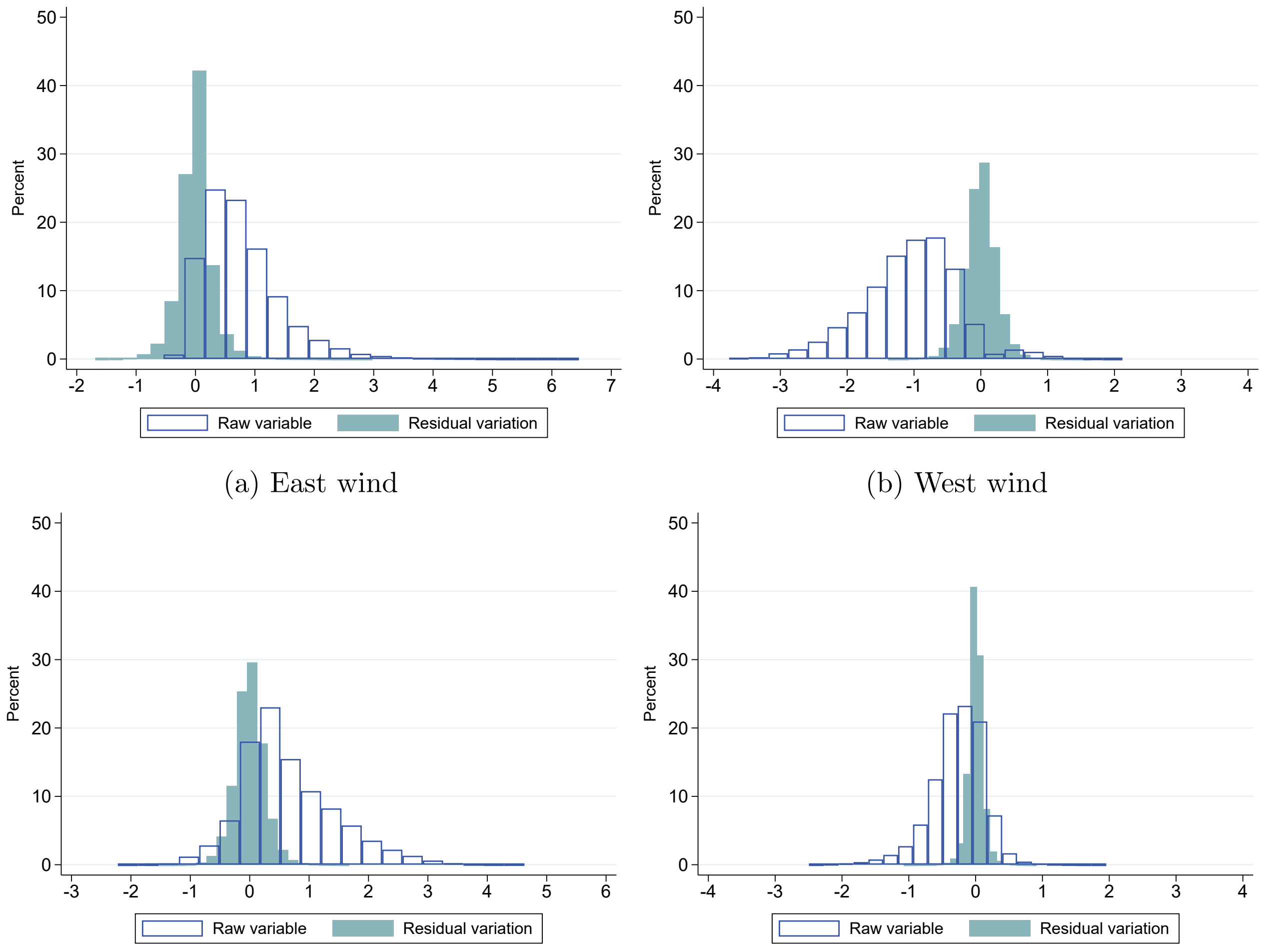
The validity of our research design requires that three conditions are met. First, our set of wind instruments should be correlated with $PM_{2.5}$ (instrument relevance). Second, they should be uncorrelated with the error term from the second stage, ϵ_{fiyt} (instrument validity). Third, the monotonicity 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 industry and demographic composition of their workforce. Under heterogeneous treatment effects, we can only interpret our two-stage-least-square estimates 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.[27] 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.[28] The effective F-statistic is 490, while the critical values for a 5% worse case bias is of 29.37 and that for a 10% bias is 23. This statistic allows us to rule out the issue of weak

[26] 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).

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

[28] 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 at the municipality level.



(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 variables are 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.

instrument in our context.

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

Instrument validity. The validity of the instruments hinges on two assumptions. First, the wind direction instruments need to be as-good-as-randomly assigned. This implies that there should be no weather or seasonal patterns influencing sales which co-vary with the instrument. In our specification, we control flexibly for wind speed, temperature and precipitation, as they may be correlated with wind direction and influence sales, and we include quarter-by-county fixed effects that net out quarter- and county-specific wind and sales patterns. The latter captures location-specific seasonality patterns. The remaining variation in the instruments should be as good as randomly assigned as we do not know of any other weather variable that could influence both outcomes. We control for humidity in a robustness check and find that results are unaffected.

Second, the exclusion restriction must hold, i.e, 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 jointly capture their effects as they transform into $PM_{2.5}$. Additionally, 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 also capture the effect of PM_{10}. By contrast, ozone is typically anti-correlated with the other pollutants due to how it is formed in the atmosphere.[29] In our data, the Pearson correlation coefficient between monthly $PM_{2.5}$ and ozone is -0.3. To address the concern that our effects partly capture the effect of wind on ozone and the effect of ozone on sales, we run two robustness tests. First, we show that replacing $PM_{2.5}$ exposure with a multi-pollutant air quality index that includes ozone does not affect the magnitude of the results. Second, we show that the results hold when the sample period excludes the "ozone season" where ozone is highest, i.e, between April and September (see Table B.4).

Instrument monotonicity. We test for instrument monotonicity by plotting the relationship between residualized instruments and residualized $PM_{2.5}$ exposure. Figures A.9 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. Furthermore, Figure A.11 shows the distribution of residualized predicted $PM_{2.5}$, and its relationship with residualized $PM_{2.5}$ firm-level exposure, using the entire firm-level sample. The monotonicity assumption also seems to hold with this instrument.

Potential identification threats. Recent literature points out that the two-way fixed effects model in a difference-in-differences (DID) setting could yield biased estimates when there are heterogeneous treatment effects over time or across units (De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon, 2021). However, as stated in Corollary 2 in De Chaisemartin and d'Haultfoeuille (2020), the two-way fixed effect estimates may be robust to heterogeneous treatment effects if the residualized shocks are uncorrelated with the heterogeneous treatment effects. In our context, we can assess the plausibility of this assumption by looking at whether the residualized instruments correlate with a predictor of treatment effects, such as industry, size, or average worker age.

The two-way fixed effects regression also relies upon the assumption of stable unit treatment values, which implies that there should be no spillovers between exposed and non-exposed firms. We cannot rule out *a priori* the existence of spillovers between firms. If firms exposed to high pollution shocks see their sales decline, some of their competitors might gain market shares if they

[29] Ozone results from the chemical reaction between solar radiation, nitrogen oxide and volatile organic compound (Nasa Earth Observatory, 2003). Comparing figures 1 to A.3 reveals this anti-correlation by showing the reverse seasonality of ozone vs $PM_{2.5}$ and NO_2 concentrations.

are active on the same market. However, our focus on a low-saliency temporary shock—monthly air pollution exposure—suggests that competing firms may not respond to their competitors' shocks on a month-to-month basis. Thus, the high frequency of the shocks may limit the risk of spillovers. Any spillover effect that materializes at the annual level is absorbed by firm-year fixed effects. Additionally, when firms serve the same local demand (for instance, in the business-to-consumers trade and services sector), which implies that they operate on the same market on which they face strong competition, they are also exposed to the same air pollution shocks. Hence, firms exposed to lower pollution levels within the same industries are likely to be located sufficiently far away that they would not directly compete with exposed firms, thereby also limiting the risk of spillovers.

4.4 Econometric specification for worker absenteeism

Unlike sales, we observe worker absenteeism at the establishment level, including for multi-establishment firms. Thus we assign pollution and weather shocks to establishments based on their exact location. We also expect the effect of pollution on absenteeism to be contemporaneous, rather than lagged, given the extensive literature on short-term effects of pollution on health outcomes. We model the relationship between contemporaneous pollution and worker absenteeism at the establishment level using the following equation:

$$Y_{eiyt} = \beta^A PM_{2.5gyt} + W'_{gyt}\gamma + \nu_e + \theta_{iyt} + \delta_{dq} + \epsilon_{eiyt}, \tag{10}$$

where the dependent variable Y_{eiyt} is the sickness leave outcome measured in month t in year y in establishment e operating in industry i. The parameter of interest is β^A, the coefficient on contemporaneous monthly $PM_{2.5}$ exposure for establishment e located in municipality g. Pollution exposure and control variables W_{gyt} are defined as above for each location g. As before we control for industry-by-month-by-year (θ_{iyt}) and quarter-by-county (δ_{dq}) fixed effects. Additionally, we control for establishment fixed effects, ν_e, which isolates monthly variation in pollution exposure within an establishment and absorbs any time-invariant establishment-specific characteristic. We use the same instrumental variables as described above for the case of single-establishment firms, hence we include the four wind direction instruments.

5 Main Results

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

All Sectors. Table 3 shows that lagged monthly $PM_{2.5}$ negatively affects firms' sales recorded at 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. By 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.

Column (2) shows that a one unit (1 $\mu g/m^3$) 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, i.e., a 10 percent increase in pollution exposure decreases sales by 0.40 percent on average. Table A.2 shows how the magnitude of the estimates responds to the set of fixed effects used in the specification of equation (7). The IV point estimate is consistently significant and negative across specifications. Adding quarter-by-county fixed effects reduces the magnitude of the estimates compared to only using firm-by-year and month-by-year-by-industry fixed effects.

Columns (3) and (4) of Table 3 show the point estimates from running equation (7) on the sub-sample of single-establishment firms. In this case, pollution and weather exposure is more precisely measured, as it is defined at a single location rather than averaged across locations. Hence, 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 the ones for 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—because they are working outdoors or because they breathe specific work emissions (as in construction and manufacturing activities)—could face stronger negative effects from air pollution due to the cumulative exposure or, on the contrary, could have adapted to a more polluted environment. Second, different sectors have different proportion of high-skilled versus low-skilled workers, and these different workers may have heterogeneous vulnerabilities of their cognitive skills and health conditions to pollution shocks. Third, some sectors may face strong demand effects from pollution, while others are immune to it. Indeed, business-to-consumers trade and services sector, as well as construction, often serve a local demand, resulting in their consumers

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 (7) 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 the 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 $p < 0.01$.

being exposed to the same pollution shocks as their workers. As a result, the effects from high pollution exposure may be magnified by the simultaneity of supply-side and demand-side responses to pollution shocks. By contrast, sectors that serve a demand that is not necessarily local should rarely experience these simultaneous responses. As industries tend to serve markets located in different locations, their demand-side channel will be absorbed in the industry-month-of-sample fixed effects. For instance, manufacturing and business-to-business trade and services sector are more likely to serve a demand from different regions in France and from abroad.

Table 4 shows that the heterogeneous effects of lagged monthly $PM_{2.5}$ on firm-level sales are 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) for the entire sample of firms, 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.

Column (2) shows that, with our baseline specification, a one unit increase in firm-level $PM_{2.5}$ exposure decreases firms' sales in the following two 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. Sectors directly serving final consumers tend to respond more strongly to air pollution shocks than production sectors, such as manufacturing or construction. These results imply that a 10 percent increase in pollution exposure in the previous month decreases firms' sales in the following two 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. Column (4) shows that, when we run the analysis on the sub-sample of single-establishment firms using the four wind IV instruments, the point estimates have similar magnitudes, but are 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 exhibit higher vulnerability to environmental shocks by comparing the effect of air pollution on firms' sales for firms with 25 employees or less to the effect on firms with more than 25 employees.[30] We consider the average number of employees by firm over the entire period. Table A.3 shows that firms with fewer than 25 employees are the most affected, overall and across all sectors. By contrast, we cannot reject that large firms suffer no significant sales losses from pollution exposure, except in the business-to-consumer trade and services sector. These results suggest that large firms may employ adaptation strategies (such as reallocating tasks among employees as in Adhvaryu et al. (2022) or flexibly adjusting working hours) to reduce the adverse effect of pollution effects on their sales.

Economic benefits of reducing air pollution. These impacts represent substantial losses to economic production in months with high levels of pollution. To illustrate, we provide back-of-the-envelope calculations 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 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, which represents a 25% decrease relative to the average levels observed over 2009-2015. Based on our main estimates, this decrease in pollution could have avoided 27 billion euros of foregone sales annually on average for the period 2009-2015, which is equivalent to 1.5% of average total sales in the French private sector. Taking the average value added over sales ratio of 27% from French private sector firms' accounting data in 2015,[31] this translates into 7.3 billion euros of foregone value added in the short-term, with the caveats related to averaging across sectors, and ignoring long-term effects or potential general equilibrium effects.

[30] In our sample, the median number of employees in manufacturing firms is 25, while the median number of employees across all four sectors is 12. We consider the threshold of 25 employees as it lies between the definition of micro-enterprises (less than 10 employees) and the definition of small-and-medium enterprises (less than 50 employees).

[31] Data aggregated by sector are available here: https://www.insee.fr/fr/statistiques/3136821?sommaire=3136881.

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 (7) 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 $p < 0.01$.

To provide a comparison with the costs of bringing $PM_{2.5}$ to this WHO threshold, we follow Dechezleprêtre et al. (2019)'s approach that uses the cost of reducing $PM_{2.5}$ emissions—rather than concentrations—obtained from a report published by the European Commission for a scenario with 33% emissions reductions (option 6D). Hence, it would cost €7.7 billions in annualised investments required for pollution abatement equipments and associated maintenance costs.[32] Although the costs are not precisely estimated, comparing them with our estimates of foregone sales or value-added provides suggestive evidence that the economic gains from meeting the WHO targets might be on par with the potential costs of doing so.

To better understand the magnitude of these benefits, we also compare them to the annual mortality benefits associated with a 25% decrease in pollution. To do so, we extrapolate from Deryugina et al. (2019)'s estimates of the short-term effects of PM2.5 on mortality among the elderly based on US data. Using the French Value of a Statistical Life Year (VSLY) of €115,000 in 2010, we estimate that each unit decrease in PM2.5 generates €1.6 billions in mortality reduction benefits in France.[33] For our scenario bringing each day above the threshold to 15µg/m^3 over our sample period, the annual benefits are worth €6.1 billions. Therefore the economic benefits that we estimated above have the same order of magnitude as mortality reduction benefits.

5.2 Dynamic Effects on Sales

Given the granularity of our data, 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.

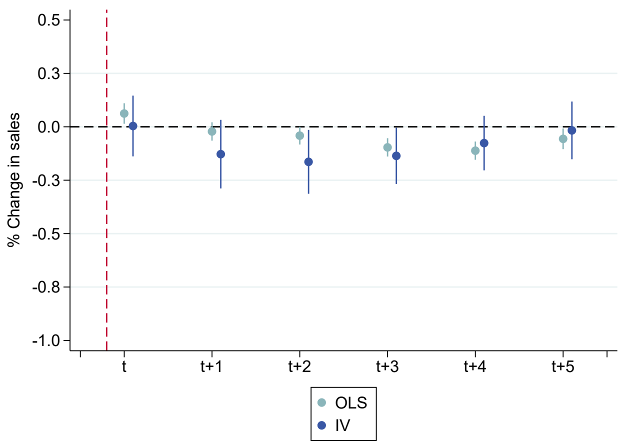
We examine in a single regression the effects of pollution at t, $t-1$,... up to $t-5$ on sales at t by sector, assuming a cubic polynomial functional form on the coefficients β_l, for $l \in \{0, .., 5\}$: $\beta_l = \sum_{k=0}^{3} \gamma_k l^k$. For example, $\beta_0 = \gamma_0$, $\beta_1 = \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$, 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.

Figure 4 shows the estimates for β_0 with label t, β_1 with label $t+1$, up to β_5 with label $t+5$. The OLS estimates are often positive for the contemporaneous month of exposure, non statistically different from zero in the following two months, and eventually become negative for

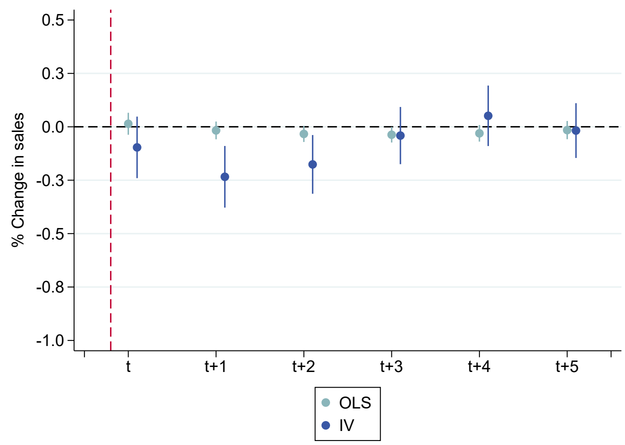
[32]See https://ec.europa.eu/environment/archives/air/pdf/Impact_assessment_en.pdf The estimated cost can be found in part 3, page 43.

[33]This is calculated using Deryugina et al. (2019)' point estimate of a 2.991 increase in life-years per million 65+ elderly for each unit-decrease in daily PM2.5, assuming the annual effects scale linearly, converting the VSLY to 2013 euros, and considering that France had 11.7 million 65+ individuals in 2013.

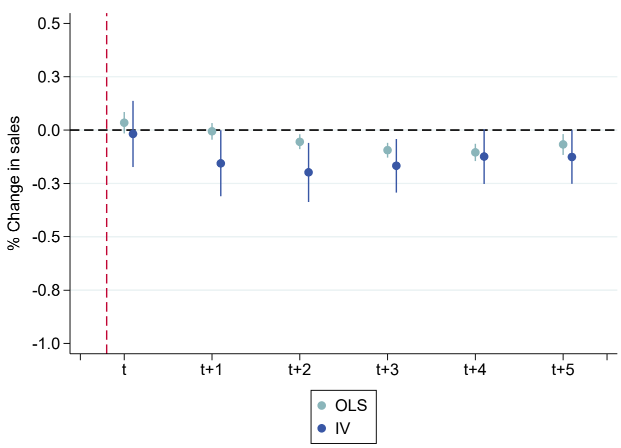
some sectors afterwards before returning to zero after 5 months. The IV point estimates at $t+1$ are generally larger than the main results described above, in particular for construction. But the relative effects across sectors remain the same, with orders of magnitude twice to thrice as large for the business-to-consumer trade and services sector compared to the rest. Focusing on the IV estimates, these dynamic effects 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 sub-sample of single-establishment firms, which are very similar to the results for the whole sample.



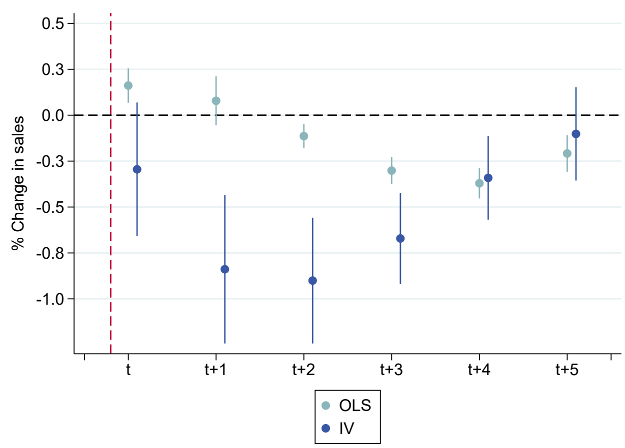
(a) Manufacturing



(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 assess the validity of the identifications assumptions and the robustness of our main results. First, we run a falsification test using future pollution exposure to rule out that our effect is driven by a spurious correlation. Second, we consider 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 avoidance behaviors that they may induce. Finally, we verify the robustness of our results to the specification of weather variables, to outliers, and to the source of pollution information using monitoring stations data.

Falsification test. Since future air pollution shocks should have no effect on current sales, we run a placebo test that evaluates the effect of pollution exposure at time $t+2$ on sales at time t, while including controls for the period t to $t+2$. Table 5 shows the results, which are small and insignificant for all sectors and for most sectors. 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 (7) 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 with all firms using our main specification as reported in column (2) of Table 3. In columns (2) and (3), we assess the risk of violation of the exclusion restriction due to ozone acting as an omitted variable in the instrumented regression. We expect that if ozone exposure also decreases sales, omitting ozone exposure is likely to bias our estimate downward, since a wind direction that increases $PM_{2.5}$ generally decreases ozone. In this case, we expect to replacing $PM_{2.5}$ with a multi-pollutant index as the endogenous variable will induce a larger effect size than our main estimate. Conversely, if ozone has no measurable effect on sales, 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, which has little effect on sales.

We build a synthetic air quality index similar to the regulatory index used in France at the daily level and take its monthly average for each municipality. Although the index is based on 6 pollutants, its variation is mostly driven by $PM_{2.5}$ in Fall and Winter months and by ozone in Spring and Summer months.[34] 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 $PM_{2.5}$ (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 anti-correlated only in Winter months (both with and without controlling for weather and fixed effects), not in Summer months (where the raw correlation is positive and the correlation after partialling out weather and fixed effects is close to 0), to build another test, conditioning on Winter months. 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, column (3) shows a very similar point estimate as the main result. Hence, these two tests make us confident that even if 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 PM2.5-sales relationship.

The role of air quality alerts. In column (4), we discard observations subject to a PM_{10} air quality alert, ensuring 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} and there is a high correlation between PM_{10} and $PM_{2.5}$. We use the regulatory thresholds for the issuance of PM_{10} alerts.[35] For each municipality-month we build a variable corresponding to the

[34]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.

[35]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

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, weather controls, and clustering. In column (5), we winsorize sales from the 2nd percentile and 98th percentile of the monthly sales distribution. The result is very close to our baseline coefficient. In column (6), 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 main estimate is conservative. In column (7), we cluster standard errors two ways at the firm and month-by-year level, to account for the potential correlation in the error term across observations of the same month of sample. While the effect of pollution on sales becomes less precisely estimated, it remains significant at the 5% level.

Reanalysis $PM_{2.5}$ data versus $PM_{2.5}$ data from monitors. Columns (8) and (9) of Table 6 compare the main estimate using reanalysis data with a measure of $PM_{2.5}$ exposure entirely based on observations from monitoring stations for the shorter period 2011-2015. Using monitoring station data, we can rule out that the strength of the first stage linking wind directions and $PM_{2.5}$ could be partly driven by the use of weather variables as inputs in the chemistry transport model used to produce the reanalysis data. Following the literature, we build a municipality-level measure of $PM_{2.5}$ equal to 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 the inverse distance between the centroid of the municipality and each monitor as weights. Due to availability constraints of $PM_{2.5}$ monitor-level data, we restrict the sample to the 2011-2015 period.[36] 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 (9), we find a point estimate similar to the one based on $PM_{2.5}$ reanalysis data (column 8).

France, Paris, air pollution alerts for PM_{10}—which involve recommendations from the health authorities targeting the most vulnerable individuals—were issued on 4% of the days in our study period. More severe alerts involving restrictions in car traffic were issued on 0.7% of the days only.

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

Table 6: Robustness checks for the effect of lagged $PM_{2.5}$ on contemporaneous firm-level sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
	Baseline	AQI	Winter months	No alerts	Winsorized outcome	Other weather	Two-way clustering	Shorter period	PM2.5 monitors
$PM_{2.5t-1}$	-0.259***		-0.346***	-0.272***	-0.270***	-0.424***	-0.259**	-0.304***	-0.292***
	(0.0264)		(0.0501)	(0.0298)	(0.0262)	(0.0280)	(0.105)	(0.0310)	(0.0294)
AQI_{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	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 (7) 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 $p < 0.01$.

6 Identifying Channels

The temporary decline in sales following a month of high $PM_{2.5}$ levels may result from several mechanisms outlined in our analytical framework: increased worker absenteeism, decreased worker productivity, and reduced demand. In this section, we examine these potential channels in detail.

6.1 Pollution-induced sickness absenteeism

Table 7 reports the main OLS and IV estimates of the effect of $PM_{2.5}$ on sickness leave outcomes, for the sample of workers whose firm is included in our sales data. Columns (1) and (2) report the estimates based on equation (10). 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, with a 0.15 increase, which is consistent with the OLS estimate being downward biased due to omitted variable and attenuation bias from classical measurement error. All the estimates are highly statistically significant. 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 aggregated at the municipality level, replacing establishment fixed effects and industry-by-month-by-year fixed effects with municipality fixed effects and month-by-year fixed effects. The estimates are very similar. Figure A.13 shows the dynamic effects using the same Polynomial Distributed Lag specification as for the sales outcome. The effect of air pollution at t on sick leaves is concentrated on the contemporaneous month of exposure and quickly decreases back to zero two months later.

Table 7: The effect of $PM_{2.5}$ on the contemporaneous number of workers entering a sick leave (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 (10) 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 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 (i.e., the entire Hygie dataset). Figure A.15 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.

Appendix B contains the same set of robustness checks for absenteeism as for the sales outcome. Table B.4 shows that 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.

Can the pollution-induced reduction in labor supply due to sick leave account for the observed decline in sales? Analyzing sectoral heterogeneity suggests that worker absenteeism is not the sole mechanism at play. Figure 5 shows the heterogeneous absenteeism responses 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 in the consumer-and business-oriented trade and services sectors. Comparing table 4 and figure 5 reveals that there is little 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—respectively, manufacturing and business-to-business trade and 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 decrease in sales, since for at least one sector—business-to-business trade and services—the absenteeism effect is zero.

Interpreting these sectoral differences in absenteeism due to pollution is challenging. They do not necessarily indicate varying levels of worker vulnerability to air pollution. Yet, higher absenteeism rates are observed in sectors with greater exposure to pollution, such as manufacturing and construction. Instead, they may reflect differences in the capacity to work remotely or take leave without a medical certificate, given the same pollution-related health impact. Additionally, the cost of sick leave may vary across sectors, as employer-funded sickness benefits are often shaped by industry-specific collective agreements.

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 in our sample. 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 air pollution increases absenteeism the most, sales losses caused by this absenteeism channel represent only 18% of total sales losses due to pollution.

These back-of-the-envelope calculations provide suggestive evidence that pollution-induced worker absenteeism may not be the only or even the main channel through which air pollution decreases firms' sales. However, these calculations do not take into account the insight from the analytical framework, which is that the magnitude of each channel depends not only on how absenteeism, worker productivity, and demand respond to air pollution shocks, but also on the demand elasticities. In sectors with high elasticity and low profit margins, even a minor increase in absenteeism can have a substantial impact on sales. For example, when service quality declines due to a reduced workforce in retail establishments or restaurants, dissatisfied consumers are likely to seek alternatives more quickly. Conversely, sectors with lower elasticity and higher profit margins may be less susceptible to such consumer volatility.

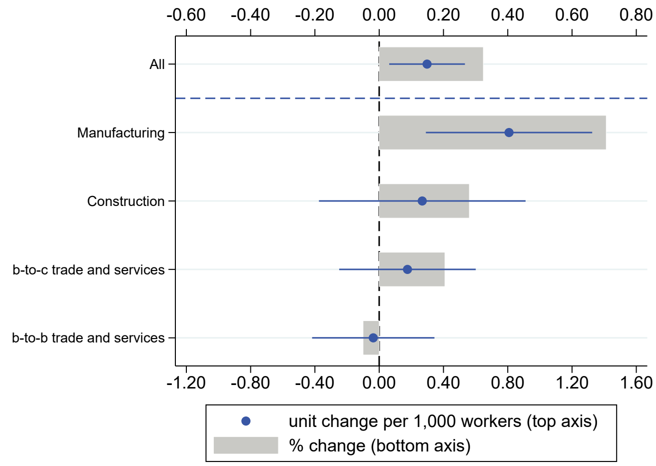


Figure 5: Contemporaneous effect of a one-unit increase in $PM_{2.5}$ on sick leave episodes

6.2 The role of productivity and demand

Productivity. Using monthly VAT data, we are unable to directly measure the productivity channel. Instead, we present suggestive evidence that pollution affects worker productivity by examining heterogeneous effects across industries within the manufacturing sector. We categorize industries based on whether their stock levels are above or below the median, utilizing a survey of manufacturing plants conducted in 2004.[37] Assuming that stock levels are orthogonal to pollution-induced worker absenteeism, we anticipate that firms with low stock levels will experience a greater decline in sales due to pollution shocks than those with high stock levels. This is because firms with ample stock can buffer production shocks by drawing on existing inventory, whereas firms with low stock levels lack this flexibility and are more vulnerable to sales decreases.

Columns (1)-(3) in panel A of Table 8 show that the decrease in sales is primarily driven by firms in industries with low stock levels, while the impact on firms with high stock levels is negligible. Additionally, Columns (4)-(6) reveal that both types of firms experience a similar rise in worker absenteeism. The average sales and employee numbers are relatively comparable across the two groups, suggesting that variations in vulnerability to air pollution by firm size do not account for the differences in sales response magnitude. Overall, this heterogeneity based on stock levels implies that air pollution affects sales, at least in part, by influencing worker productivity.

[37]Stock level information comes from a 2004 survey on 2,058 manufacturing establishments and is measured in days of production. 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 equipment 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.

Demand. We anticipate that demand responses will be more pronounced in the consumer retail and services sector, where demand is primarily local. Table 4 shows that the effect of $PM_{2.5}$ on sales is indeed larger in this sector. This larger magnitude suggests that consumers experiencing pollution-related health issues may be inclined to avoid shopping. If this demand effect is significant, we would expect industries selling discretionary goods, such as furniture and clothing, to be more adversely affected than those selling essential goods like groceries, for which forgoing consumption is less feasible. Columns (1)-(3) in panel B of Table 8 indicate that pollution reduces sales slightly more for firms selling discretionary items than for those selling staples. However, we cannot statistically reject that the effects are the same. Firms selling staples tend to be larger than those selling discretionary items, and previous results show that large firms experience less sales losses from pollution exposure. Overall, our results suggest a negative impact of air pollution on consumer demand, particularly in certain industries.

Table 8: Productivity and Demand Channels

	Sales effect			Absenteeism effect		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Manufacturing, Heterogeneity by Stock Level						
	All firms	Low stock	High stock	All firms	Low stock	High stock
$PM_{2.5t-1}$	-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
Panel B: Business-to-Consumer Trade and Services Sector, Staples vs Discretionary Goods						
	All firms	Discretionary	Staples	All firms	Discretionary	Staples
$PM_{2.5t-1}$	-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 (7) for manufacturing firms in panel A and for business-to-consumer trade and services firms in panel B. 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, controlling for weather and holidays controls at 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 $p < 0.01$.

7 Conclusion

This paper investigates the impact of increased firm-level exposure to fine particulate matter on economic performance in the French private sector. The analysis demonstrates that higher pollution levels lead to a decline in firm sales within the subsequent two months, with an estimated average elasticity of sales to pollution of -0.04. Three key mechanisms driving these effects are identified. First, worker exposure to air pollution increases sickness-related absenteeism, with an elasticity of 0.1. Second, a reduction in worker productivity induces output reductions, especially for manufacturing firms with low levels of stock. Third, sectors serving primarily a local demand experience more pronounced sales decreases following episodes of high levels of pollution. Overall, the economic costs associated with these pollution-induced sales losses significantly exceed those linked to absenteeism, when the latter is 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 links higher density to higher 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.

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Appendix

A Additional Figures and Tables

A.1 Figures

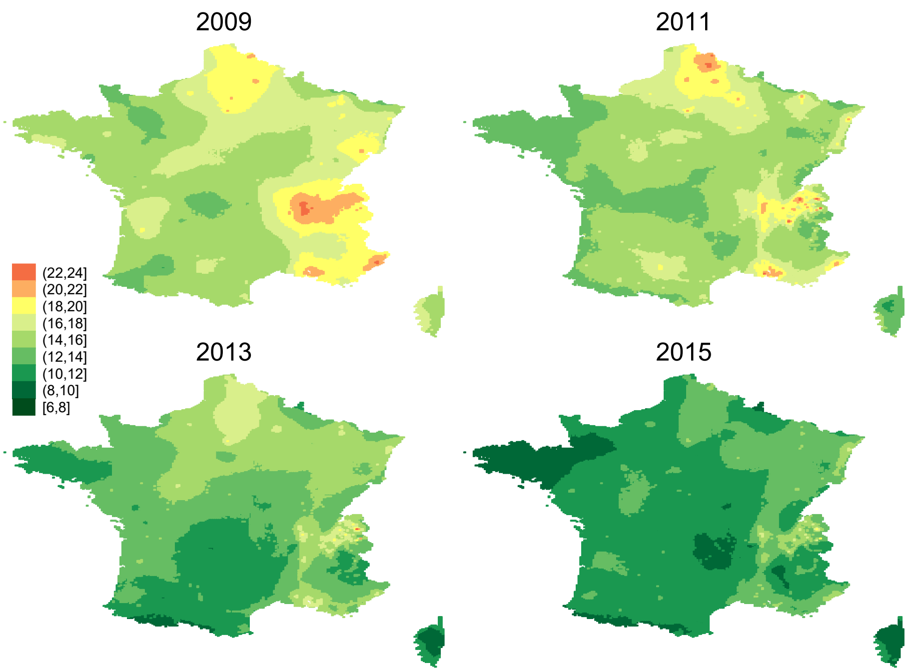
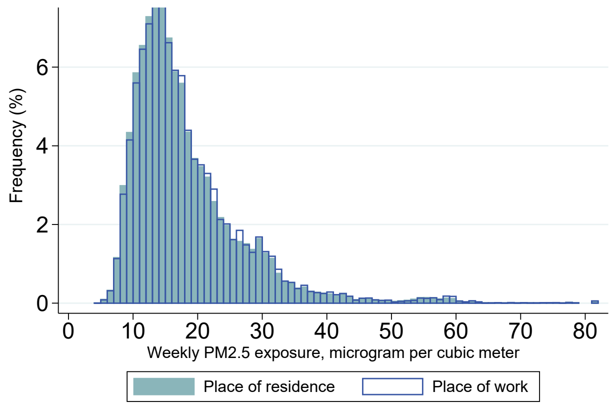
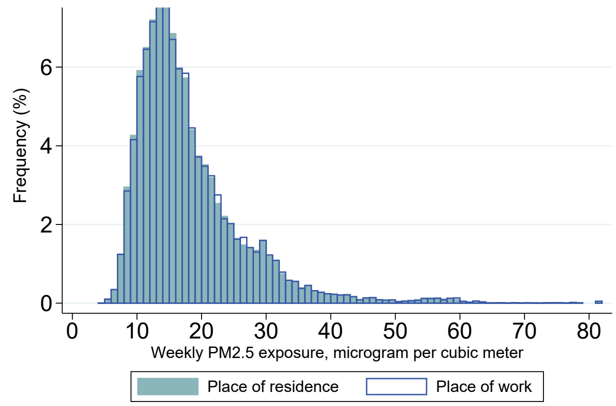


Figure A.1: Average annual concentrations of $PM_{2.5}$ (µg/m^3)

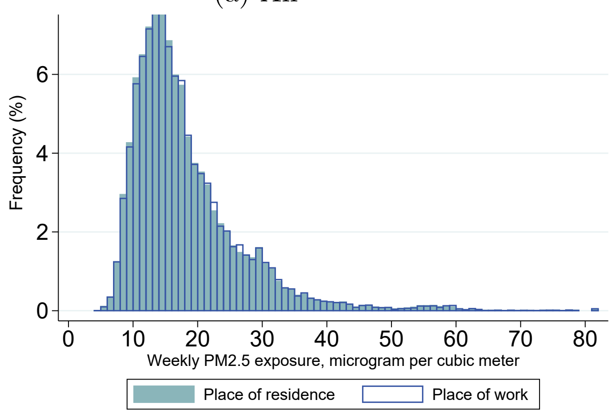
Notes: Figure shows the average annual concentration of $PM_{2.5}$ measured at the 4km x 4 km grid cell level using the reanalysis CHIMERE data, for selected years. There are 33,252 Chimere grid cells in metropolitan France.



(a) All



(b) Q1



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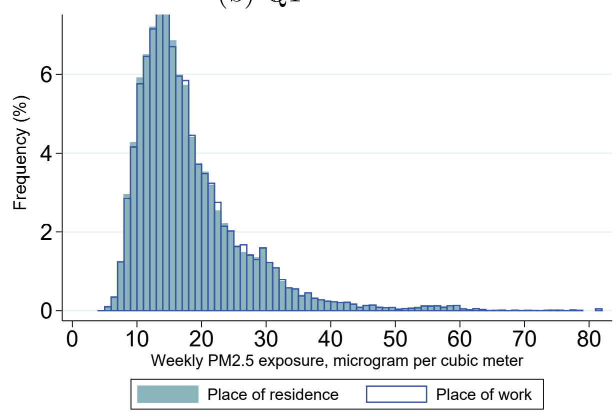
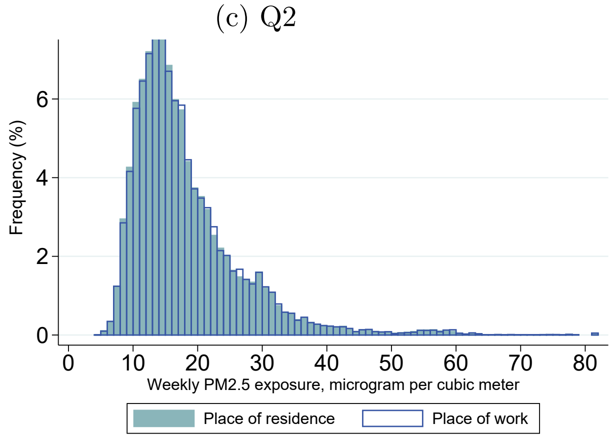
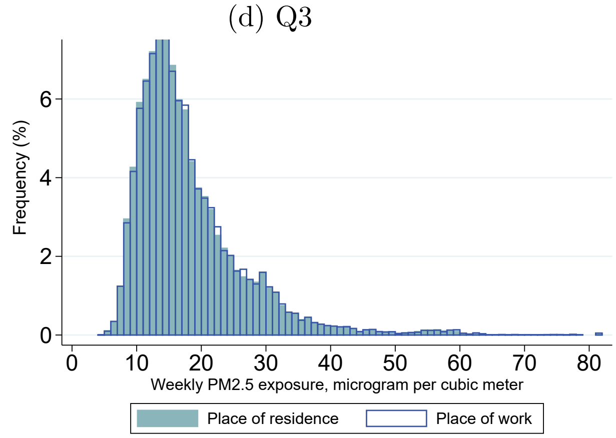


(d) Q3



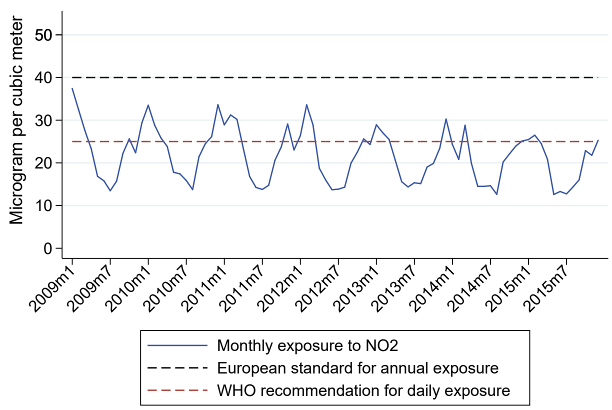
(e) Q4



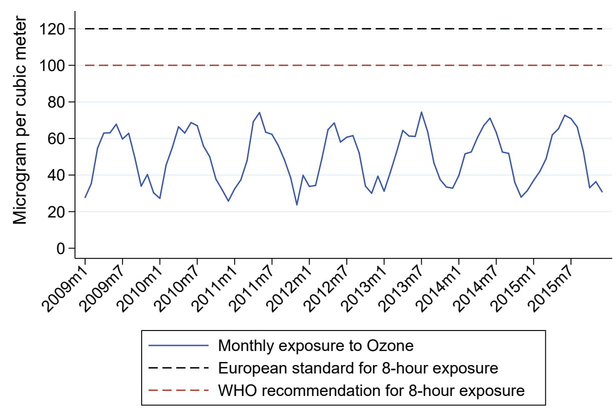
(f) Q5

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.



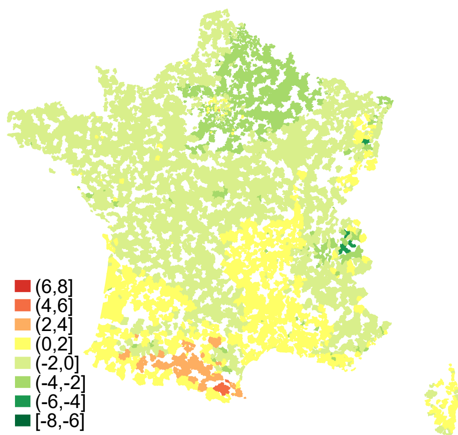
(a) NO_2



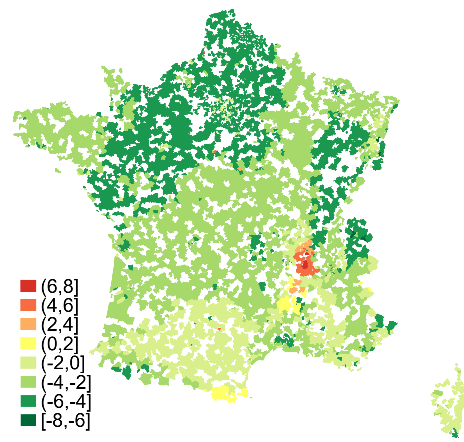
(b) Ozone

Figure A.3: Average monthly exposure to other pollutants

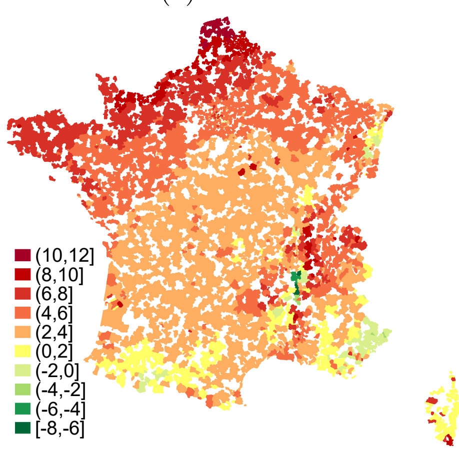
Notes: Figure presents the monthly average of workers' exposure to $PM_{2.5}$ measured at workers' municipalities. The sample of workers is the one used for the analysis of pollution effects on sickness leaves described in section 3 (unbalanced panel, N≈450,000). For NO_2, the European standard for annual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



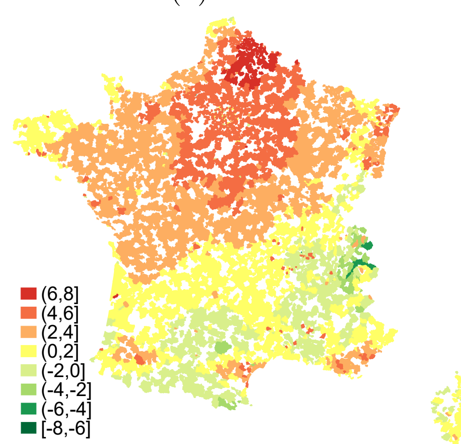
(a) South wind



(b) West wind



(c) East wind



(d) North wind

Figure A.4: 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.

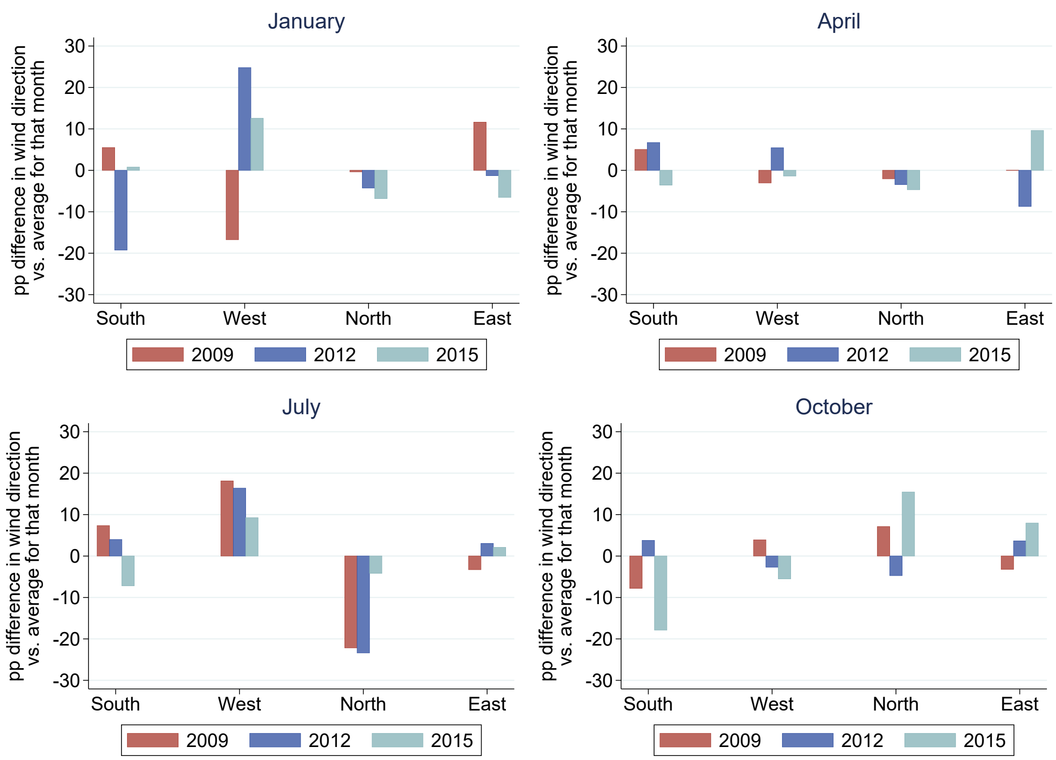


Figure A.5: Within-calendar month variation in wind direction, Paris

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).

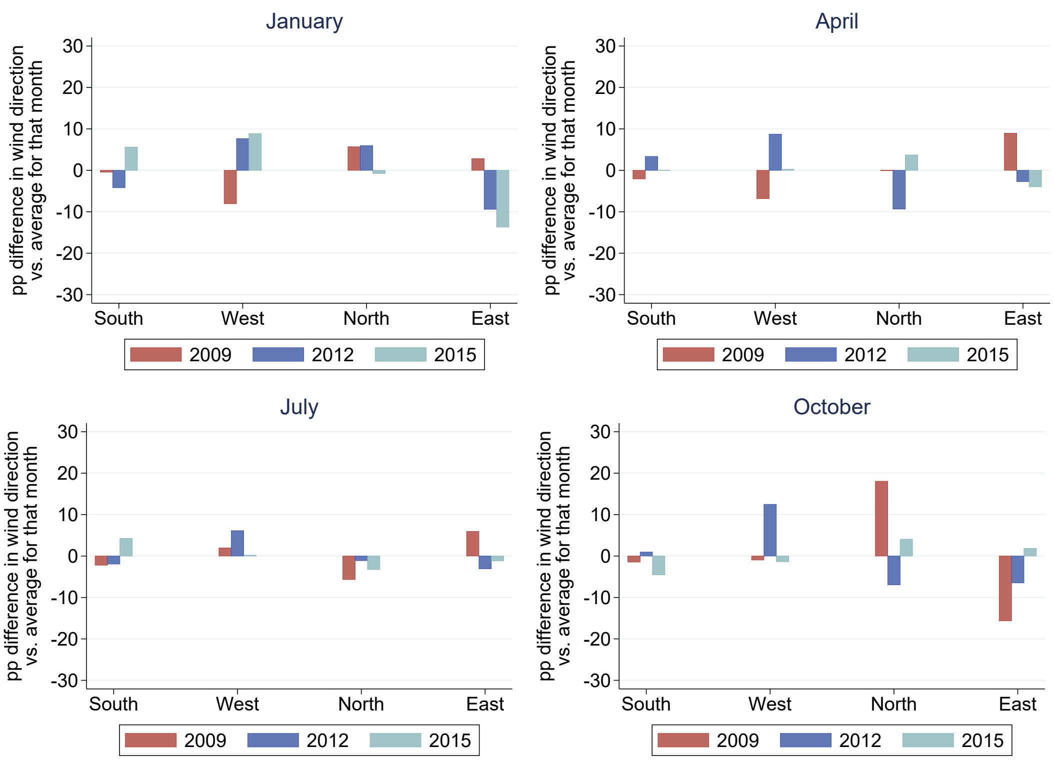
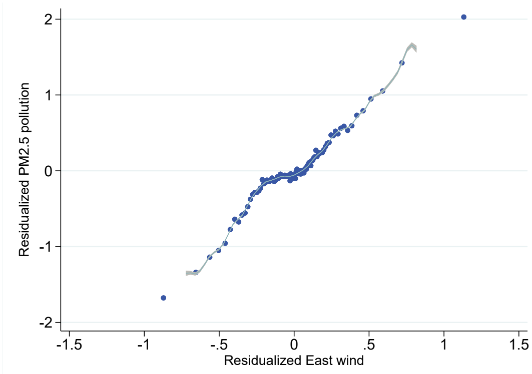
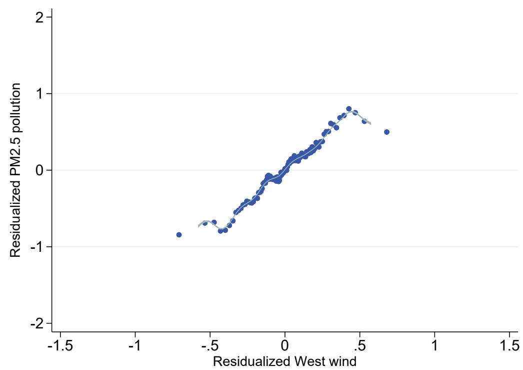


Figure A.7: Within-calendar month variation in wind direction, Marseille (South-East of France)

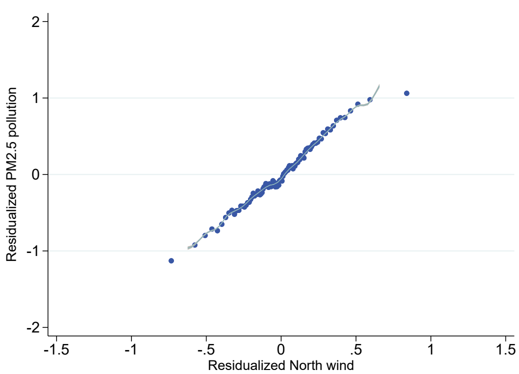
Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, demeaned by the average for the month, for four different months (Month 3=March, Month 6=June, Month 9=September, Month 12=December and three different years (2009, 2012, 2015).



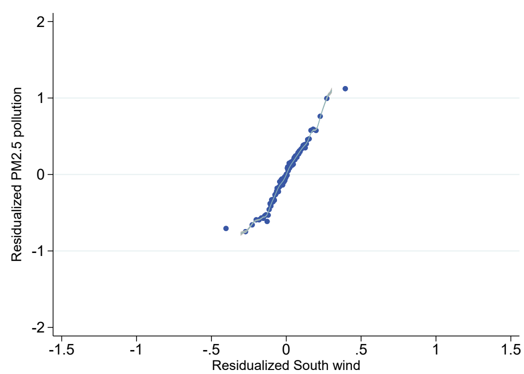
(a) East wind



(b) West wind



(c) North wind



(d) South wind

Figure A.9: 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).

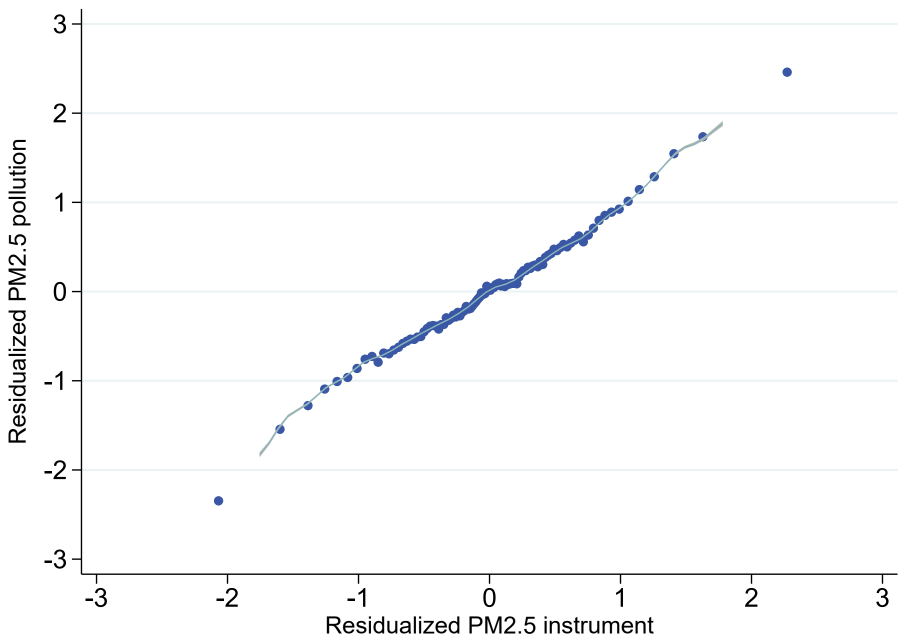
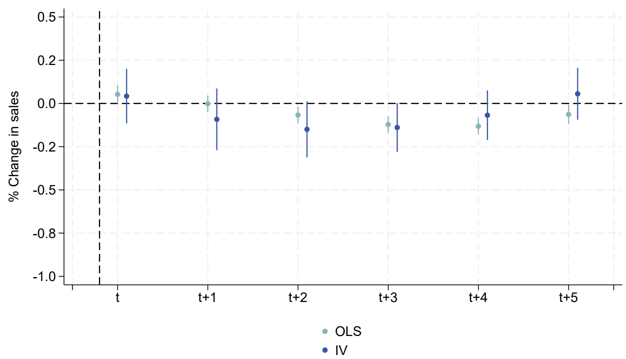
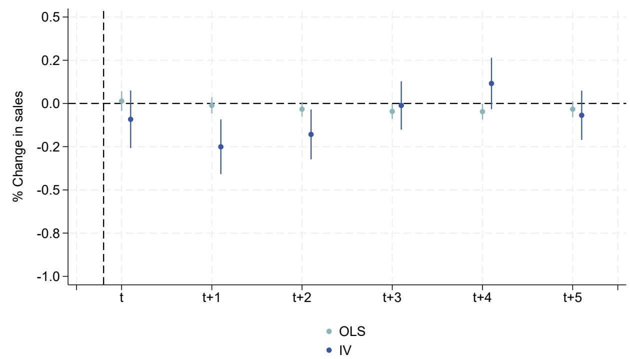


Figure A.11: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

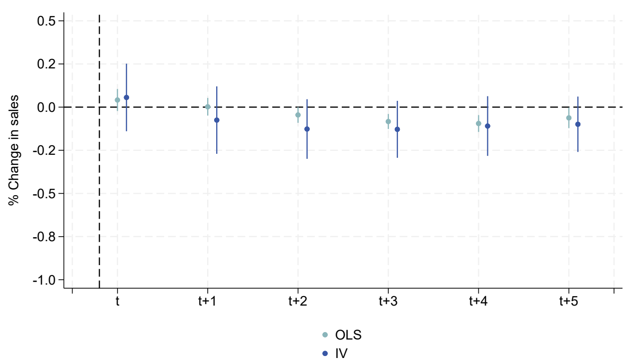
Notes: Figure is based on the sample of all firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing the predicted $PM_{2.5}$ variable $\widehat{PM_{2.5}}_{gyt}$ (resp. the endogeneous $PM_{2.5}$ variable on the right-hand side variables of equation 9: weather and holiday controls, 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).



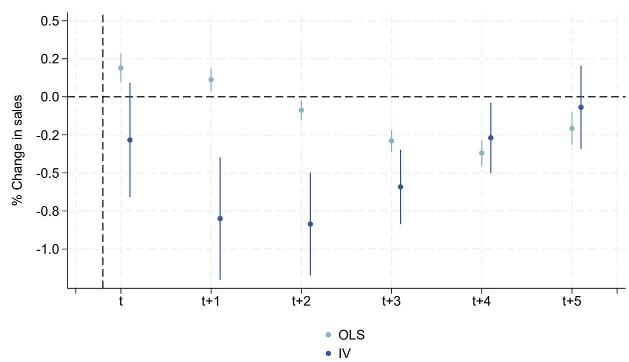
(a) Manufacturing



(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.

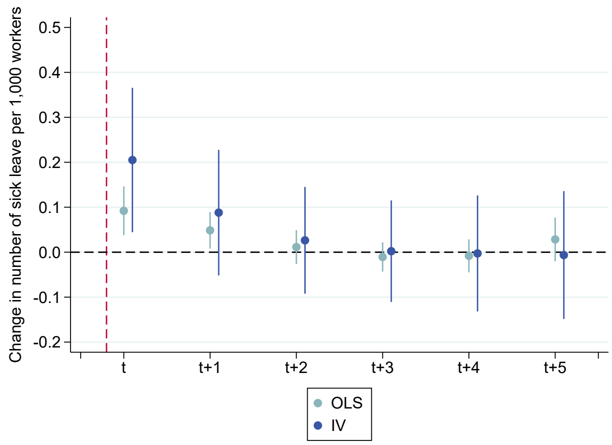


Figure A.13: Dynamic effects of $PM_{2.5}$ on absenteeism

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 $t-5$) on the number of workers entering sick leave at t per 1,000 workers, using the polynomial distributed lag method. All regressions include month-by-year-by-industry fixed effects, establishment 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.

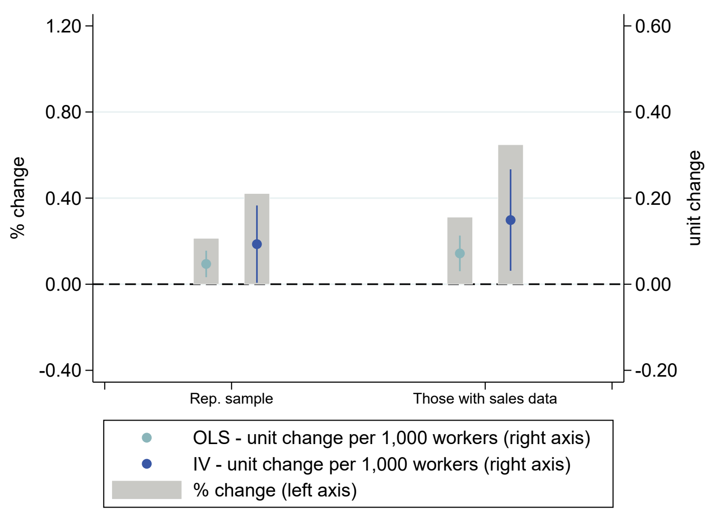


Figure A.15: Absenteeism results for the sample of workers employed at firms included in our firm sample, compared to the representative sample of workers included in the absenteeism dataset

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

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (7) 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

	(1) Below 25 workers	(2) Above 25 workers
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 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 (7) 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 $p < 0.01$.

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.4 shows the baseline estimate for the specification at the establishment level (same as column (2) of table 7). 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.4: The Effect of $PM_{2.5}$ on worker absenteeism, all sectors, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	AQI	No PM_{10} alert	Winsorized outcome	continuous weather	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 (10) 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.16 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,[38] 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

[38]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.

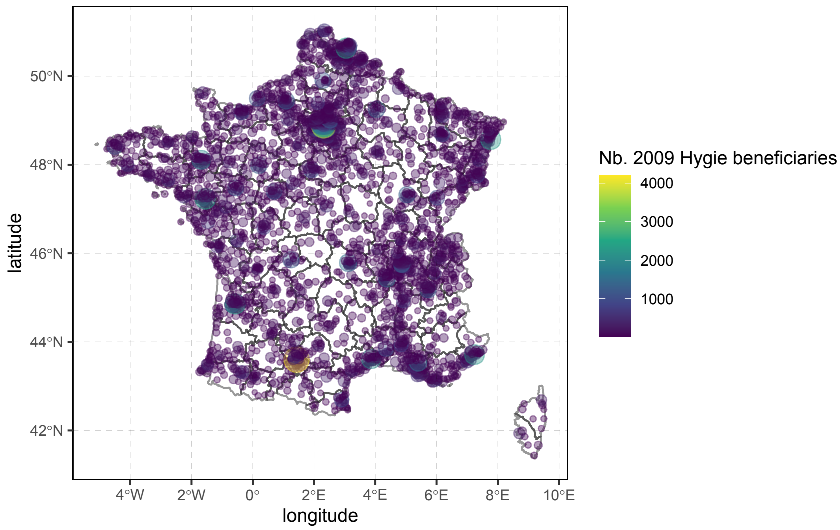
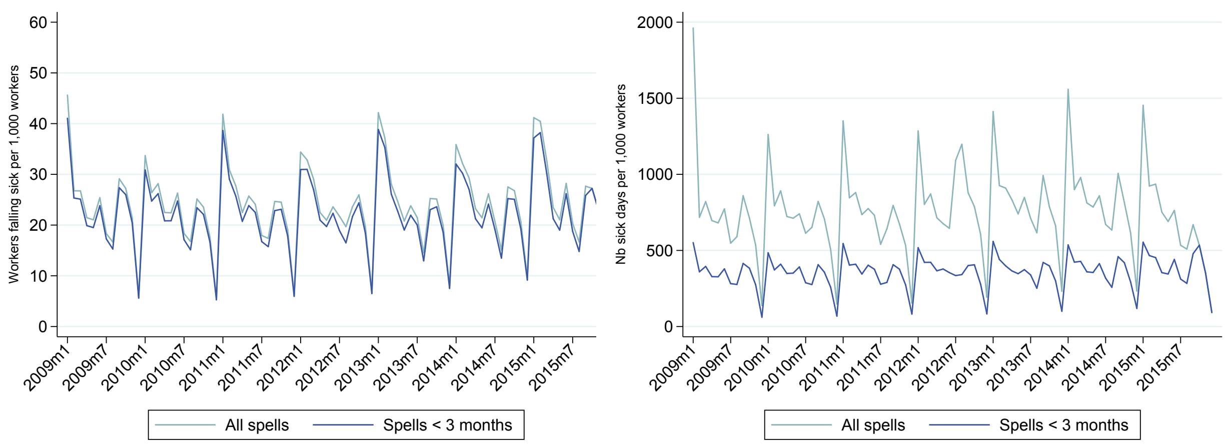


Figure C.16: Location of workers from the Hygie dataset based on the workplace municipality, in 2009

sector employees in France took at least one sick leave during 2013.[39]

We



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

Figure C.17: 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.

[39]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.[40] 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.[41] 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.

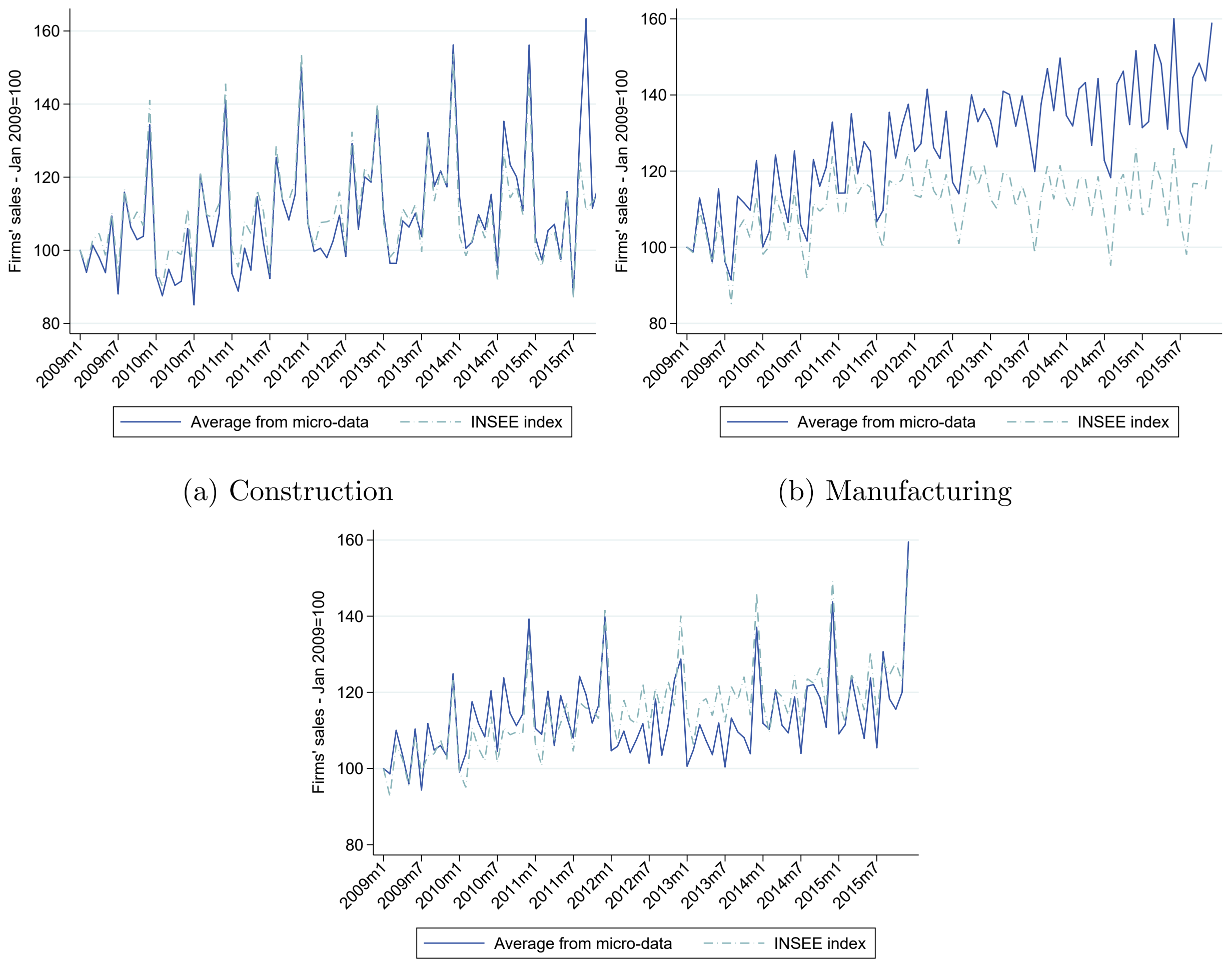
We determine sectors of activity based on the sectoral classification available at the establishment level and we use the mode of sector categories across establishments for multi-establishment firms. We define 4 sectors of interest: manufacturing, construction, business-to-consumer trade and services, 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.18c shows

[40] 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

[41] 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.18a), manufacturing (C.18b) and all services (C.18c) 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.18: 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.