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The Cost of Air Pollution for Workers and Firms*

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Abstract

This paper shows that even moderate air pollution levels, such as those in Europe, harm the economy by reducing firm performance. Using monthly firm-level data from France, we estimate the causal impact of fine particulate matter ($PM_{2.5}$) on sales and worker absenteeism. Leveraging exogenous pollution shocks from local wind direction changes, we find that a 10 percent increase in monthly $PM_{2.5}$ exposure reduces firm sales by 0.4 percent on average over the next two months, with sector-specific variation. Simultaneously, sick leave rises by 1 percent. However, this labor supply reduction explains only a small part of the sales decline. Our evidence suggests that air pollution also reduces worker productivity and dampens local demand. Aligning air quality with WHO guidelines would yield economic benefits on par with the costs of regulation or the health benefits from reduced mortality.

Keywords: Cost of air pollution, Absenteeism, Firm performance
JEL codes: Q53, I1, J22

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1 Introduction

It is widely acknowledged that air pollution has detrimental effects on human health. Air pollution exposure causes higher medical expenditures (Barwick et al., 2024), emergency admissions and mortality (Schlenker and Walker, 2016; Deryugina et al., 2019). Cognitive performance and mental health may also be impaired (Aguilar-Gomez et al., 2022; Bruyneel et al., 2022). These large health costs directly affect the utility of many individuals and are sufficient to justify public intervention. Yet, there might be even wider economic costs if air pollution's impacts on individuals translate into substantial production losses for firms. Although 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.

In this paper, we estimate the causal effects of monthly air pollution exposure on firms' monthly sales in France, a country with moderate pollution levels representative of Western Europe. We use confidential micro-level 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 nonabsent workers' productivity, either because they suffer from mild health symptoms or because their work is disrupted by the absence of co-workers who took a sick leave. Finally, it can reduce demand if local consumers, also exposed to the same 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 three channels with different degrees of precision.

We assemble a unique data set that combines the monthly sales of 160,000 firms, granular measures of air pollution and weather conditions at the municipality level, as well as sick 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, as well as cognitive skills.[1] Particulate pollution can also easily penetrate indoors and affect air quality at the workplace. Two key challenges with identifying the causal effects of pollution 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.[2] To circumvent these challenges, our analysis leverages variation in

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

[2]In an ideal setting, pollution exposure would be measured by multiplying pollution levels from each

air pollution induced by changes in monthly wind directions at the municipality level—there are 6,048 municipalities in metropolitan France.

We use the insight from previous work (Deryugina et al., 2019; Graff Zivin et al., 2023) to build our instrumental variable (IV) based on the changes in each municipality's monthly wind direction. After flexibly controlling for sectoral trends, weather variables, and firm-year characteristics, we rely on the assumption that changes in monthly exposure to cardinal wind directions at the municipality level 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 municipality nor imposes the same relationship between specific wind directions and pollution in groups of municipalities. For firms owing establishments in multiple municipalities (36% of the firms in our sample), 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 their intrafirm network and the location of each 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 sick leave episodes. Using social security data, we identify the exact workplace of each private sector employee, which allows us to link sick leave information to the employing firm's sales.

For the other two channels, productivity and demand, we identify their potential roles by comparing heterogeneous responses by sector for overall sales and sick leave. Furthermore, we exploit industry heterogeneity in stock levels within manufacturing to assess whether short-term pollution shocks primarily affect the demand side or the supply side in this sector. We also examine the role of local consumer demand by comparing the response of the retail sector across staples (i.e., essential goods like food) and discretionary goods (such as furniture and clothing) where consumption can be more easily postponed or foregone altogether.

Our study provides evidence that firm-level exposure to $PM_{2.5}$ has widespread negative effects on sales. Our estimates imply 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 ($p < 0.002$). 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. The negative effects on sales last for about two to three months after the pollution shock, and the effect dies down after five months, without rebound. These results

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 in the municipality of the workplace, where workers spend most of their waking hours.

are robust to restricting our sample to only single-establishment firms, for which pollution exposure is measured more accurately. Furthermore, they are not driven by restrictions imposed during air quality alerts and are robust to substituting a multi-pollutant air quality index for $PM_{2.5}$, winsorizing the outcome variable, and relying either exclusively on data from monitoring stations or on satellite-based data .

We then examine the mechanisms that could explain this pollution-induced decrease in sales. First, we observe a reduction in labor supply due to an increase in sick leave. Our estimates imply that a 10 percent increase in monthly $PM_{2.5}$ exposure increases sick leave episodes by 1 percent within the month of exposure ($p = 0.015$). The effect of air pollution on work absenteeism lasts just one month and is also heterogeneous across economic sectors: it is strong in manufacturing ($p < 0.01$), whereas we cannot rule out a null effect in the other sectors. These heterogeneous effects on work absenteeism do not align with the heterogeneous effects on sales, indicating that the labor supply decrease due to sick leave cannot explain the decline in sales. 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 sales losses.

Second, we show that air pollution shocks disrupt the supply side not only by increasing worker absenteeism, but also by reducing the productivity of nonabsent workers, particularly in manufacturing. Firms with large stock levels can buffer temporary supply-side shocks by drawing on inventory, mitigating the impact on their sales. In contrast, large stocks do not protect against demand-side shocks. Thus, comparing industries with high versus low stock levels helps distinguish between supply- and demand-side effects. Our findings reveal that the impact of air pollution on manufacturing sales is concentrated among firms with low stock levels. Despite experiencing similar increases in sick leave and having comparable average sizes, these firms are disproportionately affected. This underscores that air pollution shocks primarily disrupt the supply side in manufacturing.

Third, we find suggestive evidence that air pollution also acts as a demand-side shock. Since we measure pollution exposure at firms' location, we can examine demand effects only for local consumers, who are affected by the same pollution shock as workers. In the business-to-consumer retail and services sector, which predominantly serves local demand, we observe the largest sales decline. To investigate whether this stems from demand-side responses, we compare industries selling staples, where consumption is less deferrable, to those selling discretionary goods. The sales impact is slightly larger for discretionary goods, though the difference is not statistically significant. Assuming similar productivity drops across industries, these findings point to a role for the demand channel.

Finally, we underscore the economic significance of air pollution's impact on sales. Aligning with the WHO guideline of limiting daily $PM_{2.5}$ exposure to 15 µg/m^3 would require a 25% reduction in pollution levels in our sample. Our estimates suggest this improvement would have prevented €27 billion in annual sales losses (1.5% of total private sector sales) from 2009 to 2015. With an average value-added-to-sales ratio of 27%, this corresponds to €7.3 billion in short-term foregone value added. For comparison, U.S.-based estimates of the short-term mortality benefits for the elderly of a similar $PM_{2.5}$ reduction would be placed at €6.6 billion, showing that economic gains rival the widely emphasized mortality benefits. Furthermore, reducing $PM_{2.5}$ emissions by 33% has been estimated to approximately cost €7.7 billion annually in France. While this simplified comparison excludes broader health benefits, general equilibrium effects, and long-term impacts, it suggests that meeting WHO standards could deliver economic benefits in value added comparable to regulatory costs.

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 air pollution affects workers, in terms of productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lichter et al., 2017; He et al., 2019; Chang et al., 2019; Adhvaryu et al., 2022; Meyer and Pagel, 2024) and decision-making (Dong et al., 2019; Meyer and Pagel, 2024), is largely based on specific settings of one or two firms, where workers are paid by the hour or productivity is easy to observe.[3]

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; Fu et al., 2021; Hoffmann and Rud, 2024). 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 sick 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.[4] We contribute to this literature by highlighting the significant economic cost of air pollution in high-income countries, with all sectors incurring sales losses. In addition, we use matched employer-employee data to shed light on the mechanisms underlying these sales losses.

Our paper highlights additional channels through which air pollution leads to economic losses, beyond worker productivity. In doing so, we contribute to a small literature studying the labor supply response to air pollution shocks in high-income countries. Borgschulte

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

[4]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.

et al. (2024) estimate the effect of large wildfire-induced pollution shocks 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 sick 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.

Finally, Dechezleprêtre et al. (2019) quantifies the economic cost of air pollution in Europe using annual aggregate data. They find that a 10% increase in regional PM2.5 decreases regional GDP by 0.8% on the same year. While we also find substantial economic costs, our granular data capture firms' dynamic sales response at the monthly level. Annual output measures may obscure short-term shocks, such as highly polluted days, if firms smooth their responses over time. We test whether such smoothing exists and find no rebound effects five months after the shock. We also highlight the heterogeneous effects of pollution shocks by firm sector and size, and how sickness-related absenteeism, productivity decrease and demand response contribute to the sales losses.

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 and fails to detect any impact. Temperature shocks are more salient and easier to adapt to than air pollution shocks, given the widespread adoption of air conditioning in the US. We thus contribute to this literature by focusing on low-saliency shocks for which adaptation measures (e.g., air filtering systems) are not widespread. Finally, we add to a handful of papers studying how consumption behaviors change with temperature shocks (Lee and Zheng, 2025) or salient air pollution shocks (Barwick et al., 2024), by uncovering demand-side responses to less salient shocks.

The rest of the paper is organized as follows. Section 2 provides a brief background on $PM_{2.5}$ and presents an analytical framework that formalizes how pollution exposure can affect firms' sales. Section 3 presents the data. Section 4 describes our empirical strategy. Section 5 presents the main results. Section 6 discusses the channels. Section 7 puts the results in perspective. Section 8 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).[5] 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 (Calderón-Garcidueñas et al., 2008). Furthermore, $PM_{2.5}$ can travel far (hundreds of kilometers) 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 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 studies find that air pollution reduces labor supply, either in the immediate days following exposure (Hanna and Oliva, 2015; Aragón et al., 2017; Holub et al., 2021; Hoffmann and Rud, 2024) or in the subsequent months (Borgschulte et al., 2024). By reducing nonabsent workers' productivity or by reducing labor supply, air pollution will likely also reduce firms' output and sales. In the context of developing countries where high levels of air pollution are salient to workers and managers, a few studies find that firms can mitigate productivity losses among their most affected employees by reallocating tasks among staff (Adhvaryu et al., 2022), or by hiring additional workers (Fu et al., 2021). Demand-side mechanisms have received less attention than supply-side mechanisms. In the

[5] $PM_{2.5}$ 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.

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

Unlike in previous studies, air pollution appears to be a low-salience issue in France over our study period. In fact, monitoring and regulation primarily focused on PM_{10} until 2009, with $PM_{2.5}$ only gradually incorporated thereafter. There exists no maximum 24-hour concentration threshold for $PM_{2.5}$, and the annual threshold of 25 $\mu g/m^3$, defined by a European Union directive, never triggers air quality alerts. Although France, like many high-income countries, has experienced significant improvements in air quality over the past decades (Champalaune, 2020; Sicard et al., 2021; Currie et al., 2023), pollution levels regularly exceed public health recommendations. In our sample, daily exposure to $PM_{2.5}$ exceeds the WHO recommended threshold of 15 $\mu g/m^3$ on 37% of worker-days.[6] Yet, episodes where pollution levels are high enough to be visible to the naked eye are far less frequent than in heavily polluted Asian cities. Moreover, our study period and context do not include peak pollution events caused by wildfire smoke.

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

Moreover, labor market and social security 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, all private sector employees are eligible for sickness allowances as long as they provide a medical certificate and have worked at least 150 hours in the past three months. The replacement rate for sick leave varies based on the duration of the leave and can differ across firms due to collective agreements, as well as among workers within the same firm depending on their wage level and type of contract. Survey data indicate that two-thirds of private-sector employees receive full wage replacement from the first day of leave (Pollak, 2015). Workers' responses to a given health shock may differ not only because of residual variations in replacement rates, but also due to differences in workers' ability and willingness to work while sick and ability to adjust their working hours without formally taking sick leave.

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

2.2 Analytical Framework

In this section, we present a stylized model that connects individual exposure to air pollution with firms' sales. Building on existing literature, we incorporate two supply-side mechanisms: declines in labor supply and reduced productivity. Furthermore, we introduce a demand-side mechanism to capture behavioral changes among 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).[7] The utility function has two tiers. The top tier aggregates consumption in a Cobb-Douglas function across industries, which implies that expenditures on each industry i, Y_{it}, are determined as fixed shares of total expenditures, Y_t: $Y_{it} = \nu_i Y_t$. The second tier aggregates consumption via a Constant Elasticity of Substitution (CES) function across the set of varieties available in each industry i at time t, Ω_{it}. We assume varieties are imperfect substitutes within an industry and ρ_i is the parameter that governs the substitutability of varieties in industry i, with $0 < \rho_i < 1$.

On the demand side, two variables may be influenced by air pollution shocks. First, the ex-post variety-specific demand shock, $u_{fit}(c)$, depends on the level of air pollution exposure, c. Health effects from exposure or avoidance behaviors 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., health effects may increase healthcare expenditures, and staying home may induce a higher demand for food delivery services).

Second, in a developed country context with established sick 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.[8] We expect $\bar{a}'_t(c) \geq 0$ as higher pollution

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

[8] 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

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

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[9]

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

where L^A_{fit} denotes effective labor, L_{fit} denotes the number of workers employed at time t, and ω_{fit} is a Hicks-neutral productivity shock that is exogenous to air pollution exposure. Effective labor, L^A_{fit}, responds to air pollution exposure, c, through firm f's marginal productivity of workers at time t without absenteeism, $\lambda_{fit}(c)$, and through firm f's average worker absence rate at time t, $a_{fit}(c)$, 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, a firm whose employees take leaves of absence following air pollution shocks experiences an increase in the marginal cost of labor. Indeed, we express the firm-specific marginal cost of labor as $w[1 - \eta a_{fit}(c)]$, which depends on the wage rate w, the average worker absence rate $a_{fit}(c)$, and a parameter η that denotes 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

low-skilled workers are typically paid a regulated minimum wage, and high-skilled workers often negotiate their wages on a long-term basis.

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

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.[10] 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 losses associated with low replacement rates during sick leave.

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 elastici-

[10] To illustrate, we computed the public contribution share in France for a 5-day sick 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 $\eta - \theta = -0.26$.

ties, 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 trade 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, higher 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 losses associated with sick leave to be limited in the French context since two thirds of private sector employees are granted a full replacement rate, 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 2025), but through firms' sales data in retail and consumer-oriented services.

3 Data

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

Pollution. We use gridded reanalysis air pollution data produced by the French National Institute for Industrial Environment and Risks (INERIS), available at the 4 km by 4 km scale. We obtain hourly concentrations for $PM_{2.5}$, PM_{10}, ozone and nitrogen dioxide. The dataset described in Real et al. (2022) results from a spatial interpolation of measurements of air pollution concentrations from monitoring stations that is disciplined by the modeled concentrations obtained with a chemistry-transport model built for France named CHIMERE.[11]

[11] This technique provides a mapping algorithm between observed concentrations of pollutions from background monitoring stations (excluding stations located near a polluting industrial site or traffic stations, or equivalently 5% outliers from the concentration data) and a 4km-by-4km gridded map of metropolitan France using the hourly outputs of the CHIMERE model as auxiliary variables. A geo-statistical method called kriging is performed using a moving neighborhood to allow for local adjustments in the relationship between actual measurements and CHIMERE outputs. Co-kriging is an extension of the method to the multivariate case using cross-variance between $PM_{2.5}$ and PM_{10} to account for the correlation between the two pollutants and to exploit the larger network of PM_{10} monitoring stations. The CHIMERE model simulates concentrations combining geolocated emission inventory and time-varying meteorological data from the Integrated

The resulting dataset is better suited to capture the average pollution exposure of local residents than pollution-monitor readings. Monitors are sparse, so their readings may not take into account all polluting sources.[12] 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. In section 5.3, we replicate our main results using $PM_{2.5}$ exposure based on a simpler spatial interpolation of monitor readings (using inverse distances as weights), instead of reanalysis data.

During our study period 2009-2015, the average monthly $PM_{2.5}$ exposure of French workers, based on the municipality of their workplace, is 15.4 µg/m^3.[13] 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).[14] 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°).

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.[15] We restrict our sample to firms that declare their VAT every month, have

Forecasting System from ECMWF. The resulting dataset has been cross-validated using the leave-one-out strategy that computes the quality of spatial interpolation for each station from all other stations except itself. The dataset has good representativeness of background concentration for most pollutants, except for rural NO_2 stations (Real et al., 2022).

[12] 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.

[13] We define a municipality as a postcode area. There are 6,048 such areas in metropolitan France. An average French municipality is thirty times smaller than an average US county.

[14] 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

[15] The industry-specific threshold is €818,000 of annual sales for manufacturing and hospitality industries,

at least one employee observed in the sick leave dataset, and 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 totaling €1.9 billion sales in 2013, which represents 52% of all French firms' sales (excluding agriculture and the financial sector).

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.[16] 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 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 employed in each establishment owned by the firm.

Sick leave episodes. We obtain data on sick leave episodes (SLE) for a representative sample of private sector employees born between 1935 and 1989 and affiliated to France's universal sick leave insurance (Hygie dataset). 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 measure of absenteeism is an indicator for an individual starting a SLE in a given month. In the main analysis, we only consider SLEs that last less than three months, which represents 93% of the spells.[17]

We restrict our dataset to employees that we can match to their exact workplace via an establishment-level identifier (see Appendix C for more details). This restriction enables us to attribute pollution and weather exposure to each employee based on conditions at the municipality of their workplace, as information on their municipality of residence is unavail-

and €247,000 of annual sales for the other sectors. Firms with monthly VAT declarations represent 66% of French firms, but 91% of total sales (France Stratégie and Inspection générale des Finances, 2021).

[16] $PM_{2.5}$ exposure in a municipality-month is based on the value from the nearest grid cell in the pollution data, while weather variables are based on the values in the nearest Copernicus grid cell.

[17] In our data, the average sick leave episode lasts 29 days whereas the median duration is only 9 days. Figure C.18 shows the small proportion of SLEs that last more than 3 months and their strong influence on the average number of sick days.

able. It also facilitates the matching of worker-level data with firm-level information. We consider workplace pollution exposure a reliable proxy for individual exposure, supported by our analysis of exhaustive matched employer-employee data, which shows that the distributions of $PM_{2.5}$ exposure at workplace and residential municipalities are nearly identical.[18] We aggregate sick leave data at the establishment-month level.

Descriptive statistics. Panel a of Table 1 shows that the average firm in our sample employs 60 workers and reports an average monthly sales of €1,316,300, whereas the median number of workers is 15 and the median monthly sales only amount to €145,372. Manufacturing accounts for 20% of firms, construction for 16%, business-to-business trade and services for 31%, and business-to-consumer trade and services for 33%.

Panel B of Table 1 presents descriptive statistics for the sample of workers with observed sick leave data who are employed by firms with monthly VAT records. This sample, which forms the basis of our analysis on the impact of air pollution on worker absenteeism, includes approximately 400,000 individuals employed in 353,155 private sector establishments between 2009 and 2015. These workers are, on average, 40 years old, earn an annual gross wage of €28,542, and incur €442 in annual medical expenses. Each month, an average of 23 out of every 1,000 workers begin a sick leave lasting less than three months.

Appendix Table A.1 compares our analysis sample of workers to a representative sample before restricting to those employed by firms with monthly VAT records. As firms with monthly VAT records are generally larger, workers in our analysis sample have higher average earnings than those in the representative sample. Nevertheless, the two samples exhibit similar average demographic characteristics, sick leave rates, and pollution exposure.

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 worker 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

[18]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, 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). Figure A.2 shows that the distributions of pollution exposure at the workplace and at the place of residence almost overlap, both for the full population and by income quintile, based on exhaustive matched employer-employee data.

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 months 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).[19] 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.[20] 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, and even more importantly, in wind patterns for the instrumented version, that are specific to a county and may be correlated with local seasonal fluctuations in economic activity. It captures for instance the seasonal demand variation in ski or sea resort areas.

[19] 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.

[20] 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.

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 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.[21] When firms own multiple establishments, we build these weather controls based on 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.[22] 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 Econometric specification for worker absenteeism

Unlike sales, we observe worker absenteeism at the establishment level, even in the context of multi-establishment firms. 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:

$$Y_{eiyt} = \beta^A PM_{2.5gyt} + W'_{gyt}\gamma + \nu_e + \theta_{iyt} + \delta_{dq} + \epsilon_{eiyt}, \tag{8}$$

where the dependent variable Y_{eiyt} is the sick 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 at the municipality g level. 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.

[21] 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.

[22] 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.

4.3 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 municipality 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 with OLS regressions of equations (7) and (8) arises from unobserved local shocks that may influence pollution concentration while also affecting firms' sales and/or workers' absenteeism. For instance, a positive shock to local demand outside seasonal patterns could boost retail sales and consumer services while increasing transport demand. Although stores themselves do not generate pollution, the resulting rise in car usage directly contributes to local $PM_{2.5}$ levels.

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

$$\mathrm{Z}_{jgyt} = \underbrace{\mathrm{WIND}_{jgyt}}_{\text{A: Time-varying}} \underbrace{\left(\frac{1}{N_j}\sum_{d\in T_j} PM_{2.5gd} - \frac{1}{N}\sum_{d\in T} PM_{2.5gd}\right)}_{\text{B: Time-invariant}} \tag{9}$$

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.[23] N_j and T_j are the number and set of days where the

[23] A one-unit increase in $\mathrm{Z}jgyt$ reflects different combinations of the frequency of wind j and its influence on the pollution level in municipality g. For instance, a 10 pp increase in the share of North wind in municipality A, where North wind deviates from the mean pollution by 0.1µg/m^3, and a 20 pp decrease in the share of North wind in municipality B, where North wind deviates from the mean pollution by -0.05µg/m^3, would

dominant wind blows from direction j, and N and T are the total number and set of days over the period of analysis.

Figure 2 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.

For the simple case of single establishment firms, the specification of the first stage is:

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

with $PM_{2.5fyt}$ and weather controls varying at the municipality level g, and β_js the parameters of interest. For a given wind direction j, β_j captures the average 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 municipality within a year, after partialling out quarter-by-county-specific variation, industry-specific national trends in exposure, and after controlling for weather parameters other than wind direction.

Figure A.8 plots the distribution of the raw and residualized wind instrument variables for the subsample of single-establishment firms, and shows that there remains substantial variation in each instrument after partialling out the fixed effects and controls. There is also substantial variation in wind direction within a given municipality, as illustrated in Figures A.4 and A.6 showing the variation in wind direction within a given calendar month in the two largest French cities, Paris in the North and Marseille in the South-East.

For multi-establishment firms, we generate a plausibly exogenous predicted pollution exposure using the results from a first stage equation specified at the municipality level. After regressing $\mathrm{PM}_{2.5gyt}$ on the same exogenous variables as in equation (10), except that we control for municipality-year and month-by-year fixed effects, and after saving the vector of estimated $\widehat{\beta_j}$, we compute the predicted pollution exposure in each municipality as $\widehat{PM_{2.5gyt}} = \sum_{j=1}^{4} \widehat{\beta}_j \mathrm{Z}_{jgyt}$. We then compute the firm-level predicted pollution exposure,

both result in a one-unit increase in $\mathrm{Z}_{NorthAyt}$ and $\mathrm{Z}_{NorthByt}$.

$\widehat{PM}_{2.5fyt}$, as the weighted average of $\widehat{PM}_{2.5gyt}$ across municipalities 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).[24]

Throughout the analysis run at the establishment level, we cluster standard errors at the Copernicus grid cell level, corresponding to the scale at which component A of the wind instrument varies. There are 1,090 such grid cells in our final dataset. When the sample includes both single- and multi-establishment firms, we use as an instrument the predicted pollution measure and we cluster the standard errors at the Copernicus grid cell level based on the location of the firm's headquarter. We show in Table A.5 that the results hold when we cluster the standard errors at the firm level, at the county level and two-way at the Copernicus grid cell and time level.[25]

4.4 Identification assumptions

The validity of our research design requires that three conditions are met. First, our set of wind instruments must be correlated with $PM_{2.5}$ (instrument relevance). Second, they must be uncorrelated with the error term from the second stage, ϵ_{fiyt} (instrument validity). Third, to interpret our estimates as local average treatment effects (LATE), the monotonicity assumption must hold. The assumption of constant treatment effects is unlikely in our context, as the impact of $PM_{2.5}$ on sales likely varies with firm characteristics, such as industry type and workforce demographics. With heterogeneous treatment effects, the two-stage least squares estimates can be interpreted as LATE only if the monotonicity assumption is satisfied. Below we discuss the plausibility of these three conditions.

Instrument relevance. Table 2 report the first stage results and shows that the effects of the wind instruments on pollution exposure are similar whether the regression is run at the municipality level (column (1)) or for single-establishment firms only (column (2)). 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. All the coefficients are positive and significant. We test for weak-IV using the effective F-statistic (Montiel Olea and Pflueger, 2013) on a random 2% sample of the single-establishment firms.[26] The effective F-statistic

[24]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).

[25]Implementing Conley standard errors to address concerns of spatial autocorrelation in wind patterns is too computationally demanding due to the combination of several high-dimensional fixed effects, an instrumental variable, and a large sample size, given the constraint of accessing the data on a secure server.

[26]Testing for weak instruments is only possible on a subsample due to computational constraints. Since the effective F-statistic does not accommodate more than one endogenous regressor, instead of instrumenting

is 365, while the critical values for a 5% worse case bias is of 26 and that for a 10% bias is 16. Thus, we can rule out a weak instrument concern.

Instrument validity. The validity of the instruments relies on two key assumptions. First, the wind direction instruments must be as-good-as-randomly assigned, meaning no weather or seasonal patterns influencing sales should co-vary with the instruments. To address this, we control for wind speed, temperature, and precipitation, which may correlate with wind direction and affect sales, and include quarter-by-county fixed effects to account for location-specific seasonality and quarter-specific wind and sales patterns. The remaining variation in the instruments is assumed to be random, as no other weather variables are known to influence both sales and the instruments.

Second, the exclusion restriction must hold: the wind instruments should affect firms' sales only through their impact on $PM_{2.5}$. This assumption could be violated if other pollutants affecting health and productivity co-vary with wind direction. Among 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 data monthly, we capture their effects as part of $PM_{2.5}$. PM_{10} is highly correlated with $P_{2.5}$ ($\rho = 0.93$) and includes $PM_{2.5}$, so our estimates also reflect PM_{10}'s impact. Ozone, however, is typically anti-correlated with these pollutants due to its atmospheric formation process.[27] In our data, $PM_{2.5}$ and ozone have a Pearson correlation coefficient of -0.3. To address concerns about ozone effects, we conduct a robustness check where we replace$PM_{2.5}$ with a multi-pollutant air quality index that includes ozone, which does not alter the results.

Instrument monotonicity. We test for instrument monotonicity by plotting the relationship between residualized instruments and residualized $PM_{2.5}$ exposure. Figure A.10 presents binned scatter plots of these variables using the panel of single-establishment firms, showing a predominantly monotonically increasing and approximately linear relationship, except at the distribution tails. Additionally, Figure A.12 displays the distribution of residualized predicted $PM_{2.5}$ and its relationship with residualized firm-level $PM_{2.5}$ exposure for the entire firm-level sample, confirming that the monotonicity assumption holds for this instrument.

Potential threats to identification. Our identification relies on comparing firm-months exposed to plausibly exogenous air pollution shocks driven by wind direction changes with those less exposed, under the assumption of stable unit treatment values (SUTVA), meaning

for pollution at $t-1$, t, $t+1$ in equation 7, we instrument only for pollution at $t-1$, our time period of interest, and we control for the wind instruments at t and $t+1$

[27] Ozone forms through reactions involving solar radiation, nitrogen oxide, and volatile organic compounds (Nasa Earth Observatory, 2003). Figures 1 and A.3 illustrate this anti-correlation, showing reverse seasonality between ozone and $PM_{2.5}$ or NO_2.

no spillovers between exposed and non-exposed firms. While spillovers cannot be ruled out *a priori*, such as competitors gaining market shares from firms experiencing sales declines due to pollution, the low saliency and temporary nature of monthly air pollution exposure make it unlikely that firms adjust to competitors' shocks on a month-to-month basis. The high frequency of shocks reduces the likelihood of spillovers, and any effects occurring over a longer horizon are absorbed by firm-year fixed effects. Moreover, firms serving the same local demand, such as in business-to-consumer sectors, face the same pollution shocks, limiting competitive advantages. Firms experiencing lower pollution within the same industries are likely geographically distant, reducing direct competition and further minimizing spillover risks.

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) shows a positive association between lagged $PM_{2.5}$ and contemporaneous sales in the OLS model, likely driven by reverse causality and omitted variables. Within a firm-year, even after accounting for industry-specific time-varying shocks and local seasonality in sales and pollution, months with positive local economic shocks tend to be more polluted and also boost firm sales. When instrumenting pollution with changes in wind direction (column 2), the effect of pollution on sales turns negative and is statistically significant at the 1% level. A one-unit (1 $\mu g/m^3$) increase in firm-level $PM_{2.5}$ exposure reduces firm sales by 0.26 percent over the next two months, corresponding to an elasticity of -0.04, i.e., a 10 percent rise in pollution exposure lowers sales by 0.40 percent on average. Columns (3) and (4) confirm similar results in the sub-sample of single-establishment firms for which the first stage equation is (10).

Table A.2 shows how the magnitude of the estimates responds to the set of fixed effects used in equation (7). The IV point estimate remains consistently significant and negative across specifications. Adding quarter-by-county fixed effects reduces the magnitude of the estimates compared to using only firm-by-year and month-by-year-by-industry fixed effects. These fixed effects may capture some of the relevant exogenous variation, such as seasonal diseases like flu epidemics, which may exacerbate the health effects of air pollution (Graff Zivin et al., 2023). More importantly, they account for any systematic correlation between wind seasonality and local economic activity, which, if not controlled for, could violate the exclusion restriction.

Heterogeneous Response by Sector. Examining how sales respond to air pollution by sector provides insights into which sectors might benefit most from air quality improvements. Table 4 shows that the effect of lagged monthly $PM_{2.5}$ on firm-level sales is consistently negative and significant across all sectors. In Column (1), an OLS model reveals a positive association between lagged $PM_{2.5}$ and contemporaneous sales, especially in the business-to-consumer trade and services sector. However, when pollution is instrumented using wind direction changes in Column (2), the effect on sales becomes negative and statistically significant at the 1% level, except in the construction sector, where the effect is smaller and less precise. Column (2) indicates that a one-unit increase in firm-level $PM_{2.5}$ exposure decreases sales in the following two months by 0.14 percent in manufacturing, 0.08 percent in construction, 0.13 percent in business-to-business trade and services, and 0.46 percent in business-to-consumer trade and services. These results imply that a 10 percent increase in pollution exposure decreases sales 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. Finally, Column (4) shows that, for the sub-sample of single-establishment firms, the point estimates remain similar but are less precise (except for construction and business-to-consumers sectors).

As discussed in Section 2.2, both supply-side and demand-side mechanisms likely influence sectoral responses differently. On the supply side, workers in different sectors may have varying vulnerabilities to pollution shocks. Although workers in sectors like construction and manufacturing face more direct and cumulative exposures, they also self-select into these occupations and could have adapted to higher levels of pollution. Our results suggest that sectors directly serving final consumers tend to experience stronger responses to air pollution shocks than production sectors, such as manufacturing or construction. This finding highlights the fact that, in sectors serving local demand, the impact of high pollution exposure is likely amplified by both supply-side and demand-side responses. Whereas manufacturing firms, for instance, have the capacity to serve distant markets to counteract the negative impact of local demand shocks (Almunia et al., 2021), no such strategy is available to stores and service providers attending local consumers only. Additionally, sectors with larger elasticities of substitution across varieties, such as business-to-consumer and business-to-business trade and services, will see more pronounced effects from supply-side and demand-side responses, as demonstrated by our theoretical framework in section 2.2. Finally, since we examine short-term effects based on sales data, sectoral differences in the timing of production and sales recording may explain some of the observed heterogeneity. For instance, large-scale construction projects or business-to-business services often involve payment delays, meaning that the timing of sales responses may not align with the two-month period used in our analysis.

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 examine whether small firms are more vulnerable to environmental shocks by comparing the impact of air pollution on sales for firms with a below-median average size over the study period, that is to say strictly fewer than 15 employees, to those above-median, with 15 employee or more.Table A.3 shows that firms with strictly fewer than 15 employees are the most affected overall and in every sector except business-to-consumer. In manufacturing, construction and business-to-business trade and services, large firms show no significant sales losses from pollution exposure. This suggests that large firms may mitigate workers' absenteeism or declining productivity through adaptation strategies, such as reallocating tasks (Adhvaryu et al., 2022) or flexibly adjusting working hours. In the business-to-consumer sector, even large firms may lack such strategies, suggesting they primarily face a demand-side shock beyond their control.

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. Hence, 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 3 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, insignificant in the following two months, and turn negative for some sectors before reverting to zero after five months. This pattern suggests reverse causality or omitted variable bias: contemporaneous positivity likely reflects increased economic activity driving both pollution and sales, while delayed negative effects capture pollution's adverse impacts on productivity or demand. The IV estimates at $t+1$ are generally larger than the main results, particularly for construction, but the relative sectoral effects remain consistent. The business-to-consumer trade and services sector experiences impacts two to three times greater than other sectors. These dynamic IV results indicate that the negative effects of pollution on sales can intensify over time (peaking around $t+2$ or $t+3$) before gradually diminishing, returning to zero by $t+4$ or $t+5$, depending on the sector. Figure A.13 reports the results for the sub-sample of single-establishment firms, which are very similar to the ones for the whole sample.

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. Fourth, we verify that the assumption of a linear effect of air pollution on the sales outcomes is plausible. Finally, we verify the robustness of our results to the specification of weather variables, outliers, and source of pollution information.

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 taken together and for every sector.

The exclusion restriction and the case of ozone.

Column (1) of Table 6 presents the main result for all firms, replicating the primary specification reported in column (2) of Table 3. Column (2) presents the effect of the AQI, instrumented by the same four wind instruments. The magnitude of the coefficient cannot be directly compared to our main $PM_{2.5}$ estimate due to differences in scale. However, expressed in standard deviations, the results are similar: a 1-SD increase in lagged $PM_{2.5}$ (SD=6.2 µg/m^3) reduces sales by 1.6%, while a 1-SD increase in AQI (SD=0.41) reduces sales by 1.3%. The slightly lower AQI estimate may reflect its dual representation of $PM_{2.5}$ in fall/winter and ozone in spring/summer. If ozone has no significant effect on sales, using AQI dilutes the impact of $PM_{2.5}$.

The role of air quality alerts. To ensure our results are not influenced by behavioral responses to air quality alerts, we create a new sample by excluding monthly observations with PM_{10} alerts. While no $PM_{2.5}$ alerts exist in France, PM_{10} alerts—triggered by PM_{10} concentrations exceeding regulatory thresholds—are highly correlated with high $PM_{2.5}$ levels.[28] Column (3) of Table 6 shows that the estimated coefficient remains consistent with

[28] There are two distinct levels of alerts: i/ level 1 provides information on air pollution, advises

the main result.

Results' sensitivity to outliers and weather controls Column (4) of Table 6 shows that winsorizing sales at the 2nd and 98th percentiles of the monthly sales distribution does not affect our main estimate. In column (5), we control for weather using simple and quadratic terms for daily maximum temperature, wind speed, and rainfall, instead of all possible interactions between these variables. The larger estimated coefficient on pollution suggests that our main estimate is conservative.

Non-linear effects of air pollution. Our main specification assumes a linear effect of $PM_{2.5}$ exposure on the log of sales. In section 7, we extrapolate the benefits of avoiding days of high-pollution from our point estimates based on this (log)-linear specification. If the effect of air pollution on sales becomes larger with higher levels of pollution, our extrapolation based on a linear effect will underestimate the expected economic benefits from reduced pollution. Figure A.14 plots the relationship between the residualized instrument of predicted $PM_{2.5}$ and the residualized sales outcome and confirms that the relationship looks approximately linear.

Reanalysis $PM_{2.5}$ data vs. satellite-based $PM_{2.5}$ vs. monitor data. Column (6) of Table 6 replicates our main analysis using satellite-based monthly $PM_{2.5}$ data produced by van Donkelaar et al. (van Donkelaar et al., 2021; Shen et al., 2024). The data is based on satellite observations of Aerosol Optical Depth (AOD) and a chemical-transport model used to establish a flexible relationship between AOD and PM2.5, and is cross-validated using $PM_{2.5}$ monitoring station data. The satellite-based pollution exposure is highly correlated with the reanalysis data ($\rho = 0.90$). The estimated coefficient has the same order of magnitude as our main result in column (1). Additionally, columns (7) and (8) compare our main estimate using reanalysis data with $PM_{2.5}$ data from monitoring stations in 2011-2015, when monitor data is available.[29] The use of monitor data rules out the possibility that the strength of the first stage linking wind directions and $PM_{2.5}$ is driven by weather variables serving as inputs in the reanalysis model. Following the literature, we create a municipality-level $PM_{2.5}$ measure as the weighted average of nearby monitor data, excluding monitors more than 150 kilometers away and weighting by inverse distance. The monitor-based exposure measure,

vulnerable individuals to avoid physical activities outside, and recommends decreasing driving speed to mitigate pollution; ii/ level 2 adds strict enforcement measures such as driving restrictions (see https://www.airparif.asso.fr/procedure-dinformation-et-dalerte for more information). We use the regulatory thresholds for all PM_{10} alerts, which are triggered when daily averages exceed 80 µg/m^3 (level 1) or 125 µg/m^3 (level 2) before November 2014, and 50 µg/m^3 (level 1) or 80 µg/m^3 (level 2) after. Even in Paris, the most polluted city, level 1 alerts occurred on only 4% of the days in 2009, with level 2 alerts on 0.7% of the days.

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

which is highly correlated with the reanalysis measure ($\rho = 0.95$), produces a point estimate in column (9) similar to the reanalysis-based estimate in column (8).

Results' sensitivity to the scale of clustering. In Table A.5, we show how standards errors change with clustering strategies. Column (1) shows the baseline where one-way clustering is done at the wind grid cell of the firm's headquarter—the spatial scale at which the instrument varies for single-establishment firms. Column (2) clusters standard error at the firm level, which is the scale at which treatment varies for multi-establishment firms. The latter yields smaller standard errors, as it neglects the spatial correlation in wind exposure for two firms located near each other. Column (3) clusters at the county level, which indirectly accounts for spatial correlation at a broader scale than the wind grid cell (each county includes 10 wind grid cells on average). Standard errors become slightly smaller than in our baseline, which is the most conservative option among the three. Columns (4) to (6) cluster standard errors two-way using for spatial aggregation the Copernicus grid cell (column 4), firm (column 5) and county (column 6) level, and for time the 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.

6 Identifying Channels

The temporary decline in sales following a month of high $PM_{2.5}$ levels may stem from several mechanisms identified in our analytical framework, including increased worker absenteeism, reduced worker productivity, and lower demand. In this section, we explore each of these potential channels in greater detail.

6.1 Pollution-induced sickness absenteeism

Table 7 reports the main OLS and IV estimates of the contemporaneous effect of $PM_{2.5}$ on sick leave using equation (8), for the sample of workers whose firm is included in our sales data. The OLS estimate in column (1) shows that a one-unit increase in average $PM_{2.5}$ exposure is associated with a 0.07 increase in sick leave per 1,000 workers. The IV estimate in column (2) is twice as large, at 0.15, suggesting that the OLS estimate is downward biased due to omitted variables and classical measurement error. Both estimates are highly statistically significant. With a baseline average of 23 per 1,000 workers, our IV results imply that a 10 percent increase in monthly $PM_{2.5}$ raises absenteeism by 1 percent, corresponding to a 0.1 elasticity of sick leave to pollution.

These estimated effects are robust to aggregating at the municipality level, using municipality fixed effects and month-by-year fixed effects, as shown by Table B.6. Additionally, Appendix B contains the same set of robustness checks for absenteeism as for the sales outcome. Table B.7 shows that the effect of air pollution on sick leave is not driven by a confounding effect of ozone, by air quality alerts, by the specification of weather controls, or by the data source we use for $PM_{2.5}$. Figure A.15 shows the dynamic effects of pollution using the same Polynomial Distributed Lag specification as for sales. We find that the impact of air pollution on sick leave is concentrated in the month of exposure, quickly dissipating to zero within two months. Figure A.16 compares the OLS and IV estimates for the representative sample of workers (left) vs. our main sample (right), and reveals that they are comparable.

We compare the magnitude of our estimates of the effect of pollution exposure on sick leave to the existing literature. 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 0.08. Thus, the order of magnitude is similar to our elasticity (0.10), despite differences in the type of pollutant and time horizon (monthly vs. weekly).

Can the pollution-induced reduction in labor supply due to sick leave explain the observed decline in sales? Not across all sectors. Figure 4 shows that absenteeism is mainly driven by manufacturing (the only sector with a statistically significant effect) and, to a lesser extent, construction. In contrast, absenteeism in the consumer- and business-oriented trade sectors is minimal. Comparing Table 4 and Figure 4, we find little correlation between absenteeism and sales effects. For example, manufacturing and business-to-business trade sectors have similar sales responses to pollution, despite differing absenteeism rates. While absenteeism effects are negligible in the business-to-business trade sector, sales still decrease in this sector. We note that higher absenteeism rates are observed in sectors with greater pollution exposure and strong collective agreements (ensuring higher replacement rates), such as manufacturing and construction, whereas services sectors experience lower absenteeism. Because our measure of absenteeism only captures recorded sick leave episodes, these lower responses in the services sectors are possibly due to the ability to work remotely or take leave without a medical certificate, or reflect higher pressure to work while sick due to lower replacement rates.

To estimate the sales loss from absenteeism, we multiply the increase in sick days by sales per worker-day. For an average manufacturing firm, a one-unit increase in $PM_{2.5}$ raises absenteeism by 5.5 sick days per 1,000 workers (see Appendix Table A.4). With 95 workers on average, this amounts to 0.52 lost days per month. Given average sales of €1,170 per worker-day, the total sales loss due to absenteeism is roughly €611 in manufacturing. By contrast, our result on firms' sales shows that a one-unit increase in $PM_{2.5}$ reduces manufacturing sales by 0.14%, or €3,173, implying absenteeism accounts for only 19% of the total sales loss in manufacturing. These back-of-the-envelope calculations suggest that absenteeism may not be the primary channel through which air pollution affects sales. However, they 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 small increases in absenteeism can significantly impact sales. For example, reduced service quality in retail or restaurants may quickly drive dissatisfied customers to competitors. Conversely, sectors with lower elasticity and higher profit margins may be less affected by such changes.

6.2 The role of productivity and demand

Productivity. Lacking monthly worker productivity data, we cannot directly measure this channel. Instead, we provide suggestive evidence by examining heterogeneous effects across manufacturing industries. Using a 2004 survey of manufacturing plants, we categorize industries based on whether their stock levels are above or below the median.[30] Assuming similar absenteeism responses, we expect firms with low stock levels to experience a greater sales decline from supply-side pollution shocks than those with high stock levels. Firms with ample inventory can buffer production disruptions, while those with low stock are more vulnerable to sales decreases.

Columns (1)-(3) in panel A of Table 8 show that sales declines are mainly driven by firms with low stock levels, while the impact on firms with high stock levels is negligible. Columns (4)-(6) show similar increases in absenteeism for both groups. With comparable average sales and employee numbers across the two groups, firm size differences do not explain the variations in sales response. These results cannot be attributed to differences in demand shocks either, as having stocks does not mitigate demand-side effects. Overall, this heterogeneity suggests that air pollution reduces sales, at least in part, by lowering worker

[30] 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.

productivity.

Demand. As noted earlier, demand responses are likely more pronounced in the consumer retail and services sector, where demand is primarily local. Table 4 confirms that the impact of $PM_{2.5}$ on sales is indeed larger in this sector. This suggests that consumers experiencing pollution-related health issues may avoid shopping or cut back on purchases, especially when their healthcare expenses rise. This may also suggest that consumers avoid returning to stores or restaurants where they experienced reduced service quality, mistakenly perceiving temporary disruptions as permanent. Such behavioral changes would likely affect discretionary goods like furniture and clothing more than staples like groceries, where consumption is harder to forego. Columns (1)-(3) in panel B of Table 8 show a slightly larger sales decline for firms selling discretionary items, though the difference is not statistically significant.

7 Discussion

In this section, we summarize the evidence that identifies the key mechanisms driving pollution-induced sales decreases across sectors, and demonstrate that high pollution levels result in significant economic losses.

All sectors are negatively affected by air pollution shocks. Our results on the heterogeneous responses to air pollution shocks enable us to infer that, in manufacturing and construction, absenteeism and reduced productivity are the main channels explaining the pollution-induced sales decrease. In these sectors, we can rule out the importance of demand-side shocks because large firms are able to mitigate the impact and avoid sales declines. In business-to-business sectors, productivity reduction is the primary mechanism, as there is no absenteeism response, and large firms also effectively manage supply-side shocks. In business-to-consumer sectors, all three mechanisms—absenteeism, productivity reduction, and demand-side shocks—contribute, with demand-side effects particularly impacting discretionary goods, even large firms unable to fully offset the shocks, and absenteeism particularly impacting staples goods.

Using back-of-the-envelope calculations, we estimate the benefits of meeting the WHO daily $PM_{2.5}$ target in terms of avoided lost sales. Over our 7-year study period, the 15µg/m^3 threshold was exceeded on 37% of worker-days. Reducing all days above the threshold to 15µg/m^3 would lower monthly average pollution exposure from 15.4 to 11.5µg/m^3, a 25% decrease from 2009–2015 levels. Based on our main estimates and assuming a linear effect of pollution on the sales outcome in log (see Figure A.14), this reduction could have avoided 28 billion euros in annual lost sales—1.5% of average total sales in the French private sector.

With an average value-added-to-sales ratio of 27%,[31] this corresponds to 7.5 billion euros in annual foregone value added, ignoring long-term and general equilibrium effects. The European Commission's recent update to air quality regulations introduced a 24-hour $PM_{2.5}$ standard of 25 µg/m^3 by 2030. Based on our estimates, over the study period meeting a 25 µg/m^3 threshold would have brought economic benefits 60% lower than meeting the WHO 15 µg/m^3 target.

To compare the potential economic gains of reducing $PM_{2.5}$ to the WHO threshold with the costs of doing so, we follow Dechezleprêtre et al. (2019)'s approach, using the cost of reducing $PM_{2.5}$ emissions rather than concentrations based on a European Commission report for a scenario with 33% emissions reductions (option 6D). Achieving this target, which reduces pollution more than needed to meet the WHO threshold, is estimated to cost around €7.7 billion in annualized investments for pollution abatement equipment and maintenance.[32] While these costs are approximate, they suggest that the economic gains from reduced pollution could rival an upper bound of the costs of achieving the target.

To contextualize these benefits further, we compare them to annual mortality benefits from a 25% reduction in air pollution. Using Deryugina et al. (2019)'s estimates of $PM_{2.5}$'s short-term mortality effects on the elderly in the U.S., and the French Value of a Statistical Life Year (VSLY) of €115,000 in 2010, we calculate that each unit decrease in $PM_{2.5}$ generates €1.6 billion annually in mortality reduction benefits in France.[33] For our scenario, bringing daily $PM_{2.5}$ above the threshold to 15µg/m^3, annual mortality benefits amount to €6.1 billions. This places the economic gains from avoided sales losses on par with mortality reduction benefits.

8 Conclusion

This paper examines the impact of fine particulate matter ($PM_{2.5}$) exposure on economic performance in the French private sector. We find that higher pollution levels reduce firm sales within two months, with an estimated average elasticity of sales to pollution of -0.04. Three key mechanisms drive this effect. First, workers' exposure to air pollution increases sickness-related absenteeism, with an elasticity of 0.1. Second, a reduction in worker productivity induces output reductions, which we show in particular in manufacturing firms

[31] Data from 2015 aggregated by sector are available here: https://www.insee.fr/fr/statistiques/3136821?sommaire=3136881.

[32] See https://ec.europa.eu/environment/archives/air/pdf/Impact_assessment_en.pdf, part 3, page 43.

[33] This uses Deryugina et al. (2019)'s point estimate of a 2.991 life-year gain per million elderly (65+) for each unit decrease in daily PM2.5, assuming the annual effects scale linearly, converting the VSLY to 2013 euros, and considering France's 11.7 million elderly population in 2013.

with low stock levels. Third, firms serving local demand experience more pronounced sales decreases, especially those selling discretionary goods. Importantly, the economic costs of pollution-induced sales losses far exceed those attributed to absenteeism, when the latter is valued at the marginal product of labor.

Our analysis highlights important policy implications and underscores the positive direction of recent regulatory changes in Europe. First, ex-ante cost-benefit analyses of air pollution regulations that overlook the negative effects of pollution on firm performance risk significantly underestimating their net benefits. Second, our findings suggest that tightening $PM_{2.5}$ standards to align with WHO recommendations would yield substantial economic gains, potentially exceeding available cost estimates. Incorporating health benefits for the entire population into these estimates—beyond the sales losses we quantify—would amplify the net benefits, making a strong case for stricter standards. The European Commission's recent update to air quality regulations, including the introduction of a 24-hour $PM_{2.5}$ standard of 25 µg/m^3 by 2030, marks a step in the right direction.

Finally, a large body of research in economic geography and urban economics links higher population density to increased productivity, highlighting the benefits of agglomeration (Combes et al., 2012; Ahlfeldt and Pietrostefani, 2019). However, recent studies show that higher density also contributes to elevated air pollution levels (Carozzi and Roth, 2023). Our findings suggest that pollution may be an important omitted variable in estimating agglomeration effects, likely biasing estimates downward. This bias arises because density is positively correlated with pollution, which in turn negatively impacts productivity. Future research could explore agglomeration effects on productivity while accounting for pollution, offering a more accurate assessment of the net benefits of density.

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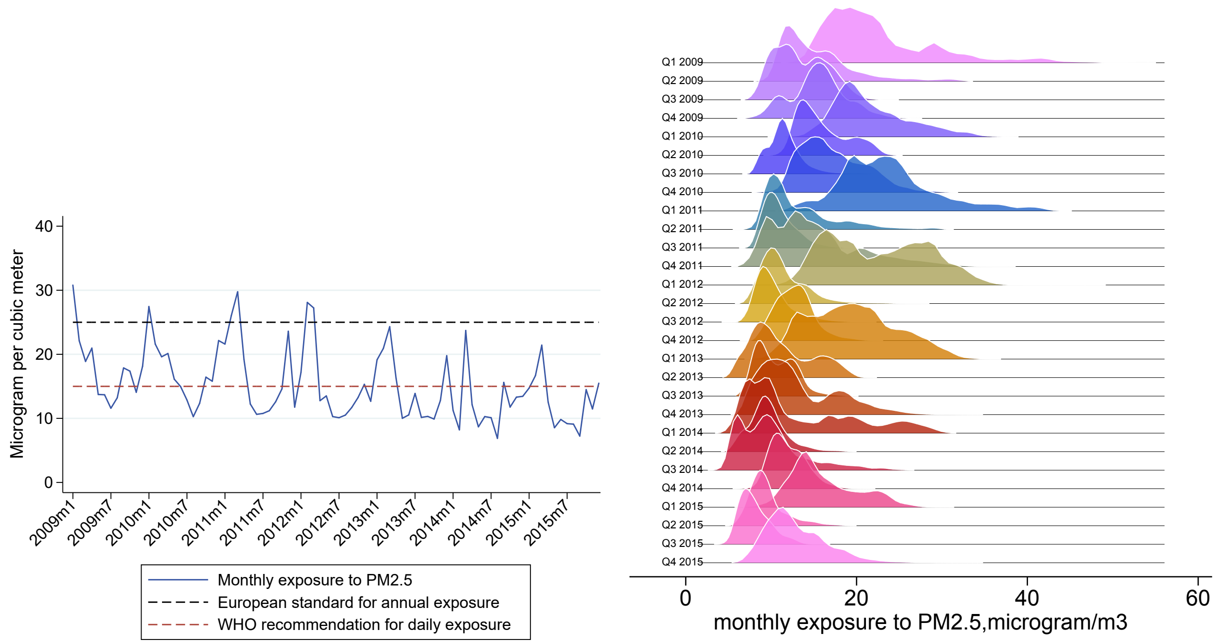
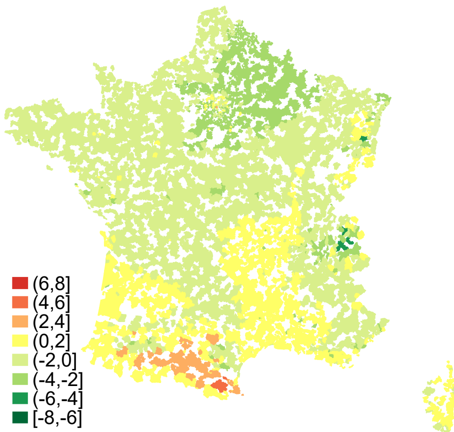
9 Figures



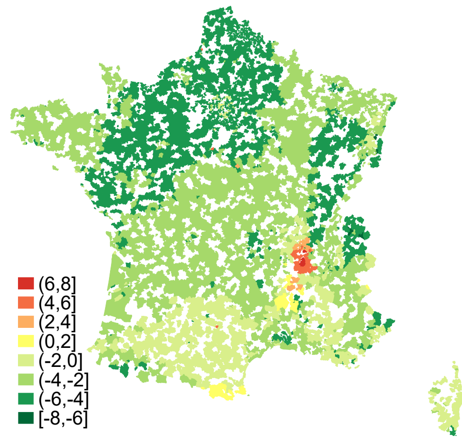
(a) Monthly average exposure to $PM_{2.5}$ (µg/m^3) (b) Distribution from Q1 2009 to Q4 2015

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

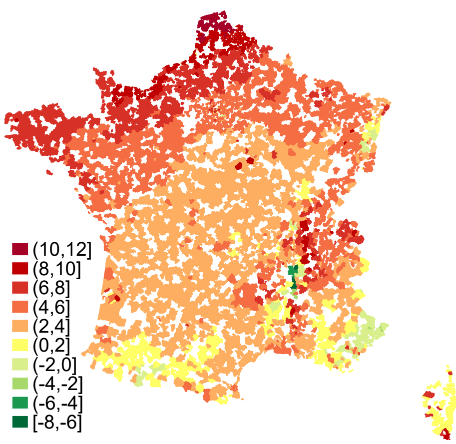
Notes: Figure a) shows municipality-level $PM_{2.5}$ exposure in 2009-2015, weighted by the number of workers employed in each municipality in the absenteeism dataset. Figure b) shows the unweighted distribution of monthly exposure to $PM_{2.5}$.



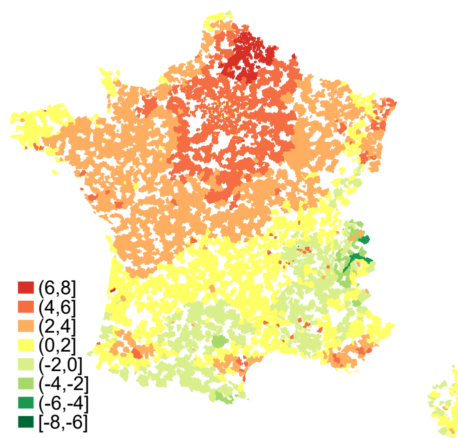
(a) South wind



(b) West wind



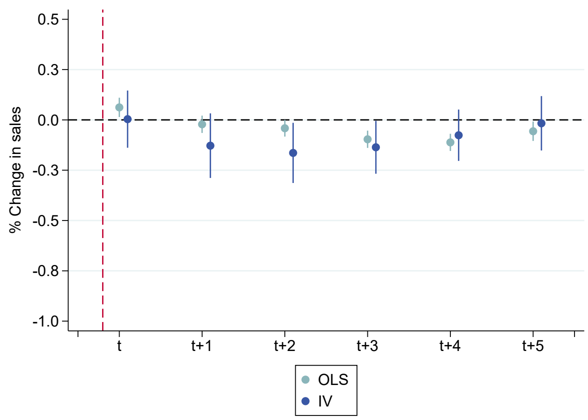
(c) East wind



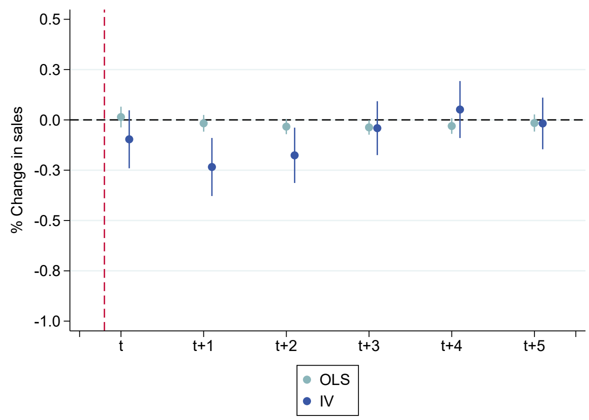
(d) North wind

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

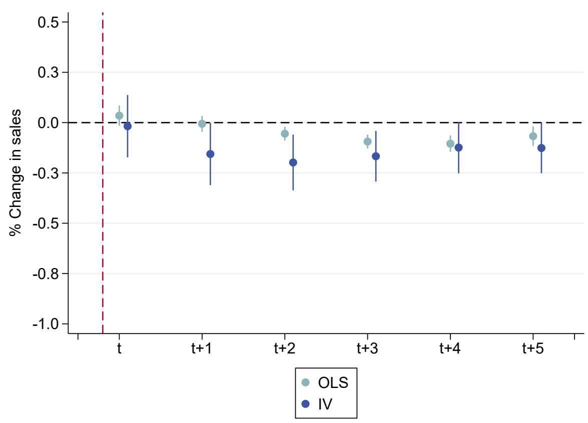
Notes: Figure shows for each municipality the component of the instrument Z_{jgyt} which described the variation from daily mean pollution levels on days where the dominant wind blows from direction j.



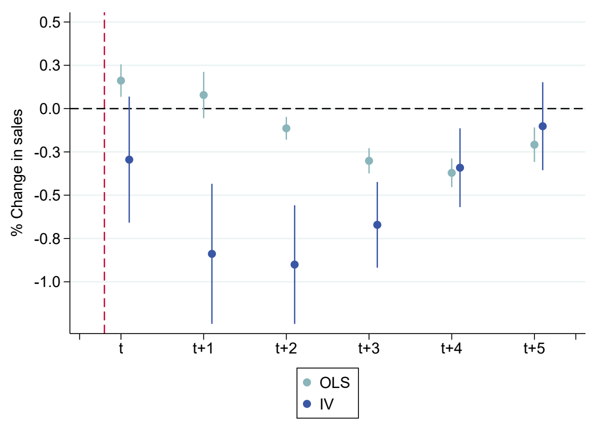
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure 3: 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 Copernicus grid cell of the firm's headquarter level.

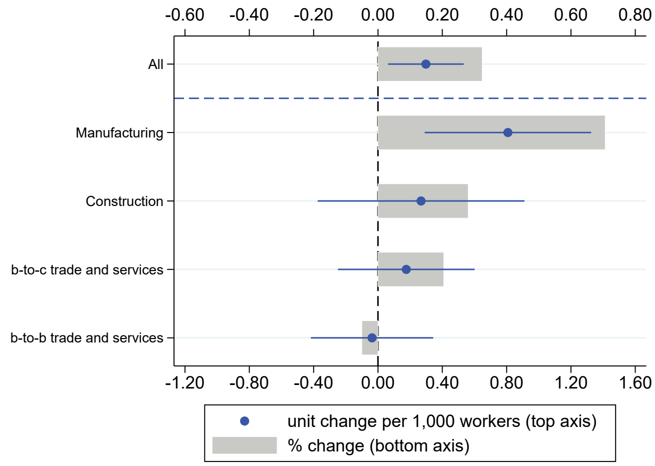


Figure 4: Contemporaneous effect of a one-unit increase in $PM_{2.5}$ on sick leave episodes

10 Tables

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	59.68	482.76	9,832,620
Monthly sales (k€)	1,316.30	18,153.87	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 €)	28,541.97	20,576.10	8,233,440
Annual medical expenditures (€)	442.02	809.78	8,233,440
Annual out-of-the-pocket medical 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	9,404.01	8,239,344
incl: for <93 days	363.52	2,655.22	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.

Table 2: First stage results

	PM$_{2.5}$ exposure	
	Municipality aggregation	Single-establishment firms
	(1)	(2)
$Z_{\text{South}\,gyt}$	1.432***	1.468***
	(0.097)	(0.152)
$Z_{\text{West}\,gyt}$	0.529***	0.575***
	(0.0635)	(0.148)
$Z_{\text{North}\,gyt}$	1.112***	1.231***
	(0.0484)	(0.055)
$Z_{\text{East}\,gyt}$	1.645***	1.610***
	(0.0481)	(0.0748)
Holiday and weather controls	Yes	Yes
Municipality-by-year FE	Yes	No
Firm-by-year FE	No	Yes
Month-by-year FE	Yes	No
Month-by-year-by-industry FE	No	Yes
Quarter-by-county FE	Yes	Yes
N	391,234	6,322,128
R-squared	0.93	0.93

Notes: Table reports the first stage results at two levels of aggregation. In the first column, the data is at the municipality-month level, and in the second column the data is at the firm-month level, keeping only single-establishment firms. We report standard errors in parentheses, clustered at the Copernicus grid cell. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$PM_{2.5t-1}$	0.0822***	-0.259***	0.109***	-0.255***
	(0.0229)	(0.0819)	(0.0263)	(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 columns (1) and (2), and for single-establishment firms in columns (3) and (4), 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 instruments are either the predicted firm-level pollution measure (column 2) or the four wind direction instruments (column 4). Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Manufacturing				
$PM_{2.5t-1}$	0.0352	-0.137**	0.0178	-0.0811
	(0.0217)	(0.0575)	(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**
	(0.0228)	(0.0499)	(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
	(0.0216)	(0.0563)	(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**
	(0.0466)	(0.156)	(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 instruments are either the predicted firm-level pollution measure (column 2) or the 4 wind direction instruments (column 4). Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

	All	Manuf	Const.	B2B	B2C
$PM_{2.5t+2}$	-0.0197	-0.0839	0.000437	-0.0323	-0.0196
	(0.0441)	(0.0527)	(0.0607)	(0.0498)	(0.101)
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 $t+2$. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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)
	Baseline	AQI	No AQ alerts	Winsorized outcome	Other weather	Satellite -based PM2.5	Shorter period	PM2.5 monitors
$PM_{2.5}$	-0.259***		-0.271***	-0.269***	-0.422***	-0.296**	-0.304***	-0.292***
	(0.819)		(0.0918)	(0.0898)	(0.127)	(0.123)	(0.0895)	(0.0832)
AQI		-3.17***						
		(1.38)						
N	9,403,173	9,411,803	8,959,529	9,411,935	9,411,803	9,411,803	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. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table 7: The contemporaneous effect of $PM_{2.5}$ on sick leave (per 1,000 workers), all sectors

	OLS	IV
	(1)	(2)
$PM_{2.5t}$	0.0703***	0.147**
	(0.0212)	(0.0603)
N	8,238,888	8,238,888
R-squared	0.0637	0.0637
Dep. var. mean	23	23
First-stage effective F-statistic		306

Notes: Table reports OLS and IV estimates from (8) for the effect of $PM_{2.5t}$ on the number of workers starting a sick leave per 1,000 workers at the establishment level. All regressions include industry-by-month-of-sample, establishment, and quarter-by-county fixed effects, as well as weather and holidays controls. Observations are weighted by the number of workers in each establishment. Standard errors are clustered at the Copernicus grid cell level. The effective F-statistic is based on a 2% random sample of single-establishment firms. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

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
$PM_{2.5t-1}$	-0.145**	-0.218***	-0.026	0.313*	0.316	0.378*
	(0.0613)	(0.0774)	(0.0920)	(0.165)	(0.194)	(0.226)
Avg Nb. employees	90	83	96	90	83	96
Median Nb. employees	27	25	29	27	25	29
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	1,351,931	865,271	486,658
R-squared	0.9640	0.9708	0.9530	0.1273	0.1279	0.1271
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***	-0.504***	-0.313**	-0.125	-0.048	-0.350
	(0.156)	(0.171)	(0.126)	(0.129)	(0.151)	(0.229)
Avg. Nb. employees	48	41	73	48	41	73
Median Nb. employees	11	11	13	11	11	13
Avg. sales	883,728	690,286	1,567,431	883,728	690,286	1,567,431
N	3,124,507	2,430,224	694,278	1,882,246	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 (excluding extraction and utilities) 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. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Appendix – For online publication only

A Additional Figures and Tables

A.1 Figures

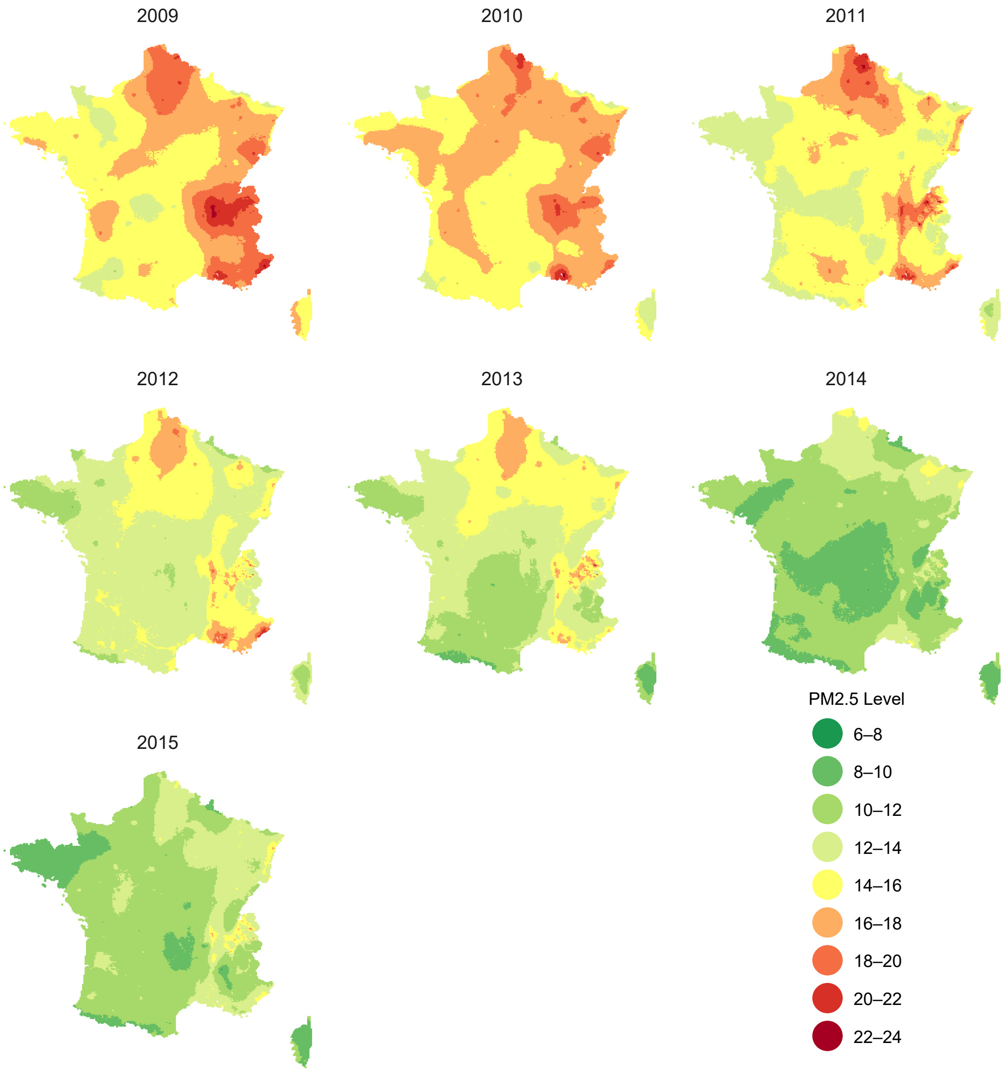
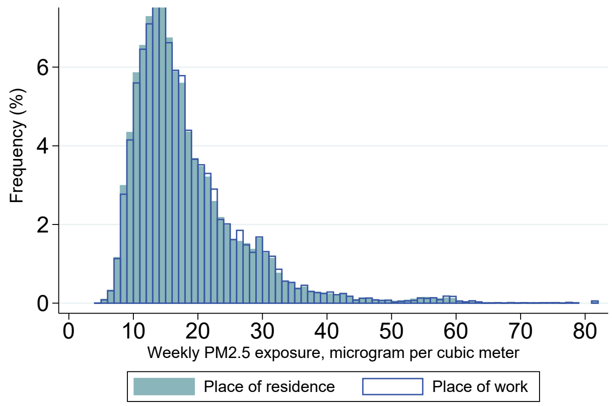
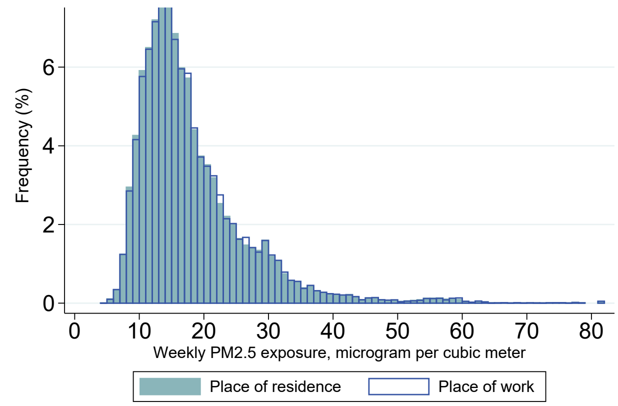


Figure A.1: Average annual concentrations of $PM_{2.5}$ (µg/m^3)

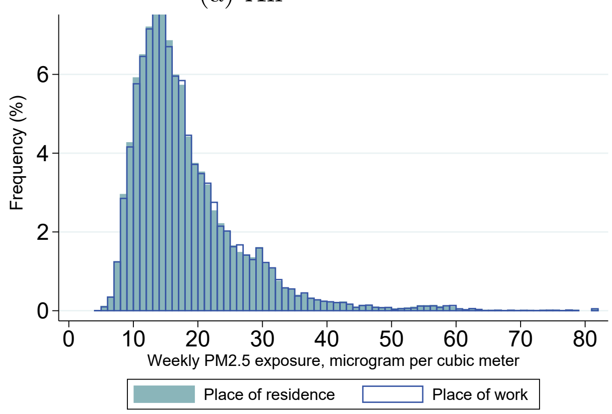
Notes: Figure shows the average annual concentration of $PM_{2.5}$ measured at the 4km x 4 km grid cell level using the reanalysis CHIMERE data. There are 33,252 Chimere grid cells in metropolitan France.



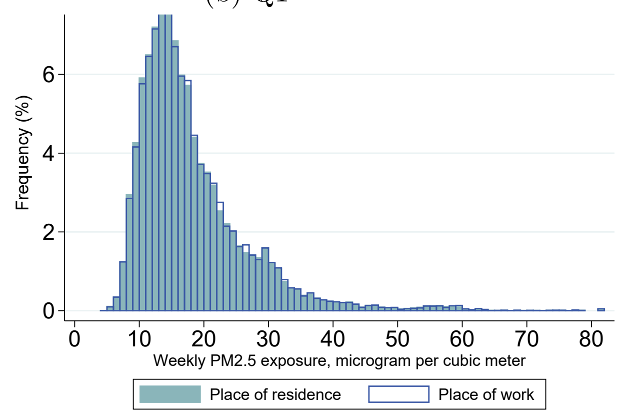
(a) All



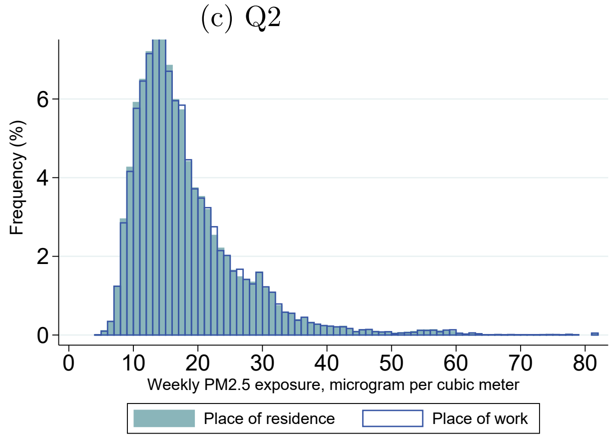
(b) Q1



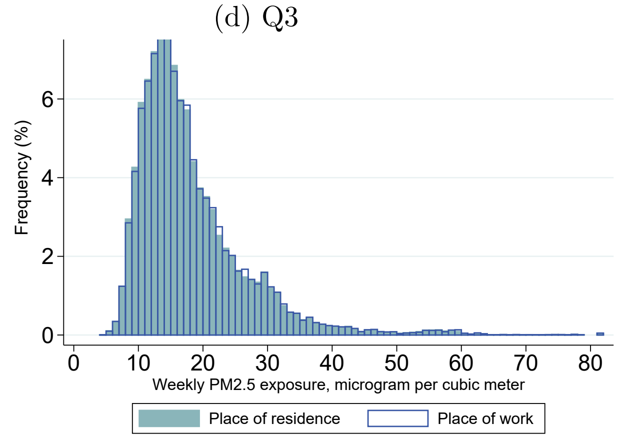
(c) Q2



(d) Q3



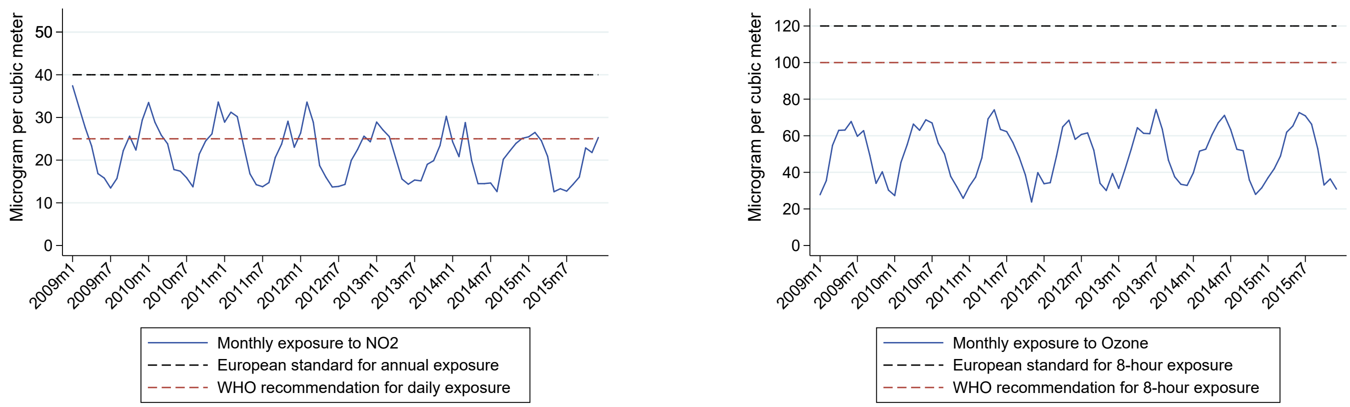
(e) Q4



(f) Q5

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

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



(a) 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 sick 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.

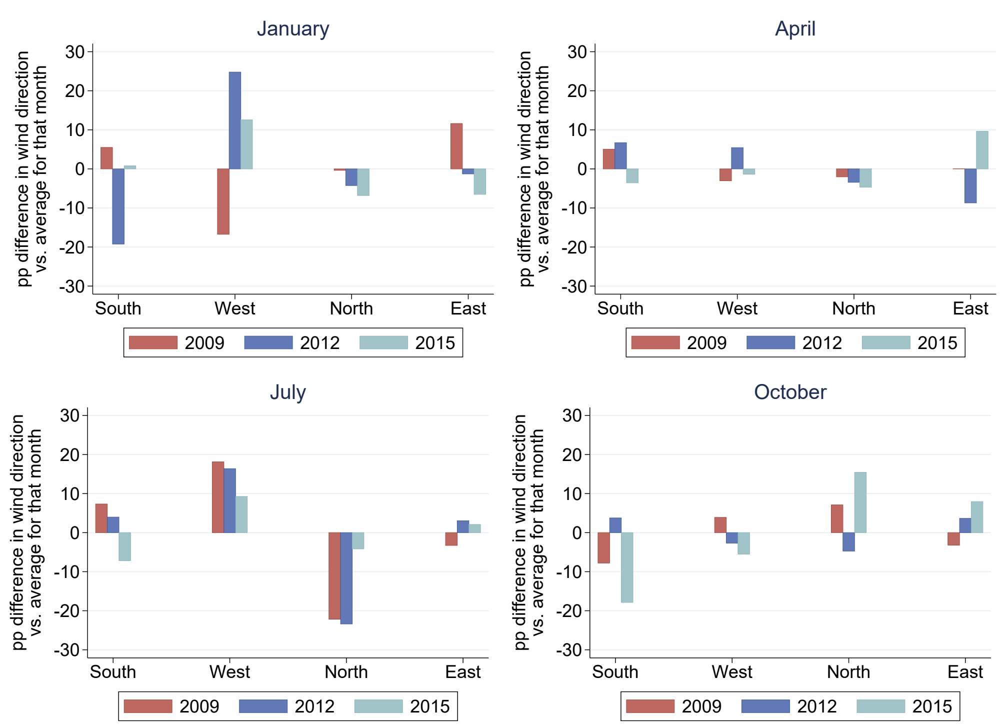


Figure A.4: Within-calendar month variation in wind direction, Paris

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

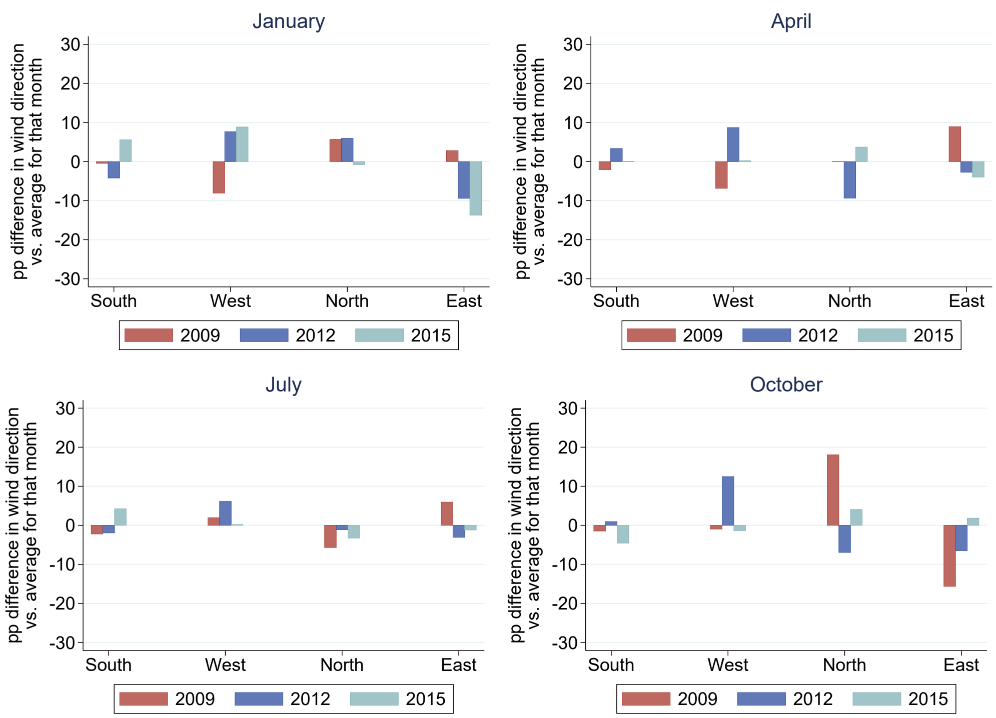
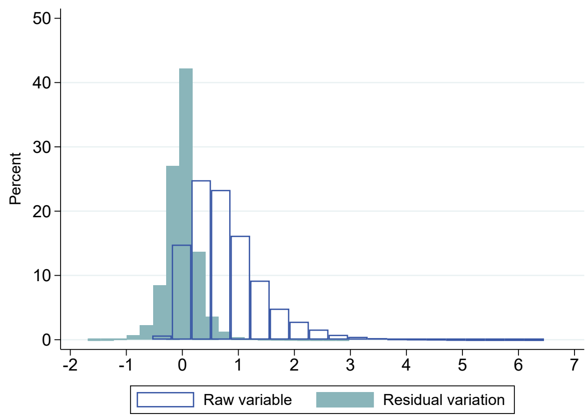
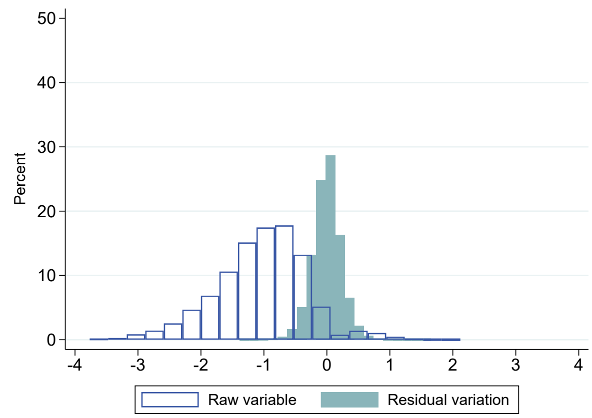


Figure A.6: Within-calendar month variation in wind direction, Marseille (South-East of France)

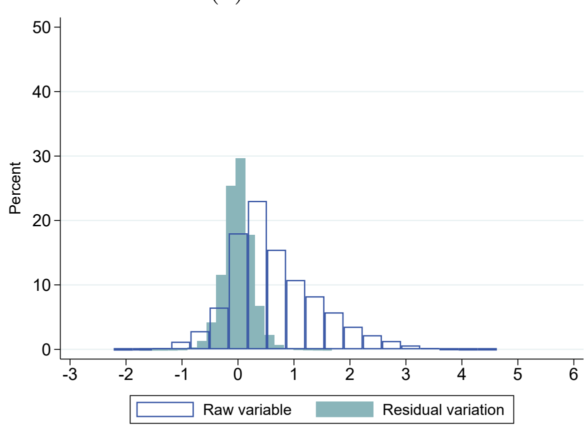
Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, demeaned by the average for the month, for four different months (Month 3=March, Month 6=June, Month 9=September, Month 12=December and three different years (2009, 2012, 2015).



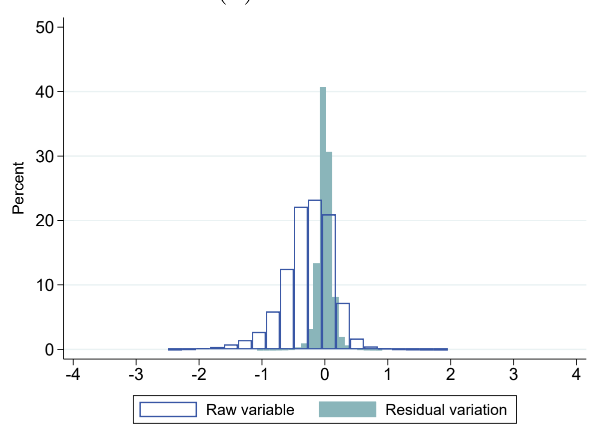
(a) East wind



(b) West wind



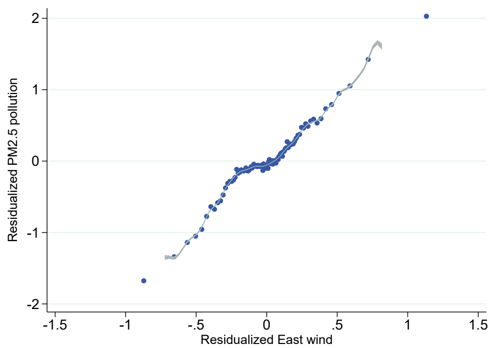
(c) North wind



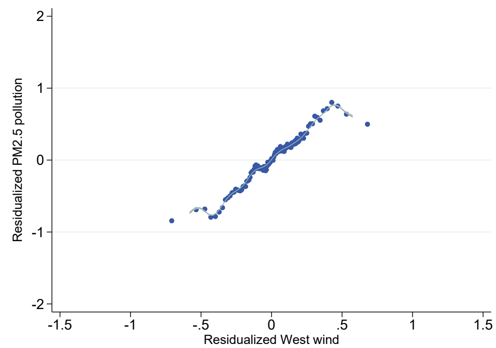
(d) South wind

Figure A.8: Identifying variation - Distribution of raw and residualized wind instrument

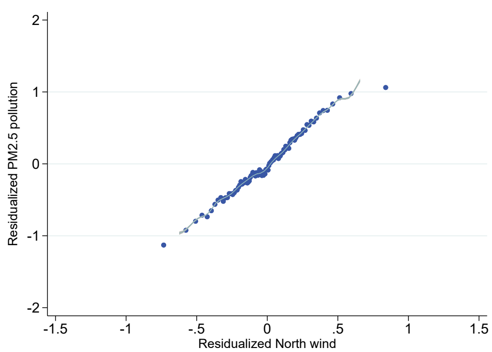
Notes: Residualized variables are obtained by regressing each wind instrument value on the right-hand side variables of equation (10) for the sample of single-establishment firms: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-county fixed effects, and firm-by-year fixed effects.



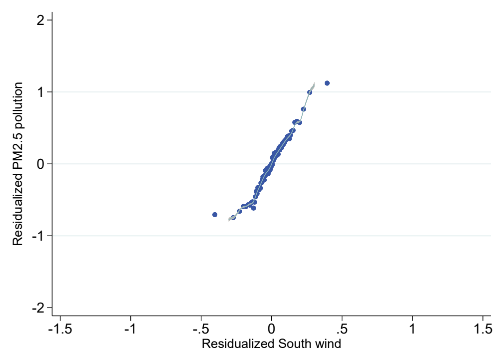
(a) East wind



(b) West wind



(c) North wind



(d) South wind

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

Notes: Figure is based on the sample of single-establishment firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing each wind instrument value (resp. $PM_{2.5}$) on the right-hand side variables of equation 10: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-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).

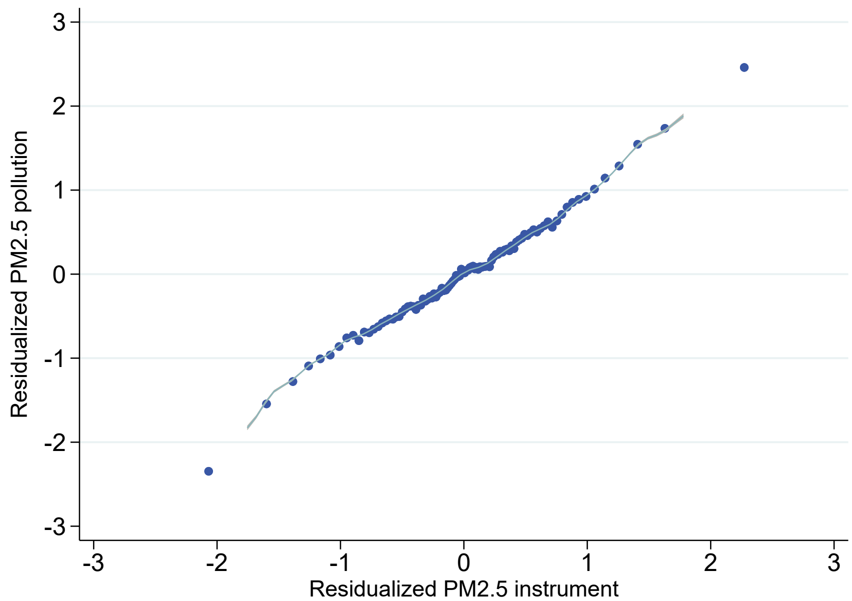
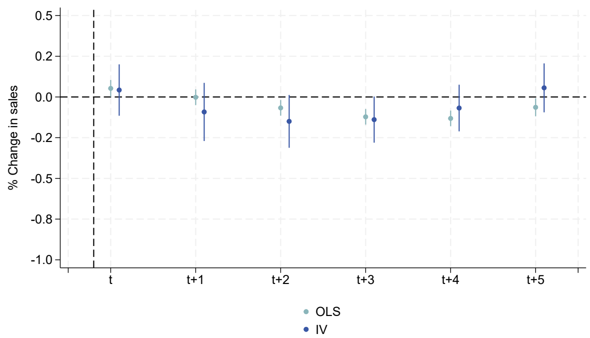
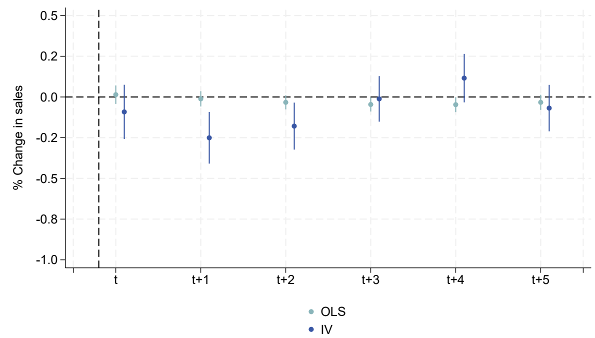


Figure A.12: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

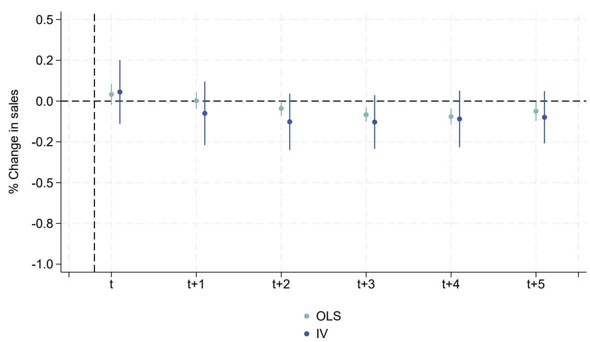
Notes: Figure is based on the sample of all firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing the predicted $PM_{2.5}$ variable $\widehat{PM_{2.5}}_{fyt}$ (resp. the endogeneous $PM_{2.5}$ variable) on the right-hand side variables of equation 10: weather and holiday controls,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



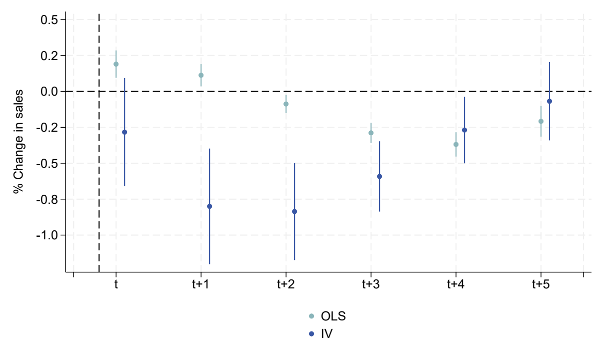
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure A.13: 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, firm-by-year, and quarter-by-county fixed effects, as well as weather and holidays controls (the latter at all the relevant leads and lags). Standard errors are clustered at the Copernicus grid cell level.

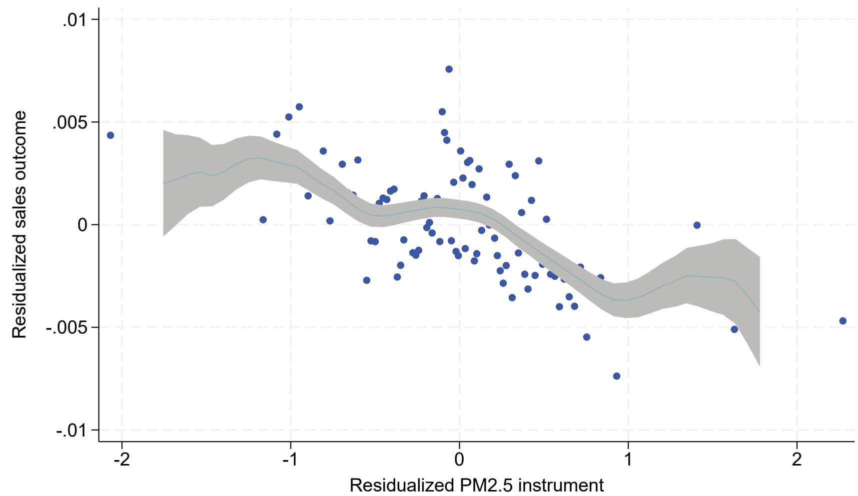


Figure A.14: Residualized binned scatter plot between sales and $PM_{2.5}$ instrument and local polynomial fit

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

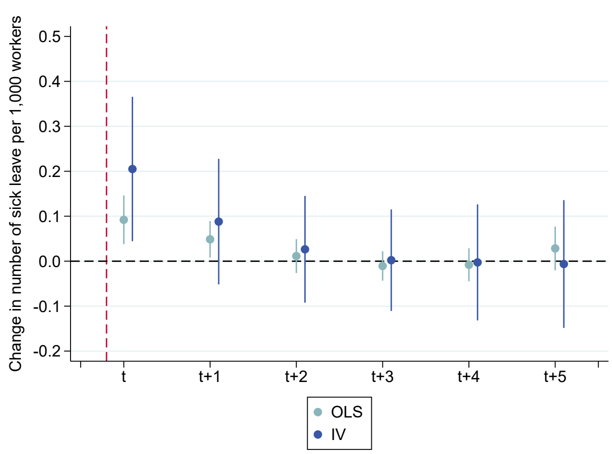


Figure A.15: Dynamic effects of $PM_{2.5}$ on absenteeism

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals from equation (8) for the effect of contemporaneous and lagged $PM_{2.5}$ (up to $t-5$) 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, establishment, and quarter-by-county fixed effects, as well as weather and holidays controls (the latter at all the relevant leads and lags). Standard errors are clustered at the Copernicus grid cell level.

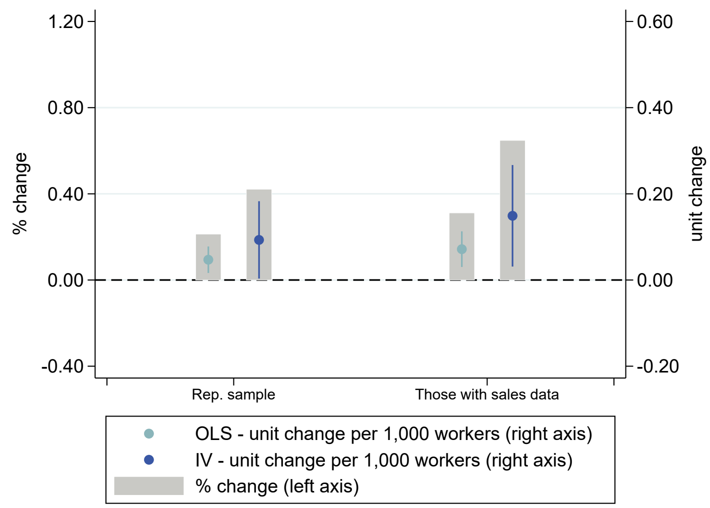


Figure A.16: Absenteeism results for our main sample (right) vs. a representative sample (left)

A.2 Tables

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

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

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

Table A.2: The Effect of Lagged $PM_{2.5}$ on Firm-level Sales in the next Two Months, All Sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	IV	IV	IV
$PM_{2.5t-1}$	-0.0404*	-0.582***	-0.535***	-0.493***	-0.283***	-0.259***
	(0.0216)	(0.132)	(0.108)	(0.109)	(0.0775)	(0.0816)
Firm FE	Yes	Yes	No	No	No	No
Firm-by-year FE	No	No	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	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	9,412,076	9,412,076	9,411,967	9,403,047	9,411,967	9,403,047
R-squared	0.9208	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 $t+1$. Standard errors are clustered at the Copernicus grid cell level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.3: Heterogeneous sales responses to lagged $PM_{2.5}$ by firm size

	(1) Below 15 workers	(2) Above 15 workers
Panel A: All firms		
$PM_{2.5t-1}$	-0.285***	-0.217**
	(0.0944)	(0.0756)
N	4,518,389	4,884,534
R-squared	0.8527	0.9386
Panel B: Manufacturing		
$PM_{2.5t-1}$	-0.219**	-0.0636
	(0.102)	(0.0564)
N	603,302	1,272,790
R-squared	0.8398	0.9557
Panel C: Construction		
$PM_{2.5t-1}$	-0.167**	0.0205
	(0.0780)	(0.0616)
N	837,106	693,238
R-squared	0.8019	0.9253
Panel D: Business-to-Business Trade and Services		
$PM_{2.5t-1}$	-0.177**	-0.0789
	(0.0745)	(0.0745)
N	1,226,885	1,646,455
R-squared	0.8484	0.9281
Panel E: Business-to-Consumer Trade and Services		
$PM_{2.5t-1}$	-0.381**	-0.573***
	(0.148)	(0.180)
N	1,847,217	1,275,904
R-squared	0.8742	0.9380
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 strictly fewer than 15 workers on average (column (1)) and those with 15 workers or more (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 Copernicus grid cell level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.4: The contemporaneous effect of $PM_{2.5}$ on the number of sick days in manufacturing

	OLS (1)	IV (2)
$PM_{2.5t}$	3.086***	5.553*
	(1.024)	(2.900)
N	1,758,851	1,758,851
R-squared	0.0411	0.0411
Dep. var. mean	423	423
First-stage effective F-statistic		365

Notes: Table reports OLS and IV estimates from (8) for the effect of $PM_{2.5t}$ on the number of sick days per 1,000 workers at the establishment level, for the manufacturing sector. All regressions include industry-by-month-of-sample, establishment, and quarter-by-county fixed effects, as well as weather and holidays controls. Observations are weighted by the number of workers in each establishment. Standard errors are clustered at the Copernicus grid cell level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table A.5: Sensitivity of standard errors to the scale of clustering

	(1) Baseline Wind grid	(2) Firm level	(3) County level	(4) Two-way time, wind grid	(5) Two-way time, firm	(6) Two-way time, county
$PM_{2.5t}$	-0.259***	-0.259***	-0.259***	-0.259**	-0.259**	-0.259**
	(0.0819)	(0.0264)	(0.0681)	(0.127)	(0.105)	(0.116)
N	9,403,047	9,403,047	9,403,047	9,403,047	9,403,047	9,403,047

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, with different choices for the clustering for standard errors. 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. 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 sick leave episodes.

Table B.6: The contemporaneous effect of $PM_{2.5}$ on sick leave (per 1,000 workers), all sectors, aggregating data at the municipality level

	OLS	IV
	(1)	(2)
$PM_{2.5t}$	0.0644**	0.148**
	(0.0208)	(0.0613)
N	369,190	369,190
R-squared	0.1602	0.1602
Dep. var. mean	23	23
First-stage effective F-statistic		268

Notes: Table reports OLS and IV estimates from (8) 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 municipality level. All regressions include month-of-sample, municipality, and quarter-by-county fixed effects, as well as weather and holidays controls. Observations are weighted by the number of workers in each municipality. Standard errors are clustered at the Copernicus grid cell level. The effective F-statistic is based on a subsample of single-establishment firms aggregated at the municipality level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Column (1) of table B.7 shows the baseline estimate for the specification at the establishment level (same as column (2) of table 7). Column (2) shows that a one-unit increase in the AQI indexincreases the number of workers entering sick leave that month by 2.1 per 1,000 workers. The effect in terms of SD increase is 0.85, while the effect of a one-SD increase in PM2?5 is 0.93, 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 the order of magnitude of the effect holds if we use satellite-derived PM2.5 data instead of reanalysis PM2.5 data. Columns (7) and (8) show that the results are the same if we use monitoring station data only (restricting the period of analysis to 2011-2015).

Table B.7: The Effect of $PM_{2.5}$ on worker absenteeism, all sectors, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	AQI	No AQ alerts	Winsorized outcome	Other weather	Satellite -based PM2.5	Shorter period	PM2.5 monitors
$PM_{2.5t}$	0.147**		0.156**	0.157***	0.155**	0.191**	0.189***	0.189***
	(0.0603)		(0.0650)	(0.0496)	(0.0611)	(0.082)	(0.0604)	(0.0612)
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	5,796,540	5,796,540

Table reports IV estimates from equation (8) 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. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

C Data Appendix

C.1 Sick Leave Episodes

We obtain data on sick leave episodes (SLE) from the Hygie dataset, which follows approximately 900,000 employees during the period 2009-2015. 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).

The main subsample of interest is based on an exact match between the firm identifier of the establishment where the worker is employed and observing that firm in the sales data. When we instead consider the representative sample of private sector employees (such as in figure A.16), we make three restrictions to the Hygie sample. 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 sick leave episodes.

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

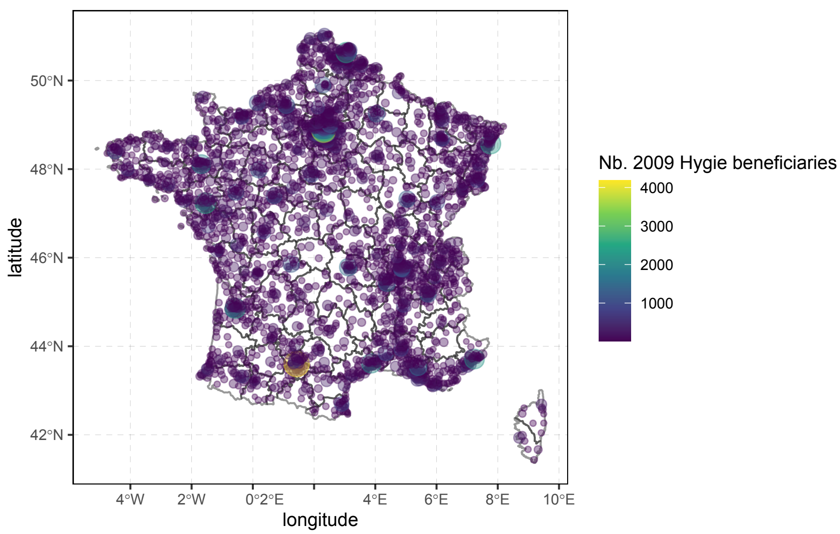


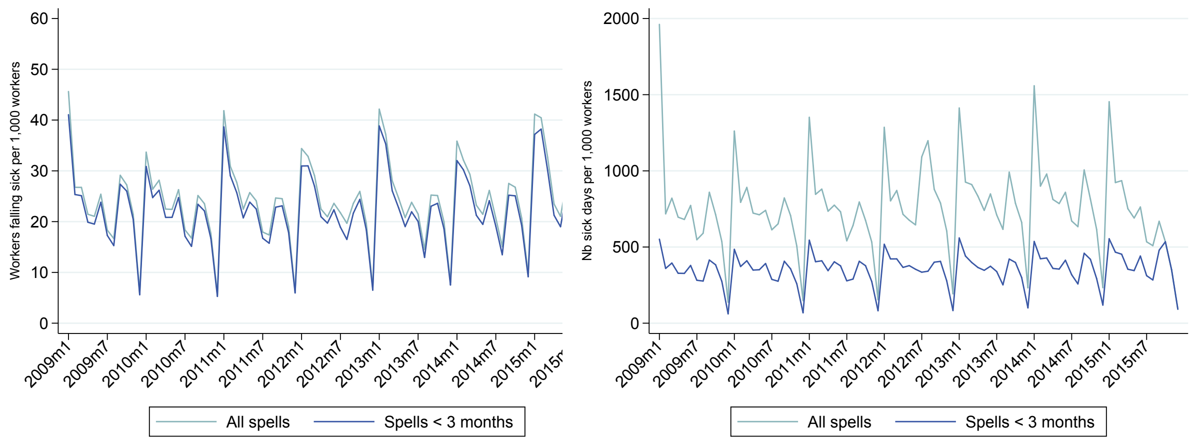
Figure C.17: Location of workers from the Hygie dataset based on the workplace municipality, in 2009

We use the exhaustive matched employer-employee data (DADS-Postes) to compare the characteristics of our representative sample of workers to the characteristics of the whole population of private sector employees. Applying the same restrictions as in the Hygie dataset,[34] we find that those workers representing the population from which our sample

[34]Namely, we keep private sector employees born between 1935 and 1989, less those older than 71 who should be retired. Note that in the matched employer-employee data, a worker having two different employers appears twice. We aggregate wage information at the worker level, summing up the wages she receives from different employers.

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 A.1 – is very close to the average private sector employee.

We



(a) Number of workers falling sick

(b) Number of sick days

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

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

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.[35] Our measure of sales includes both domestic sales and exports to EU and non-EU countries. The French tax administration imposes monthly declarations to firms with annual sales above €818,000 for the manufacturing sector and the hospitality industry and to those with annual sales above €247,000 for the other sectors. Firms below this threshold are allowed to fill declarations on a quarterly basis.

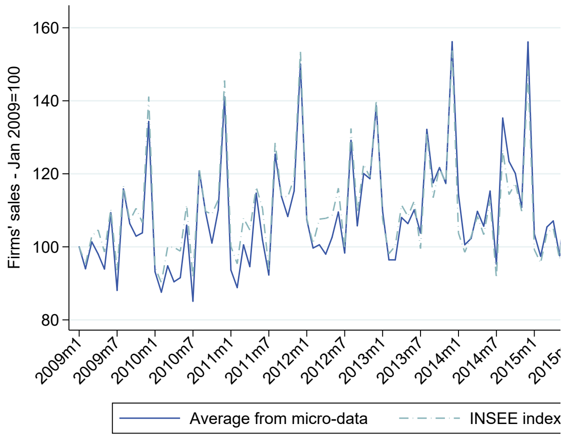
[35] For instance, the sales of natural gas and electricity is subject to a specific VAT rule in the French tax code, so they have their own subcomponent in the VAT records. See https://www.impots.gouv.fr/sites/default/files/formulaires/3310-ca3-sd/2022/3310-ca3-sd_3947.pdf

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

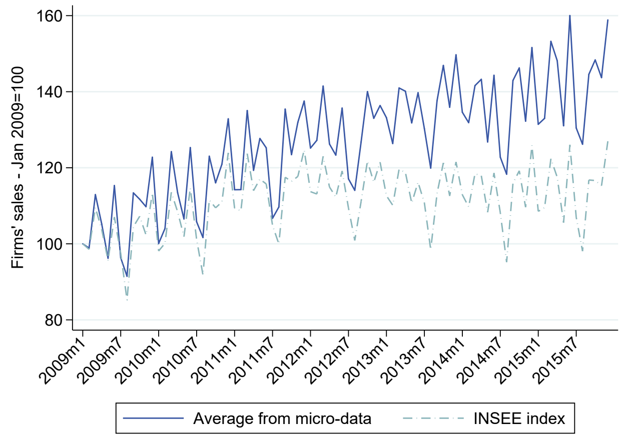
We determine sectors of activity based on the sectoral classification available at the establishment level and we use the mode of sector categories across establishments for multi-establishment firms. We define 4 sectors of interest: manufacturing, construction, business-to-consumer trade and services,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

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.19c shows the time series of monthly sales in construction (C.19a), manufacturing (C.19b) and all services (C.19c) as constructed from the VAT micro-data compared with the INSEE index. Differences may arise between our sales value and the statistical agency's because of different choices in data cleaning or the subcomponents entering the sales variable, but the correlation between the two series are above 0.9 for the three broad sectors.

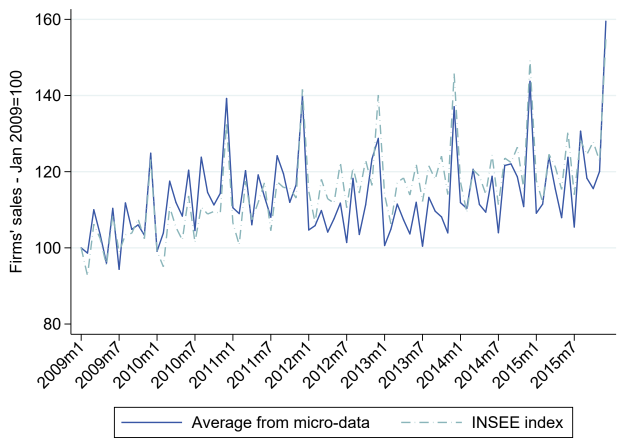
[36] See https://www.impots.gouv.fr/professionnel/questions/comment-declarer-ma-tva-en-periode-de-conges-



(a) Construction



(b) Manufacturing



(c) Services

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

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

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