The Cost of Air Pollution for Workers and Firms*

Marion Leroutier, Hélène Ollivier†

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Abstract

This paper shows that even moderate air pollution reduces economic activity. Using French monthly firm-level data and exploiting variation in $PM_{2.5}$ exposure driven by changes in local wind direction, we find that a 10% pollution increase lowers sales by 0.23% in the same month and 0.69% the next month. Effects vary by sector and operate through reduced labor supply—with a 1% increase in sick leave—, reduced productivity, and demand responses. Absenteeism explains only 3–4% of the sales decline, highlighting the importance of the other channels. Aligning air quality with WHO guidelines could yield economic benefits comparable to the costs of regulation or to health benefits from reduced mortality.

Keywords: Air pollution, Firms, Absenteeism
JEL codes: Q53, H23, I10, J22

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†Leroutier: CREST, Institut Polytechnique de Paris, ENSAE. Corresponding author. Email: marion.leroutier@ensae.fr. Ollivier: Paris School of Economics, CNRS. Email: helene.ollivier@psemail.eu.

1 Introduction

It is widely acknowledged that air pollution has detrimental effects on human health, driving up healthcare costs (Barwick et al., 2024), increasing emergency admissions and mortality (Schlenker and Walker, 2016; Deryugina et al., 2019), and potentially impairing cognitive functions and mental health (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 societal costs if air pollution's impacts on individuals translate into substantial economic 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.

In this paper, we fill this gap by estimating the causal effects of monthly air pollution exposure on firms' monthly sales in France, a country characterized by moderate pollution levels. We use confidential micro-level tax and social security data for the private sector collected by the French administration. We develop an analytical framework that formalizes how air pollution affects private-sector firms' sales in the short run, distinguishing three channels. On the supply side, air pollution may reduce labor supply through increased absenteeism or shorter working hours. It may also lower the productivity of non-absent workers, either through mild health symptoms or through disruptions caused by absent colleagues. Finally, for firms serving local demand, pollution at the firm's location may reduce sales by deterring consumers who are themselves exposed, including through reductions in their disposable income when illness reduces their ability to work. Using granular data, we estimate the overall impact on firm sales and quantify the share attributable to worker absenteeism; the residual captures the combined effects of reduced on-the-job productivity and lower demand.

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.[1] 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 bloodstream and the brain, with detrimental effects on respiratory and cardio-vascular health, as well as cognitive skills.[2] Particulate pollution can also easily penetrate indoors and affect air quality at the workplace.

[1] We define a municipality as a postcode area. An average French postcode area is thirty times smaller than an average US county and slightly smaller than an average US census tract. There are 6,048 municipalities in Metropolitan France.

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

Identifying the causal effects of pollution exposure on firms' sales and workers presents three main challenges: first, air pollution is often a byproduct of economic activity; second, individual exposure is typically measured with noise; third, there may be a lag between the time of production and the time of sales.[3] To address reverse causality, measurement error and endogeneity issues, we leverage variation in air pollution driven by changes in monthly wind directions at the municipality level, across 6,048 municipalities in metropolitan France. To capture the potential lag between air pollution shocks and recorded sales, we assess how pollution exposure influences sales in both the contemporaneous and following months in our main specification.

We use insights from previous work (Deryugina et al., 2019; Graff Zivin et al., 2023) to build an instrumental variable (IV) based on the changes in each municipality's monthly wind direction. After flexibly controlling for sectoral trends, weather characteristics—including temperature, rainfall and wind speed—, local seasonality and firm-year characteristics, we assume 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 owning establishments in multiple municipalities, we build an instrument for firm-level pollution exposure by computing a weighted average of predicted pollution exposure at the establishment-month level, accounting for the structure of the intrafirm network and the geographic distribution of establishments.

Knowledge of the complete intrafirm network is crucial for estimating firm-level effects of air pollution. In our sample, firms operate an average of two establishments each year, though some manage many more. Since these establishments are not necessarily located in the same region, our measure of exposure accounts for the geographic dispersion of firms' activities.[4] Furthermore, our data reveal substantial entry and exit of plants within existing firms.[5] Annual variation in firm-level outcomes therefore depends not only on changes in the level of air pollution at specific locations (controlling for common trends), but also on

[3] Two mechanisms may explain the lag between production and recorded sales. First, some production processes take time (e.g., car manufacturing, or architectural and legal services), and payment typically occurs only after the product or service has been delivered. Second, buyers may delay payment even after delivery, postponing the recording of sales for tax purposes until the payment is received. For example, the average delay of payment in the French private sector was 14 days in 2015.

[4] A key feature of our administrative data is that we observe the universe of plants per firm-year and each plant can be geolocalized.

[5] Between 2009 and 2015, firms in our sample experienced 67,878 entries or exits of plants. The symmetric churn rate, defined as the net plant turnover relative to the average number of plants per firm-year, is 2.34%.

how firms distribute their activities across multiple establishments/locations. By leveraging monthly variation in both sales and air pollution and including firm-year fixed effects, our estimation strategy isolates the causal effect of air pollution while holding the overall firm-year structure fixed.

Our main result is that firm-level exposure to $PM_{2.5}$ has widespread negative effects on sales. We show that a 10 percent increase in firm-level pollution exposure in month t reduces firm-level sales by 0.23 percent in the same month ($p = 0.025$) and by 0.69 percent in the following month ($p < 0.001$), corresponding to elasticities of -0.023 and -0.069. The magnitude varies across sectors: manufacturing sales decrease by 0.28 percent after one month; construction sales decline by 0.36 percent after one month and 0.24 percent contemporaneously; business-to-business trade and services sales fall by 0.44 percent after one month; and business-to-consumer industries experience the largest declines— 1.17 percent after one month and 0.35 percent contemporaneously. The negative effects persist for two to three months after the pollution shock and dissipate after about five months, with no rebound. The results are similar when restricting our sample to single-establishment firms, for which pollution exposure is measured more accurately. 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 pollution data from monitoring stations or on satellite-based data.

We next turn to the mechanisms behind the pollution-induced decline in sales, asking whether it can be attributed for the most part to workers taking sick leave. Among the three channels identified in our analytical framework, we are able to measure labor supply adjustments most precisely through sick leave episodes, observed daily for a representative sample of workers. In France, sick leave requires a medical certificate issued by a general practitioner starting on the first day of absence.[6] Unlike sales, which may respond with a delay, we assume (and verify empirically) that sick leave responds to contemporaneous pollution shocks only, consistent with previous literature.

We find that air pollution reduces labor supply via an increase in sick leave. Our estimates imply that a 10 percent rise in monthly $PM_{2.5}$ exposure in the municipality of work increases sick leave episodes by 1 percent within the month of exposure ($p = 0.015$), with no persistence beyond that. The effect 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. Overall, absenteeism accounts for only about 3-4% of the pollution-induced

[6] This makes our measure of sickness-driven absenteeism more accurate than in settings where sick leave is only recorded and compensated above a minimum duration. At the same time, we do not observe potential reductions in working hours by employees who continue to work while feeling unwell. Therefore these adjustments are part of the productivity channel.

sales decline, and at most 22% in the most affected sector—manufacturing. This limited contribution indicates that the other two channels—productivity and demand reductions—are also important drivers of the observed sales losses.

While micro-level studies based on daily or monthly output per worker at a few production sites can provide precise estimates of the productivity channel (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019), extending this approach to cover the entire private sector of one country is not feasible. Additionally, we cannot divide firm sales by the number of workers to construct productivity measures in our setting, because the number of employees is only reported annually, and our identification relies on within firm-year variation.

Instead, we show evidence of a supply-side mechanism going beyond the effect of reduced labor supply by exploring heterogeneous sales responses across manufacturing industries. Firms in industries typically relying on large inventories can buffer temporary supply-side shocks by selling existing stocks, thereby mitigating the impact on their sales. In contrast, large inventories do not protect against demand-side shocks. Our findings reveal that the pollution-induced decrease in manufacturing sales is concentrated in industries typically operating with low stock levels, while we detect no significant decrease in industries typically operating with high stock levels. Given that both types of firms experience similar increases in sick leave following a pollution shock and have comparable average sizes and sales, this heterogeneity in the pollution-sales effect suggests a pollution-driven decrease in worker productivity.

With the largest sales decline in the sector predominantly serving local demand—retail and consumer services—this suggests that air pollution may also act as a demand-side shock. This demand response may be delayed relative to the pollution-induced health effects, as workers often face partial wage replacement during sick leave and delayed healthcare reimbursements. We expect budget-constrained consumers to cut back more on discretionary purchases than on essential items. We indeed find a meaningful ranking across subsectors, with the largest sales drop for discretionary goods and services, contrasting with small to non-significant decline in essential goods purchases.

Our findings of pollution-induced reductions in sales are economically significant. Meeting 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 that such pollution decrease would have prevented between €25 and €38 billion in annual sales losses from 2009 to 2015, depending on whether dynamic effects after one month are included. With an average value-added-to-sales ratio of 27%, this corresponds to between €6.9 and €10.3 billion in annual foregone value added. We show that these economy-wide costs of air pollution approximately rival the widely emphasized associated mortality costs and may also be equivalent to the associated cost of reducing $PM_{2.5}$ emissions.

To the best of our knowledge, this is the first nationwide study establishing a causal link between air pollution and firm-level sales for the entire private sector. One related paper by Fu et al. (2021) examines the effect of air pollution on annual output among large Chinese manufacturing firms in a high-pollution setting. Average pollution levels in France are four to five times lower than in China or India, similar to those in Europe and fifty percent above those in the US.[7] We highlight the significant economic cost of air pollution in high-income countries, with all sectors incurring sales losses, not just manufacturing. In the European context, Dechezleprêtre et al. (2019) document that a 10% increase in regional $PM_{2.5}$ in Europe decreases regional deflated GDP per capita by 0.8% on the same year, using aggregate data.[8] While we also find substantial economic costs, our granular data capture firms' monthly sales response and our identification relies on within firm-year variation. Annual output measures may obscure short-term shocks if firms smooth their responses over time. We test whether such smoothing exists and find no rebound effect five months after the shock. Finally, by leveraging high-frequency sales data available for many sectors and firm types, we investigate the heterogeneous effects of pollution shocks and their underlying mechanisms.

By exploring the channels underlying these sales reductions, our paper is connected to the literature examining how air pollution affects workers' productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lichter et al., 2017; He et al., 2019; Chang et al., 2019; Dong et al., 2019; Adhvaryu et al., 2022; Meyer and Pagel, 2024). This literature is largely based on specific settings of one or two firms, where workers are paid by the hour or productivity is easy to observe.[9] In 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). In our high-income context, we show that manufacturing firms in industries operating with ample inventory can buffer supply-side

[7]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.

[8]In many countries, and in particular in France, establishment-level output data is not collected. As a result, the regional GDP reported by Eurostat and used by Dechezleprêtre et al. (2019) likely suffer from measurement error as proxies (e.g., number of workers) are used to allocate value added per industry at the regional level.

[9]This point was highlighted in a review paper by Aguilar-Gomez et al. (2022). For studies that measure productivity as value added per worker (Dechezleprêtre et al., 2019; Dechezleprêtre and Vienne, 2025) at the annual level, it is important to note that they typically cannot disentangle the three channels we consider. Because value added is constructed from recorded sales, the demand channel is inherently embedded in the measure. Moreover, worker counts are usually based on the number of employment contracts at year-end, which precludes distinguishing productivity effects from those driven by absenteeism.

disruptions, while those in industries operating with low stock are more vulnerable to sales losses.

We also contribute to a small literature that finds 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). We extend this literature by examining a high-income country with institutionalized sick leave. Borgschulte et al. (2024) show that severe wildfire-related pollution shocks in the US reduce average earnings in affected counties, partly because workers exit the labor force. This reflects an extreme labor supply adjustment, likely activated only when more flexible margins—such as reducing hours, taking short-term sick leave, or switching jobs—are unavailable. By contrast, we focus on temporary absenteeism, a more frequent adjustment margin that reveals how pollution disrupts day-to-day work continuity and firm-level productivity. Holub et al. (2021) also show that exposure to PM_{10} increases sick leaves in Spain. Drawing on our matched employer-employee data, we demonstrate that the cost of pollution in terms of foregone sales far exceeds the cost attributable to pollution-induced lost work days alone.

In the literature on the economic effects of environmental shocks, demand-side mechanisms have received less attention than supply-side mechanisms. We thus 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). In China, Barwick et al. (2024) find a negative impact of daily $PM_{2.5}$ on necessities and supermarket spending within two weeks of exposure, which can be rationalized with reductions in disposable income and short-term avoidance behaviors. Using firms' recorded sales instead of credit card transaction data, we uncover demand-side responses to less salient shocks.

The rest of the paper is organized as follows. Section 2 provides a brief background on the French context and presents our analytical framework. Section 3 presents the data. Section 4 describes our empirical strategy. Section 5 presents the main results, while section 6 discusses the channels. Section 7 puts the results in perspective, and section 8 concludes.

2 Background and Framework

2.1 The Effects of Air Pollution 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).[10] $PM_{2.5}$ 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).

Despite these detrimental health effects, 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.[11] 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. On the one hand, moderate pollution may lead to fewer workers experiencing severe health issues or reduced productivity, and fewer consumers avoiding shopping due to health concerns or mild symptoms. This would suggest minimal impact on output. On the other hand, reduced visibility of pollution shocks could hinder managers' ability to mitigate potential declines in productivity or labor supply.

Moreover, labor market and social security institutions likely influence how workers, firms, and consumers 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 signed by a general practitioner and have worked at least 150 hours in the past

[10] $PM_{2.5}$ 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.

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

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 60 percent of private-sector employees receive full wage replacement from the first day of leave (Pollak, 2015). For the remaining 40 percent, the first three days of leave are not compensated, the replacement rate from day 4 to 7 is 50% of the daily wage, and it increases to 90% of the daily wage from day 8.

Given incomplete replacement rate during sick leave and associated healthcare costs, pollution can trigger a significant loss in disposable income for exposed workers-consumers. We calculate that for a 3-day sick leave episode (hereafter SLE), income loss amounts to roughly 10% of median monthly wage for the 40% of workers without employer supplements.[12] Such episode is also associated with out-of-pocket healthcare expenditures worth 9% of median monthly wage, based on median daily out-of-pocket expenditures in our sample. These reductions in disposable income may only become apparent to consumers at the end of the month, when they receive their pay and any reimbursements from social security, which may result in delayed consumer responses to air pollution shocks.

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—a decline in labor supply and reduced productivity—as well as a demand-side mechanism, which captures income losses and 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).[13] 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

[12]Median wage for this group is taken from Pollak (2015).
[13]For simplicity, we assume that $E[e^{u_{fit}}] = 0$ for all firms.

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., higher healthcare expenditures reduce the disposable income for other expenditures whereas 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.[14] We expect $\bar{a}'_t(c) \geq 0$ as higher pollution concentrations likely worsen health effects.

The representative consumer's objective is to maximize her utility (1) given her budget constraint. The CES structure yields an expression for expenditures y_{fit} on each variety f at time t that depends on air pollution exposure, c, through at least the demand-side mechanism:

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

where p_{fit} is the price of variety f at time t and P_{it} corresponds to the CES price index for industry i, which is defined in the usual way: $P_{it} = \big[\sum_{f \in \Omega_{it}} (p_{fit})^{\frac{\rho_i}{\rho_i - 1}} \, e^{\frac{u_{fit}(c)}{1-\rho_i}}\big]^{\frac{\rho_i - 1}{\rho_i}}$.

Production. On the supply side, air pollution exposure influences output through two mechanisms that concur in reducing effective labor, which is the only factor of production. First, workers exposed to pollution shocks may be less productive due to health symptoms and work disruptions. 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

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

and firms interchangeably. As a result, the production technology for output Q is[15]

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

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 experiences a change 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 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 average absence rate is quite small[16] (hence, $\log(1-x) \approx -x$) and reorganizing terms yields

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

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

[16]In our data, the average number of workers starting a sick leave is 23 per 1,000 workers each month, so the absence rate is very small.

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 can be safely assumed given the negative impact of absenteeism on firms' sales.[17] 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 two 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 objectives is thus to evaluate the reduced-form effect of air pollution on firms' sales.

Second, equation (6) shows that the strength of all three channels depends on the elasticity of substitution across varieties within an industry. Industries with highly elastic demand—and therefore low profit margins—are particularly exposed to both supply- and demand-side shocks. Because firms in these sectors cannot raise prices without losing customers, they operate with thin margins and therefore likely suffer disproportionately large sales losses when pollution shocks occur. Using demand elasticity estimates from Harrigan et al. (2024) for France, we distinguish two groups. Manufacturing, construction, and administrative and support activities exhibit relatively low demand elasticities, with average $\sigma_i = 3.89$, 2.67, and 3.34, respectively. In contrast, wholesale trade, retail, and hospitality have much higher elasticities—8.93, 6.03, and 5.52. For illustration, a given log-point decline in worker productivity would reduce sales about 2.14 times more in retail than in manufacturing, purely due to the higher demand elasticity.

3 Data

We combine value added tax records available for essentially all French firms above a reporting threshold, 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 2009-2015 period, one at the firm level and one at the establishment level.

[17] In France, publicly-funded sickness allowances cover only a small share of wages: for instance, for a 5-day SLE with full replacement rate, we calculate that $\eta = 0.2$. For comparison, Zhang et al. (2017) obtain an estimate of θ equal to 0.46 on Canadian private sector employees, which is indeed higher.

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.[18] The resulting dataset is better suited to capture the average pollution exposure of local residents than monitor readings. Monitors are sparse, so their readings may not take into account all polluting sources.[19] In section 5.3, we replicate our main results using $PM_{2.5}$ exposure based on a simpler spatial interpolation of monitor readings.

Over our study period, the average monthly $PM_{2.5}$ exposure of French workers, based on the municipality of their workplace, is 15.4 µg/m^3. Figure A.1 shows the spatial distribution of annual exposure at different points in time and the significant reduction in average $PM_{2.5}$ concentration over the period. Panel (a) in Figure 1 shows the average monthly exposure over the period. Daily exposure to $PM_{2.5}$ exceeds the WHO recommended threshold of 15 µg/m3 (red line) on 37% of worker-days. Panel (b) illustrates the substantial variation in monthly exposure to $PM_{2.5}$ within a quarter-year.

Weather. We use gridded reanalysis weather data from the Copernicus Climate Change Service (C3S) (ERA5 dataset).[20] 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.[21] Firms filling

[18]Pollution concentrations are obtained by co-kriging measurements from background monitoring stations onto a 4km×4km grid, using outputs from the CHIMERE chemistry-transport model as auxiliary variables. The procedure follows Real et al. (2022), who validate the resulting dataset through leave-one-out cross-validation and show that it provides reliable estimates of background pollution levels across most pollutants.

[19]Over the study period, there are between 62 and 105 background monitoring stations for $PM_{2.5}$.

[20]We acknowledge using the ERA5 dataset (Hersbach et al., 2018) downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store.

[21]The threshold is €818,000 of annual sales for manufacturing and hospitality, and €247,000 of annual sales for the other sectors.

monthly VAT declarations account for 66% of all French firms, but generate 91% of total sales (France Stratégie and Inspection générale des Finances, 2021). Our dataset therefore provides broad coverage of the French private sector.

We restrict our sample to firms that operate in one of four broad economic sectors: manufacturing , construction, business-to-business trade and services (communication and IT services, wholesale trade, professional services, and cleaning services), and business-to-consumer retail and services (groceries and supermarkets, restaurants, hairdressers, clothing stores, furniture stores, and car sales and repair). This restriction excludes farming, the financial sector, the not-for-profit sector, and two industries for which the timing and location of sales are often disconnected from the timing and location of consumption: hotels and transportation. Our final dataset includes firms with at least one employee covered in the sick leave dataset described below. It comprises 158,223 firms totaling €1.9 billion sales in 2013 which represents 56% of all sales in the four broad sectors defined above.[22]

Sales are reported at the firm level. For the 64% of firms with a single establishment, we assign monthly pollution and weather exposure from the nearest grid cell to the establishment's municipality in the pollution and weather data. The remaining 36% percent of firms own more than one establishment and 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, with weights equal to 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 (Hygie dataset). This dataset reports for each worker the exact start date and duration of each SLE that occurred between 2009 and 2015, as well as individual characteristics (gender, age, wage, annual medical expenditures). Our measure of absenteeism is an indicator for an individual starting a SLE in a given month. We focus on SLEs that last less than three months, capturing 93% of the spells.[23]

We restrict our dataset to workers with an establishment-level identifier (see Appendix C for more details). This enables us to attribute pollution and weather exposure to each employee based on the municipality of their workplace, absent information on their munici-

[22]We restrict our sample to firms for which we can evaluate air pollution effects on sales and on worker absenteeism to compare their respective magnitude. Our final dataset covers 73% of nationwide manufacturing sales, 43% of construction sales, 55% of sales in the business-to-consumer goods and services sector, and 49% of the sales in the business-to-business trade and services sector.

[23]In our data, the average sick leave episode lasts 29 days whereas the median duration is only 9 days. Figure C.2 shows the small proportion of SLEs that last more than 3 months and their strong influence on the average number of sick days.

pality of residence. We consider workplace pollution exposure a reliable proxy for individual exposure: our analysis of exhaustive matched employer-employee data shows that the distributions of $PM_{2.5}$ exposure at workplace and residential municipalities are nearly identical (see Figure A.2).[24] We aggregate sick leave data at the establishment-month level.

Descriptive statistics. Panel (a) of Table 1 shows that firms in our sample employ on average 60 workers and report €1.32 million in monthly sales, while the medians—15 workers and €145,372—indicate substantial skewness. The sectoral composition is balanced, with 20% of firms in manufacturing, 16% in construction, 31% in business-to-business trade and services, and 33% in business-to-consumer industries.

Panel (b) reports descriptive statistics for workers with sick leave information employed in firms with monthly VAT records. This sample—used for our absenteeism analysis—includes roughly 400,000 workers in 353,155 establishments between 2009 and 2015. Workers are on average 40 years old, earn €28,542 annually, and incur €442 in annual medical expenditures, including €140 out-of-pocket. Each month, about 23 per 1,000 workers begin a sick leave lasting less than three months. Appendix Table A.1 compares this sample with the initial representative worker sample. Because firms with monthly VAT filings are typically larger, workers in our main sample have somewhat higher earnings. However, both samples exhibit similar demographics, 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 or demand seasonality. To address these concerns, our econometric specification combines a rich set of fixed effects with instrumental variables.

[24] Individual exposure reflects pollution at home, at work, during commuting, and in leisure locations. Yet most workers experience similar exposure across these locations. In 2015, 27% of employees lived and worked in the same municipality, and the median commuting distance in 2017 was only 9.2 km (INSEE, 2021). Consistently, Figure A.2 shows that pollution exposure at the workplace and at the place of residence have nearly identical distributions—both overall and by income quintile—based on exhaustive matched employer–employee data from 2009.

4.1 Firm-level econometric specification

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

$$Y_{fiyt} = \sum_{\tau=0}^{T} \beta_\tau PM_{fyt-\tau} + \mathbf{W}'_{\mathbf{fyt}}\gamma + \nu_{fy} + \theta_{iyt} + \delta_{cq} + \epsilon_{fiyt}, \tag{7}$$

where the unit of observation is a 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 smooths sector-specific and idiosyncratic variability in the lag between the economic transaction and its recording as sales.[25] $PM_{fyt-\tau}$ is either contemporaneous ($\tau = 0$) or lagged pollution exposure ($\tau > 0$) at firm level, and T is the number of lagged pollution variables.

We include a rich set of time-varying controls $\mathbf{W}_{\mathbf{fyt}}$ for contemporaneous and lagged weather conditions and holiday. Specifically, we generate indicators for monthly averages of daily maximum temperatures, wind speed and precipitation in each location, and include the set of indicators for all possible interactions of these weather parameters as controls.[26] 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 holiday periods, we also include the monthly count of days of school holiday in each location. Given that our outcome is averaged at t and $t+1$, our regressions also include monthly $PM_{2.5}$ exposure and time-varying controls at $t+1$. [27]

We also control for firm-by-year fixed effects (ν_{fy}), industry-by-month-by-year fixed effects (θ_{iyt}), and quarter-by-county seasonality (δ_{cq}).[28] Firm-by-year fixed effects 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 capture monthly shocks that are common across all firms in the same industry. We use the 2-digit level of

[25] Sales and VAT must be declared to the tax administration: in the month of delivery for domestic goods, in the month of payment for domestic services, and one month after delivery for exported goods and services See https://entreprendre.service-public.fr/vosdroits/F31412.

[26] There are 12 temperature bins spanning 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.

[27] 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.

[28] We use "county" to denote a French *département*, the second smallest administrative subdivision after municipality. There are 96 *départements* in mainland France.

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 capture seasonality in pollution, and also 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.

The key parameters of interest are β_τ, which capture the contemporaneous and delayed effects of monthly air pollution exposure on firms' sales. In our main specification, we include one lag of pollution exposure ($T = 1$) and interpret β_1 as our main coefficient of interest, but still report β_0. The reasons for focusing on this delayed effect vary by sector. First, in some industries, there is a lag between production and delivery of the finished product. These lead times depend on product complexity and supply-chain structure, and can be substantial: for example, lead times for steel, concrete, and prefabricated components in France are estimated at 6 to 12 weeks.[29] Second, sales may be recorded either at delivery—as in manufacturing, wholesale trade and retail—or at payment, as in construction, business-to-business or consumer services. When consumers delay payment, a gap arises between the time of purchase and the time of recorded sales, and these delays can be substantial.[30]

We also explore the dynamic effects of air pollution on sales up to five months after exposure by considering five lags in (7). 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; Barwick et al., 2024) and impose a smooth polynomial function on the lag structure to discipline the coefficients. We assume 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 the coefficients γ_1, γ_2, and γ_3 by OLS and two-stage-least-squares for the instrumented version. Combining these point estimates and associated standard errors, we recover the point estimates β_ls and their associated standard errors.

4.2 Econometric specification for worker absenteeism

Following the extensive literature on the short-term effects of pollution on health outcomes, we model the relationship between contemporaneous pollution exposure and worker absen-

[29] These estimates are components of the HCOB France Manufacturing Purchasing Managers' Index (PMI), compiled by S&P Global. See https://www.spglobal.com/market-intelligence/en/solutions/products/pmi.

[30] For instance, mean payment delays in 2015 amount to 11 days in construction, 17 days in business support activities, and 15 days in business-to-consumer services on average (Prost and Villetelle, 2018).

teeism at the establishment level using the following equation:

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

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. Unlike sales, we observe worker absenteeism at the establishment level, even within multi-establishment firms. 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 $\mathbf{W_{gyt}}$ are defined as before, and computed at the municipality level. As in (7), we control for industry-by-month-by-year (θ_{iyt}) and quarter-by-county (δ_{cq}) fixed effects. Additionally, we control for establishment fixed effects, ν_e, which isolate monthly variation in pollution exposure within an establishment and absorbs any time-invariant establishment-specific characteristic. To assess the robustness of our specification, we explore the dynamic effects of pollution exposure on worker absenteeism using five lags, as we do for sales.

4.3 Wind direction instruments

Despite the inclusion of high-dimensional fixed effects, OLS estimates of equation (7) remain vulnerable to bias from reverse causality, measurement error in pollution exposure, and omitted variables. Higher sales can mechanically raise air pollution through higher production and higher road traffic, creating reverse causality. Measurement error also arises when individuals' pollution exposure is assigned based on the workplace municipality only. Under classical (mean zero and i.i.d) measurement error, this induces attenuation bias, potentially amplified by fixed effects (Griliches and Hausman, 1986). Unobserved local shocks that jointly affect pollution and economic outcomes are also a concern. For instance, a positive shock to local demand outside seasonal patterns—e.g., due to sports or cultural events—could raise retail and service-sector sales while increasing transportation activity. Although stores may not emit pollution directly, the associated surge in car traffic can increase 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 municipalities, depending on the location of polluting sources. Following Graff Zivin et al. (2023), we compute four instruments Z^j_{gyt}, one for each wind direction $j \in \{South, West, East, North\}$ as follows:

$$\mathrm{Z}^j_{gyt} = \underbrace{WIND^j_{gyt}}_{\text{A: Time-varying}} \underbrace{\left(\frac{1}{N^j}\sum_{d\in D^j} PM_{gd} - \frac{1}{N}\sum_{d\in D} PM_{gd}\right)}_{\text{B: Time-invariant}} \tag{9}$$

where component A, $WIND^j_{gyt}$, identifies the share of hours in calendar month t in year y where the wind blows from direction j in municipality g, while component 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.[31] N^j and D^j are the number and set of days where the dominant wind blows from direction j, and N and D are the total number and set of days over the period of analysis.

Component B is a time-invariant component akin to a pollution intensity factor by wind direction, calculated for each municipality using the average pollution level, by wind direction and overall. Figure 2 plots this component for each wind direction across municipalities in France. While 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 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.

To the extent that component A—the month-to-month variation in wind direction—is as-good-as-random conditional on the controls and fixed effects, the potential endogeneity of component B is not a threat to identification: our design is close to a shift-share instrument with a shift-based identification (Borusyak et al., 2025), where component A is akin to the exogenous shift and component B associates different intensities to the random shifts and enhances the power of our instrument. We show in section 5.3 that our results are robust to different designs of the wind instruments.

For single-establishment firms, pollution and weather exposure can be precisely measured at a single location; hence, the specification of the first stage includes all four wind-direction instruments:

$$PM_{fiyt} = \sum_{j=1}^{4} \beta^j \mathrm{Z}^j_{gyt} + \mathbf{W}'_{\mathbf{gyt}}\gamma + \nu_{fy} + \theta_{iyt} + \delta_{cq} + u_{fiyt}, \tag{10}$$

[31] A one-unit increase in Z^j_{gyt} 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 both result in a one-unit increase in Z^{North}_{Ayt} and Z^{North}_{Byt}.

with PM_{fiyt} and weather controls $\mathbf{W'_{gyt}}$ varying at the municipality level g, β^js the parameters of interest, and fixed effects defined like in equation 7. For a given wind direction j, β^j captures the average effect of a marginal increase in the intensity of wind direction j. The identifying variation is the quasi-random change in wind direction intensity stemming from variation in component A of the wind instrument, around the mean exposure of each municipality within a year, after partialling out quarter-by-county-specific variation, industry-specific national trends, and after controlling for other weather conditions.

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. Figure A.10 plots similar distributions for the time-varying part of the instruments only (component A), and shows substantial remaining variation. We further illustrate the substantial variation in wind direction within a municipality within a calendar month in Figures A.4 and A.6 for 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. We regress PM_{gyt} on the same variables as in equation (10), except that we replace firm-by-year fixed effects with municipality-by-year fixed effects, and month-by-year-by-industry fixed effects with month-by-year fixed effects. After saving the vector of estimated $\widehat{\beta}^j$, we compute the predicted pollution exposure in each municipality as $\widehat{PM_{gyt}} = \sum_{j=1}^{4} \widehat{\beta}^j \text{Z}^j_{gyt}$. We then compute the firm-level predicted pollution exposure, $\widehat{PM_{fyt}}$, as the weighted average of $\widehat{PM_{gyt}}$ across municipalities g where firm f owns establishments in year y using labor shares as weights. We use $\widehat{PM_{fyt}}$ as an instrument for PM_{fyt} in equation (7).[32]

In our main analysis on sales, we include both single- and multi-establishment firms and we use as an instrument the predicted pollution measure. We also show how the point estimate varies when we restrict the sample to single-establishment firms and directly use the four wind direction instruments. We cluster the standard errors at the Copernicus grid cell level based on the location of the single establishment or of the headquarter (for firms owning multiple establishments). Our final dataset includes 1,090 such grid cells and it is the scale at which component A of the wind instruments varies. Figure A.16 shows that the point estimates remain quite precise 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.[33]

[32]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).

[33]Implementing Conley standard errors to address concerns of spatial autocorrelation in wind patterns

4.4 Identification assumptions

Our research design requires three conditions. First, our 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, with plausibly heterogeneous treatment effects, the two-stage least squares estimates can be interpreted as local average treatment effects (LATE) only if the monotonicity assumption holds.

Instrument relevance. Table 2 reports the first-stage results and shows that the effects of the wind instruments on pollution exposure are similar whether the regression is estimated at the municipality level (column 1) or at the firm level for single-establishment firms (column 2). The estimated coefficients $\widehat{\beta^j}$ are all positive because Z^j_{gyt} is constructed to take negative values when wind from direction j reduces pollution in municipality g. All coefficients are positive and highly significant.

To assess instrument strength, we use two complementary weak-IV diagnostics. First, we compute the Montiel Olea and Pflueger (2013) effective F-statistic on a random 2% sample of single-establishment firms.[34] The effective F-statistic equals 365, which exceeds the 5% and 10% worst-case bias critical values (26 and 16, respectively), allowing us to rule out weak instruments. The effective F-statistic is particularly appealing in settings with many instruments as it provides bias-based critical values and remains valid under arbitrary heteroskedasticity (Andrews et al., 2019). Because it does not accommodate multiple endogenous regressors and is computationally costly in large samples, we also report the Kleibergen–Paap Wald rk F-statistic for the full sample of single-establishment firms, although it might be less reliable when the instrument set is large or heterogeneous. These values are consistently above 100. Overall, both diagnostics confirm the strength of our wind-based instruments.

Instrument validity. The validity of the instruments relies on two 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

is too computationally demanding due to the combination of high-dimensional fixed effects, instrumental variables, and a large sample size, given the constraint of accessing the data on a secure server.

[34]Since the Montiel Olea and Pflueger (2013) effective F-statistic is defined for one endogenous regressor, and computing it on the full sample is infeasible given the computational constraints from accessing the data on a secure server, we instrument only for pollution at $t-1$—our main parameter of interest—and control for the wind instruments at t and $t+1$.

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. With monthly data, we capture their effects as part of $PM_{2.5}$. PM_{10} is highly correlated with $PM_{2.5}$ ($\rho = 0.93$) 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.[35] In our data, $PM_{2.5}$ and ozone have a Pearson correlation coefficient of -0.3. To address concerns about ozone effects, in section 5.3 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.12 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. Figure A.14 displays the distribution of residualized predicted $PM_{2.5}$ and its relationship with residualized firm-level $PM_{2.5}$ exposure, 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 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—e.g., in business-to-consumer sectors—typically face the same pollution shocks, limiting competitive advantages. Firms experiencing lower pollution exposure within the same industries are likely geographically distant, reducing direct competition and further minimizing spillover risks.

[35] 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.

5 Main Results

5.1 Impact of $PM_{2.5}$ on Firms' Sales

All Sectors. Table 3 shows that firms' sales decline in response to contemporaneous and lagged monthly $PM_{2.5}$ exposure when pollution exposure is instrumented. By contrast, column (1) shows a positive (non-significant) association between $PM_{2.5}$ and sales in the OLS specification, 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.[36] When instrumenting pollution with changes in wind direction (column 2), the effect of lagged $PM_{2.5}$ exposure on sales becomes negative and statistically significant at the 1% level. A one-unit (1 µg/m^3) increase in lagged firm-level $PM_{2.5}$ reduces sales over the following two months by 0.45 percent ($p < 0.001$). Given a baseline average pollution of 15.3 µg/m^3, the corresponding elasticity is -0.069, implying that a 10 percent increase in pollution exposure lowers sales by 0.69 percent on average. The elasticity for contemporaneous exposure is smaller, at -0.023 ($p = 0.025$), indicating that the sales response to pollution is more strongly driven by lagged rather than current exposure. Columns (3) and (4) confirm similar results in the subsample of single-establishment firms.

Table A.2 shows how magnitudes vary with fixed effects. The IV point estimates remain consistently significant and negative across specifications. The elasticity of sales to lagged exposure ranges from -0.089 to -0.069 (in our preferred specification), with smaller magnitudes when controlling for quarter-by-county fixed effects in addition to firm-by-year and month-by-year-by-industry fixed effects. Quarter-by-county fixed effects account for any systematic correlation between wind seasonality and local economic activity, which, if not controlled for, could violate the exclusion restriction.

Our results can be compared to the ones obtained for Europe by Dechezleprêtre et al. (2019), which reports that a 1 µg/m^3 increase in $PM_{2.5}$ lowers regional GDP (NUTS3) by 0.80 percent, using thermal inversions as an instrument and only controlling for country-year fixed effects. While the latter effect is larger in magnitude, the difference could be due to the level of aggregation, outcome definition (including agriculture production), and empirical strategy, with fewer sources of time-varying unobserved heterogeneity being absorbed in their study. Taken together, the evidence consistently points to sizable economic costs of $PM_{2.5}$.

Heterogeneous Response by Sector. Examining how sales respond to air pollution by sec-

[36] Fu et al. (2021) similarly finds a positive association between $PM_{2.5}$ and manufacturing value added per worker in their OLS regression, and a negative effect in the IV regression.

tor provides insights into which sectors might benefit most from air quality improvements. Table 4 shows that, after instrumenting for $PM_{2.5}$ exposure, firm sales decrease with lagged exposure in all sectors, with sales in construction and business-to-consumer retail and services also responding to contemporaneous exposure. Results are broadly consistent for the subsample of single-establishment firms (column 4).

Expressed as elasticities, these results indicate that a 10 percent increase in pollution exposure at $t-1$ decreases sales in the following two months by 0.28 percent in manufacturing,[37] 0.36 percent in construction (0.24 for exposure at t), 0.44 percent in business-to-business trade and services, and 1.17 percent in business-to-consumer retail and services (0.35 for exposure at t).

Why do magnitudes differ across 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. We explore the heterogeneity of workers' absenteeism response to air pollution shocks by sector in the next section.

On the demand side, business customers and final consumers are exposed to the same pollution shocks as workers only in industries serving local demand. This is the case predominantly for business-to-consumer retail and services—the sector incurring the largest sales losses. In the next section, we shed light on a potential demand channel that affects purchases of different types of consumer goods differently. By contrast, manufacturing firms typically serve distant markets, which may counteract the negative impact of local demand shocks (Almunia et al., 2021).

The larger sales elasticities to pollution observed in business-to-consumer retail and services can also be understood through the lens of the theoretical framework in Section 2.2. Sectors characterized by higher elasticities of substitution across varieties or lower profit margins are more sensitive to both supply- and demand-side disruptions. Given that retail and hospitality typically operate on thin profit margins, this amplifying mechanism likely contributes to the heightened responsiveness in the consumer-oriented sector.

Finally, sectoral differences in the timing of production and sales recording may explain some of the heterogeneity. For instance, business-to-business services often involve payment delays, meaning that the timing of sales responses may not align with the two-month period

[37] One previous study by Fu et al. (2021), focusing on manufacturing only, find a higher elasticity of -0.44 in the more polluted Chinese context and for a different outcome (value added per worker at the annual level). These differences likely explain the difference in magnitude.

used in our analysis. We investigate dynamic effects up to five month following the pollution shock in the next section.

Heterogeneity by firm size. Smaller firms are generally found to be less productive and more vulnerable to financial shocks than larger firms (Gertler and Gilchrist, 1994). We investigate this heterogeneity by comparing the impact of air pollution on sales for firms below the median size (fewer than 15 employees) versus for those above the median size (with 15 employees or more). As shown in Table A.4, smaller firms are more adversely affected overall and across all sectors, except in business-to-consumer retail and services. In manufacturing and construction, larger firms exhibit no significant sales losses from lagged pollution exposure, but losses are statistically significant for contemporaneous pollution in construction. In these sectors where supply-side mechanisms are more likely—because demand is primarily non-local— large firms may be able to offset productivity losses or absenteeism through adaptation strategies such as task reallocation or flexible scheduling (Adhvaryu et al., 2022). In contrast, the fact that even large firms appear vulnerable in the business-to-consumer sector suggests that demand-side mechanisms, less amenable to firm-level mitigation, may be the dominant channel in this context.

5.2 Dynamic Effects on Sales

Figure 3 plots the dynamic effects of pollution on sales from the month of exposure (t) through five months afterward ($t+5$), estimated using the polynomial distributed lag specification for the full sample (panel a), single-establishment firms (panel b), and all firms in each sector (panels c-f). In the full sample, sales decline in the month of exposure, reach their lowest point one month later, and gradually return to zero effect after about 4 months; the pattern for single-establishment firms is nearly identical.

In terms of magnitude, the first two estimates in panel (a) implies elasticities of -0.035 for contemporaneous exposure and -0.046 for one-month lagged exposure, which are close to the corresponding elasticities of -0.023 and -0.069 in Table 3. By imposing a smooth polynomial form on the lag structure, the PDL specification produces a slightly larger contemporaneous effect and a somewhat smaller lagged effect. The largest effects occur at $t+1$ in nearly all panels (in manufacturing, the estimates at $t+1$ and $t+2$ have almost the same magnitude), justifying our emphasis on pollution exposure at t and $t-1$ in our main specification.

The close agreement between the one-lag distributed lag model and the PDL specification is reassuring. The PDL helps mitigate serial correlation in pollution (and wind) exposure and imposes structure on the lag profile, but it may also allocate more weight to peak lags, inflating magnitudes or introducing misspecification. For these reasons, we rely on the simpler specification with just one lag for our main results. Because this approach deliberately restricts attention to effects within three months of exposure—thereby omitting potentially non-negligible longer-run responses—it yields conservative estimates of the dynamic impact of pollution on sales. As shown in Table A.3, the estimates at t and $t-1$ are not sensitive to the number of lags introduced in equation (7).

In all panels from Figure 3, the OLS estimates are either at zero or very small but positive in the first few months after exposure and become negative afterward (after $t+3$). By contrast, the IV estimates follow similar patterns for the full sample and in each sector, with the same differences in magnitude across sectors as the ones reported in Table 4. While manufacturing and business-oriented sectors respond with a lag of one or two months, construction and consumer-oriented sectors experience a sales decline in the month of exposure and recover within three months for construction and only after four months for the consumer-oriented sector.

The delayed onset of sales declines following pollution exposure can be explained by three mechanisms. First, in manufacturing and, to some extent, in business-to-business trade, there is a natural lag between production—when workers are affected—and the recording of sales upon delivery. Second, in construction and services, where sales are recorded at the time of payment, delays between service delivery and payment can lengthen the lag. Third, in consumer-oriented sectors, demand responses may materialize gradually: income losses from uncompensated sick leave typically become salient only at the end of the month when wages are paid and some consumers may temporarily smooth consumption by drawing on savings despite healthcare spending and reduced income. The absence of any rebound even six months after a pollution shock indicates that sales are not simply postponed. Instead, the decline appears persistent, consistent with a reduction in disposable income driven by both increased uncompensated absenteeism and higher healthcare expenditures.

5.3 Robustness checks

We assess the validity of the identification assumptions and the robustness of our main results in various ways. First, we run a falsification test using future pollution exposure to rule out that our effect is driven by spurious correlation. Table 5 shows that future pollution exposure, at time $t+2$, has small and insignificant effect on sales at time t, for all sectors taken together and for each sector.

Second, we consider the risk of violation of the exclusion restriction due to ozone pollution and adopt a broader measure of air pollution using the Air Quality Index (AQI). Column (1) of Table 6 reports the main result, 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 2.8%, while a 1-SD increase in AQI (SD=0.41) reduces sales by 2.5%. The slightly lower AQI estimate may reflect its dependence on $PM_{2.5}$ in fall/winter and on ozone in spring/summer. If ozone has no significant effect on sales, using AQI dilutes the impact.

Third, we check that our results are not driven by air quality alerts and the avoidance behaviors that they may induce. To do so, we replicate the analysis on a sample excluding months 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.[38] Column (3) of Table 6 shows that the estimated coefficient remains consistent with the main result.

Fourth, we test the sensitivity of our results to outliers and to the specification of time-varying 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 a quadratic function for average temperature, wind speed, and rainfall, instead of our flexible set of controls. The larger estimated coefficient on pollution suggests that our main estimate is conservative. In column (6), we add monthly averages of daily maximum humidity to the set of flexible weather controls used in the main specification—splitting the variable into quintiles and generating indicators for all the possible interactions with other weather categories.[39] In column (7), we add county-level flu cases per 100,000 inhabitants to the controls to account for seasonal illnesses that affect absenteeism and economic activity and may correlate with wind patterns. Because air pollution exacerbates influenza (Graff Zivin et al., 2023), flu incidence is likely a bad control, which is why it is omitted from the main specification. Our results remain similar when including either humidity or flu controls.

Fifth, we check that our results are not driven by the design of our wind instruments. In Table A.5, we compute component B based on the first period in our data only (2009) to alleviate concerns of potential endogeneity of this component with respect to economic activity. We report results similar to the baseline for either the 2009-2015 sample period

[38] We use the less severe alert level, triggered when daily average PM_{10} exceeds 80 µg/m^3 before November 2014, and 50 µg/m^3 after. Alerts give rise to awareness messaging advising against physical activity for vulnerable populations. Even in Paris, the most polluted city, alerts occurred on only 4% of the days in 2009. The more severe alert level, giving rise to driving restrictions, occurred only 0.7% of the days.

[39] We define humidity as the dewpoint temperature in °C, which corresponds to the temperature that the air needs to be cooled to, at constant pressure, in order to achieve a relative humidity (RH) of 100%.

(Column (2)) or the 2010-2015 sample period (Column (5)). Alternatively, we only exploit component A for the wind instruments while constraining the first stage coefficients to be the same for all municipalities within a 100km-by-100km grid cell, in an approach similar to Deryugina et al. (2019), and report estimates with lower magnitude but consistent with our main estimates in column (3).

Sixth, we assess the robustness of our results to alternative pollution measures. Column (2) of Table A.6 replicates our main analysis using satellite-based monthly $PM_{2.5}$ data from van Donkelaar et al. (van Donkelaar et al., 2021; Shen et al., 2024). These data rely on satellite-based Aerosol Optical Depth (AOD), combined with a chemical-transport model to map AOD to $PM_{2.5}$, and are cross-validated using ground monitoring stations. Satellite-based exposure is highly correlated with our main exposure measure ($\rho = 0.90$), and the estimated coefficient remains of similar magnitude to the baseline in column (1).

Columns (3)-(5) of Table A.6 compare the reanalysis-based estimates with $PM_{2.5}$ data from monitoring stations for 2011-2015.[40] Using monitor data helps rule out the concern that the first stage linking wind directions to $PM_{2.5}$ is driven by weather inputs embedded in the reanalysis model. In column (4), municipal exposure is constructed as an inverse-distance–weighted average of nearby monitors within 150 km, following standard practice. Column (5) instead uses only the nearest monitor.[41] Both monitor-based measures are highly correlated with the reanalysis data ($\rho = 0.95$) and yield point estimates closely aligned with the reanalysis-based estimate for the 2011-2015 period, reported in column (3).

Finally, we examine how our results' precision varies with the clustering level in Figure A.16. The top estimate shows our baseline with one-way clustering at the Copernicus grid cell of the firm's headquarter—the spatial scale at which the instrument varies for single-establishment firms. Clustering at the firm level (second line), the scale relevant for multi-establishment firms, yields smaller standard errors because it ignores spatial correlation in wind exposure across nearby firms. Clustering at the county level (third line), and thus indirectly capturing broader spatial correlation—the average county includes 10 wind grid cells—produces slightly smaller standard errors than the baseline, which remains the most conservative. The final three estimates apply two-way clustering by space and time, using the Copernicus grid cell (fourth line), firm (fifth) or county (sixth) as the spatial dimension and month-by-year as the temporal dimension. This accounts for correlation across observations within the same month. While these specifications reduce precision slightly, the effect remains significant at the 5% level.

[40] Monitoring stations data cover the period 2011-2015 and are available at: https://eeadmz1-downloads-webapp.azurewebsites.net/.

[41] In our sample, the average distance to the nearest monitor is 25 km and the median is 16 km.

6 Mechanisms

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

6.1 Sickness-induced 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 statistically significant at least at the 5% level. 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. This elasticity is similar to the literature, despite differences in the type of pollutant and time horizon: an analysis based on weekly data from Spain, focusing on PM_{10} pollution in urban areas, finds an increase in sick leave corresponding to an elasticity of 0.08 (Holub et al., 2021).

Appendix B contains a range of robustness checks for absenteeism. Table B.1 shows that the effects are robust to aggregating at the municipality rather than the establishment level, using municipality fixed effects and month-by-year fixed effects. Table B.2 shows that the effect of air pollution on sick leave is not driven by a confounding effect of ozone, by air quality alerts, or by the specification of weather controls. Table B.3 shows that the results are largely insensitive to the source of pollution data. Figure A.18 shows the dynamic effects of pollution using the same PDL specification as for sales. The impact of air pollution on sick leave is concentrated in the month of exposure, quickly dissipating to zero within two months. Figure A.19 shows that our estimates (left) are comparable to the OLS and IV estimates for the representative sample of workers (right).

Can the pollution-induced reduction in labor supply explain most of the observed decline in sales? A 10% increase in $PM_{2.5}$ reduces the average firm's sales by approximately €9,080 per month, based on the estimated sales elasticity and the average monthly sales of €1,316,000. Of this total, only about €310 can be accounted for by increased worker absenteeism.[42] Thus, absenteeism explains about 4% of the overall sales impact, implying

[42]This back-of-the-envelope calculation is likely an upper bound because we assume that any worker

that most of the sales decline from air pollution operates through other channels. One caveat of this back-of-the-envelope calculation is that it assumes disruptions due to worker absenteeism are similar whatever the cause of absenteeism and ignores any dynamic or non-linear effects from an increase in absenteeism.

Figure 4 reports heterogeneous effects by sector and reveals that pollution-induced sick leave is mainly driven by manufacturing (the only sector with a statistically significant effect) and, to a lesser extent, construction. In contrast, the sick leave response is minimal in the consumer- and business-oriented trade sectors. Higher absenteeism rates are thus observed in sectors with greater pollution exposure and/or strong collective agreements (ensuring higher replacement rates), such as manufacturing and construction, whereas services sectors experience lower absenteeism.[43] Because our measure of absenteeism only captures recorded sick leave episodes, these lower responses in service sectors are possibly due to the ability to work remotely or take leave without a medical certificate, or reflect higher incentives to work while sick due to lower replacement rates.

There is little correspondence between sector-level effects on sick leave and on sales: comparing Table 4 and Figure 4, manufacturing and business-to-business trade and services exhibit sales elasticities of –0.028 and –0.044, respectively, yet their absenteeism elasticities move in the opposite direction (0.22 for manufacturing versus -0.015 for business-to-business trade and service sectors). Additionally, the business-to-consumer trade and services sector experiences large pollution-induced sales losses but small pollution-induced absenteeism, indicating that absenteeism is not an important channel in that sector.

With the same calculation and assumptions as above, we quantify the share of pollution-induced sales losses that can be attributed to increased absenteeism in the most affected sector, manufacturing. For this sector, a 10% increase in $PM_{2.5}$ reduces the average firm's sales by approximately €9,336 per month. Of this total, about €2,096 can be explained by increased absenteeism due to pollution. This represents roughly 22% of the pollution-induced sales losses. This back-of the envelope calculation highlights absenteeism as a significant transmission channel through which air pollution affects firm sales, but not the main one. Other channels such as lower productivity and demand-side effects likely play an important

starting a sick leave in a month is not on the job for a full month. For comparison, the average duration of sick leave is 16 days in our sample (for less than 3 month episodes). Hence, relative to the baseline rate of absenteeism of 0.023, a 10% increase in pollution results in 0.0138 extra absent worker in an average firm of 60 employees. Given the average monthly sales of this average firm and the average number of 58.6 on-the-job workers, we compute the average monthly sales per on-the-job worker as €22,450. This yields $0.0138 \times 22,450 =$ €310 for the pollution-related absenteeism-induced sales loss. A key assumption is that the disruptions caused by absenteeism due to pollution are similar to the ones associated with other causes of absenteeism.

[43] Pollak (2015) shows that employees in retail trade and construction are less likely to receive full wage replacement during sick leave than those in manufacturing and other service sectors.

role in driving the economic costs of pollution shocks.

6.2 The role of productivity and demand

Productivity. Lacking monthly productivity data, we cannot directly measure this channel. Instead, we provide suggestive evidence on its importance by focusing on the manufacturing sector. Our calculations indicate that only 22% of pollution-induced sales losses in manufacturing operate through absenteeism, leaving roughly 78% to productivity or demand channels. Since demand responses should be minimal in manufacturing—where firms typically serve national or international markets rather than local consumers—this residual is likely driven mainly by productivity losses.

To probe this mechanism, we exploit heterogeneity in production flexibility across manufacturing industries. Using a 2004 survey of manufacturing plants, we classify industries according to whether their stock levels are above or below the median.[44] With similar absenteeism elasticities across groups, industries with low inventories should be more exposed to supply-side productivity shocks, whereas industries with high inventories can buffer temporary disruptions.

Columns (1)–(3) of Table 8 confirm this pattern: pollution reduces sales sharply among firms from low-stock industries, while the effect is negligible for firms in high-stock industries. Columns (4)–(6) show that absenteeism responses are nearly identical across the two groups and, if anything, more significant for the latter. Because average sales and employment are similar, differences in firm size cannot account for the divergent sales effects. Nor can demand shocks explain the heterogeneity, as keeping high stocks does not insulate firms from demand-side fluctuations. Overall, this pattern strongly suggests that pollution reduces sales in part by reducing worker productivity, and that firms can partially absorb these shocks by drawing on existing inventories.

Demand. Our results indicate that the impact of $PM_{2.5}$ on sales is particularly pronounced in the business-to-consumer trade and services sector (Table 4). Unlike other sectors, even large firms in this sector experience substantial sales losses (Table A.4). Firm size may buffer productivity-related shocks—for instance, by allowing greater flexibility in hiring

[44]The survey covers 2,058 manufacturing establishments and measures stock level in days of production. Industries with high stock 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. Industries with low stock 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.

temporary workers or reallocating tasks—but it offers little protection against demand fluctuations. This asymmetry highlights the importance of a demand-side channel: retail and consumer services primarily serve local customers who are exposed to the same pollution shocks as workers.[45] Consumers affected by pollution may face reduced disposable income—because sick leave is only partially compensated and because health shocks raise medical expenses—leading them to cut back more on discretionary purchases, such as clothing, than on essential goods like groceries or necessary repairs.

Figure 5 shows the estimated coefficients by industry within the consumer-oriented sector, revealing a clear ordering across subsectors. In the food segment, supermarkets exhibit the smallest decline in sales (close to zero in the contemporaneous month and with a sales elasticity of -0.08 after one month), followed by specialized high-quality food retailers, while restaurants experience the steepest drop after one month with an elasticity of -0.19 (but the sharp decline does not materialize as much in the contemporaneous month). Although confidence intervals overlap, this pattern is consistent with stronger consumer responses for less essential spending. Similarly, sales of cars and furniture decline less than clothing sales, and essential services—such as vehicle and goods repairs—show no significant decrease, both contemporaneously and after a month. The health and beauty sector, which includes pharmacies and veterinary services, displays only a modest reduction. Taken together, the evidence suggests that consumer behavior—shaped by both health concerns and temporary financial constraints—plays a meaningful role in mediating the economic impact of pollution.

7 Discussion on the overall effects of $PM_{2.5}$ reductions

In this section, we demonstrate that a policy ensuring that daily $PM_{2.5}$ concentrations in French municipalities never exceed 15 µg/m^3 would generate substantial economic benefits to the private sector—comparable in magnitude to the upper bound of estimated implementation costs and to estimated health benefits.

To quantify the economic benefits of meeting the WHO daily $PM_{2.5}$ target, we combine the sector-specific sales elasticities from Table 4 with granular measures of firm-specific decrease in pollution exposure under this scenario. We first compute, for each municipality, the reductions in daily $PM_{2.5}$ that would have occurred over our 7-year study period if concentrations had been capped at 15 µg/m^3, and aggregate these reductions to the monthly level. Enforcing the cap would have lowered workers' monthly average pollution exposure

[45]The assumption that most consumers in consumer-oriented sectors are local is supported by the relatively limited development of e-commerce in France before 2015. For example, Amazon's sales in France in 2011 amounted to only about 3 percent of the annual sales of Leclerc, the country's largest retailer. As e-commerce expanded in later years, the share of local consumers may have declined.

from 15.4 to 11.5 µg/m^3, a 25% reduction. We then translate these grid-cell–level reductions into firm-month–level decreases in exposure, taking intrafirm network structure into account. Finally, using the statistically significant ($p<0.05$) sectoral elasticities for contemporaneous and lagged pollution exposure in Table 4, we compute the changes in sales implied by these pollution reductions by multiplying firm-month–specific exposure decrease by firm-month–specific sales.[46]

Summing over all firm-months, we estimate that meeting the WHO target would have avoided €25 billion in annual lost sales—1.4% of average total sales in our sample.[47] Applying the average value-added-to-sales ratio of 27% (INSEE, based on 2015 data), this corresponds to €6.9 billion in annual foregone value added, abstracting from longer-term and general-equilibrium effects. By sector, avoided losses in value added amount to €1.2 billion for manufacturing (0.7% of the sector's annual value added), €0.43 billion for construction (1.4%), €2.1 billion for business-to-business trade and services (1.2%), and €3.1 billion for businesss-to-consumer retail and services (2.8%). These figures highlight the broad benefits of reducing pollution across the private sector, with the largest relative gains in retail, consumer services, and construction, and the smallest in manufacturing, while construction and manufacturing contribute more to emissions directly.

When we incorporate dynamic effects up to five months after exposure, using statistically significant ($p<0.05$) sector-specific point estimates from the PDL in Figure 3, the estimated annual foregone sales rise to €38 billion, implying €10.3 billion in foregone value added. Depending on whether dynamic effects are included, failing to meet the WHO standard resulted in €6.9–€10.3 billion in annual lost value added. For comparison, the European Commission's 2030 air-quality revision introduces a 24-hour $PM_{2.5}$ limit of 25 µg/m^3. Based on our estimates, complying with that weaker standard would have generated only about 40% of the benefits associated with meeting the WHO guideline.

To compare the potential economic benefits of meeting the WHO threshold with the associated costs, we follow Dechezleprêtre et al. (2019) and use cost estimates for reducing $PM_{2.5}$ emissions—rather than concentrations—from a European Commission report (European Commission, 2013). Achieving a 33% reduction in $PM_{2.5}$ emissions in France—which would lower pollution beyond what is required to meet the WHO threshold—is estimated to

[46] Our analysis relies on the assumption that the linear specification is a good approximation to the relationship between residualized log of sales and residualized $PM_{2.5}$ instrument. As shown in Figure A.17, this assumption appears reasonable.

[47] On the one hand, these benefits represent a lower bound because our sample covers 56% of private-sector sales each year on average. On the other hand, ignoring input–output linkages may lead to some double counting at the aggregate level because lower sales in upstream sectors may mechanically reduce sales in downstream sectors, although such effects likely occur with delays longer than the contemporaneous and one-month lag effects we use.

cost around €7.7 billion per year to the French economy in investment and maintenance for pollution abatement equipment (option 6D, Table A7.3, page 187 in European Commission (2013)). Thus, the economic gains from cleaner air could be of the same magnitude or even exceed this upper-bound estimate of abatement costs.

To further contextualize these gains, we compare them with the annual benefits associated with reduced mortality under the WHO target. Using Deryugina et al. (2019)'s estimates of the short-term mortality effects of $PM_{2.5}$ on the elderly in the U.S., together with the French Value of a Statistical Life Year (VSLY) of €115,000 in 2010, we estimate that each one-unit decrease in $PM_{2.5}$ yields about €1.6 billion in annual mortality-reduction benefits in France.[48] For our scenario—bringing days with $PM_{2.5}$ exceeding the WHO threshold right at the threshold of 15µg/m^3—the resulting mortality benefits amount to approximately €6.1 billion per year. Thus, the economic gains from avoided sales losses appear comparable in magnitude to the benefits from reduced mortality.

8 Conclusion

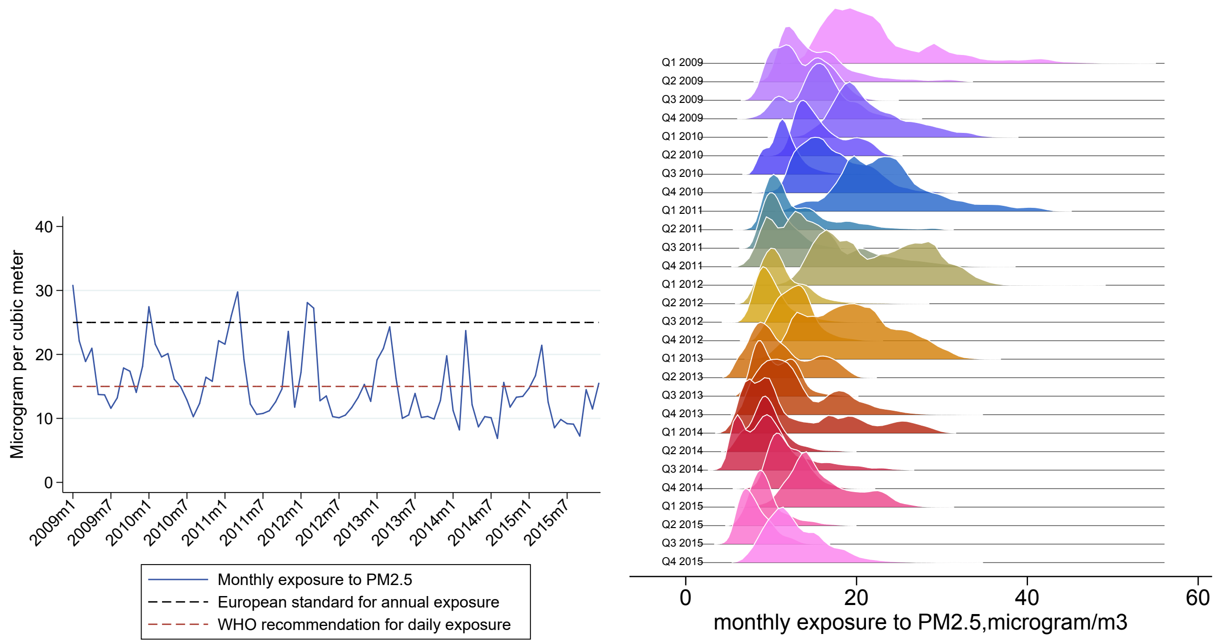
This paper examines how fine particulate matter ($PM_{2.5}$) affects economic activity in the French private sector. We show that higher pollution concentrations lead to significant reductions in firm sales within two months, with elasticities of -0.069 for lagged pollution and -0.023 for contemporaneous pollution exposure. Three key mechanisms underpin these effects. First, workers' exposure to air pollution increases sickness-related absenteeism, with an elasticity of 0.1. Yet, even in the most impacted sector—manufacturing—this channel explains at most a quarter of the total sales losses. Second, a reduction in worker productivity induces output reductions—a channel that operates in particular in manufacturing firms with low inventories. Third, firms serving local demand experience more pronounced sales decreases, especially those selling discretionary goods. These impacts are persistent: sales remain depressed for four to five months with no subsequent rebound, consistent with a reduction in consumers' disposable income.

Our findings indicate that ex-ante cost-benefit analyses of air pollution regulations that overlook the negative effects of pollution on firm sales likely understate their net benefits. A striking result is that all economic sectors—not only manufacturing or construction—would gain from lower $PM_{2.5}$ concentrations. Tightening $PM_{2.5}$ standards to meet WHO guidelines would generate sizable economic benefits that may exceed available aggregate cost estimates.

[48] This calculation 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.

Incorporating population-wide health benefits, which are well documented in the literature, would further increase the estimated net gains, providing a strong rationale for adopting stricter air quality standards.

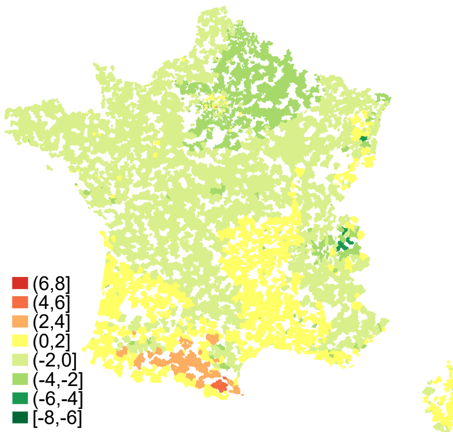
9 Figures



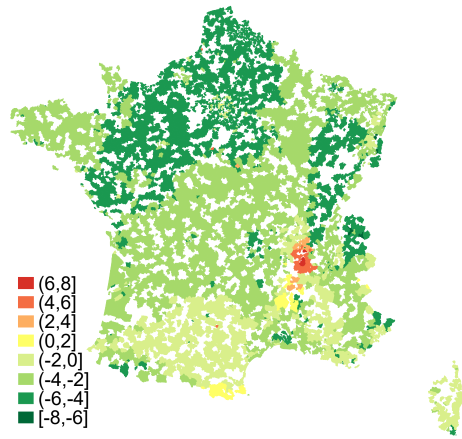
(a) Monthly average exposure to $PM_{2.5}$ (µg/m^3) (b) Distribution from Q1 2009 to Q4 2015

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

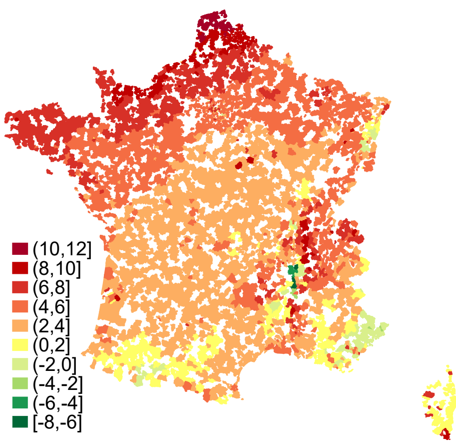
Notes: Figure a) shows municipality-level $PM_{2.5}$ exposure in 2009-2015, weighted by the number of workers employed in each municipality in the absenteeism dataset. Figure b) shows the unweighted distribution of monthly exposure to $PM_{2.5}$.



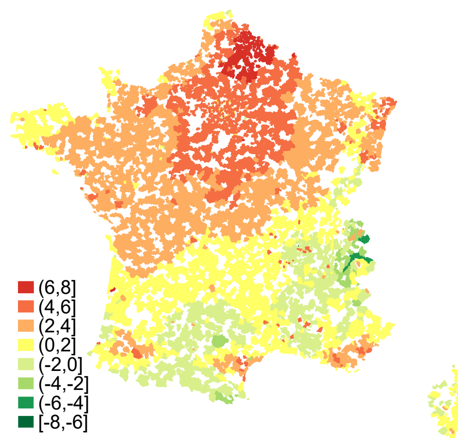
(a) South wind



(b) West wind



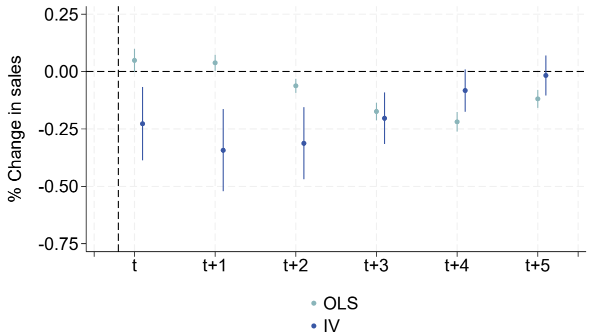
(c) East wind



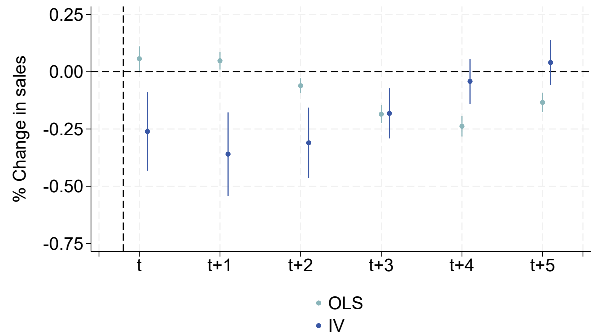
(d) North wind

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

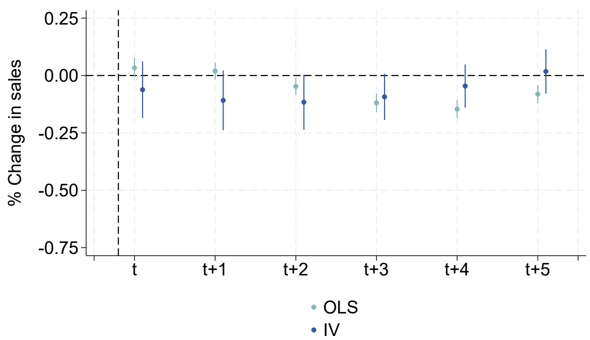
Notes: Figure shows the component B of the instrument Z_{jgyt}, which describes for each municipality the deviation from daily mean pollution levels on days where the dominant wind blows from direction j.



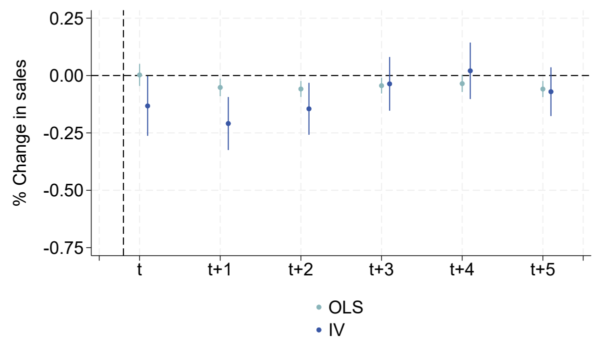
(a) All firms



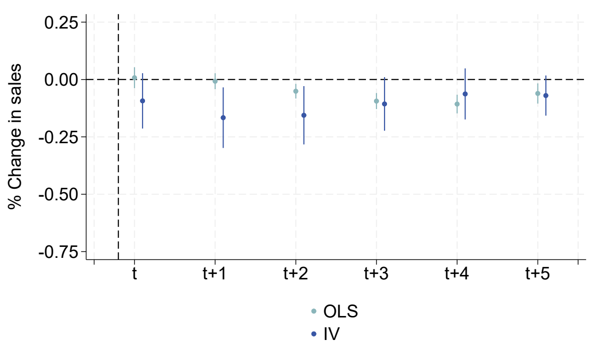
(b) All single-establishment firms



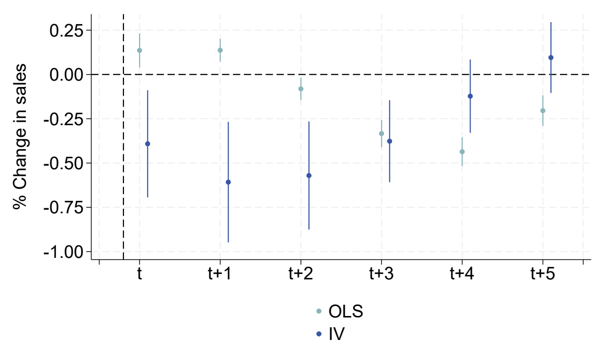
(c) Manufacturing



(d) Construction



(e) Business-to-Business Trade & Services



(f) Business-to-Consumer Retail & Services

Figure 3: Dynamic effects of $PM_{2.5}$ on sales for all firms, overall and by sector

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals for the effect of contemporaneous and lagged $PM_{2.5}$ (up to $t-5$) on firms' sales at t using a polynomial distributed lag specification based on equation (7) for all firms (a) and for single-establishment firms (b), as well as by sector: manufacturing (c), construction (d), B-to-B (e) and B-to-C (f). All regressions include month-by-year-by-industry fixed effects, firm-by-year fixed effects, quarter-by-county fixed effects, and weather and holidays controls from $t-1$ to $t+1$. The confidence intervals are based on standard errors clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability.

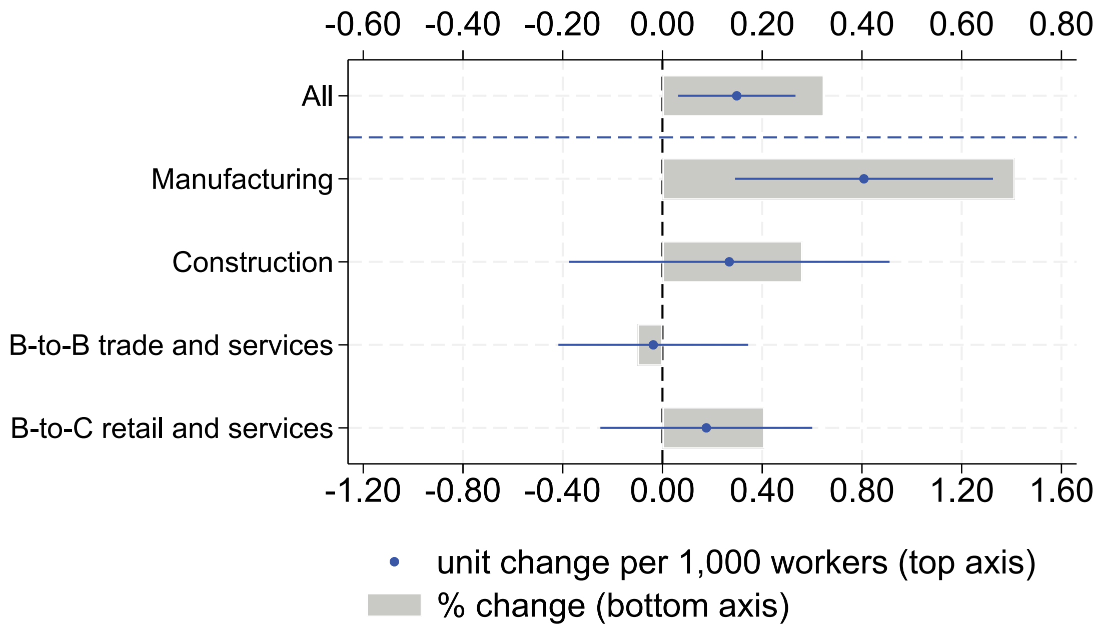


Figure 4: Contemporaneous effect of a one-unit increase in $PM_{2.5}$ on sick leave episodes

Notes: Figure shows IV point estimates and 95% confidence intervals for the effect of $PM_{2.5t}$ on the number of workers starting a sick leave per 1,000 workers at the establishment level, overall and by sector, based on equation (8). 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 of the establishment.

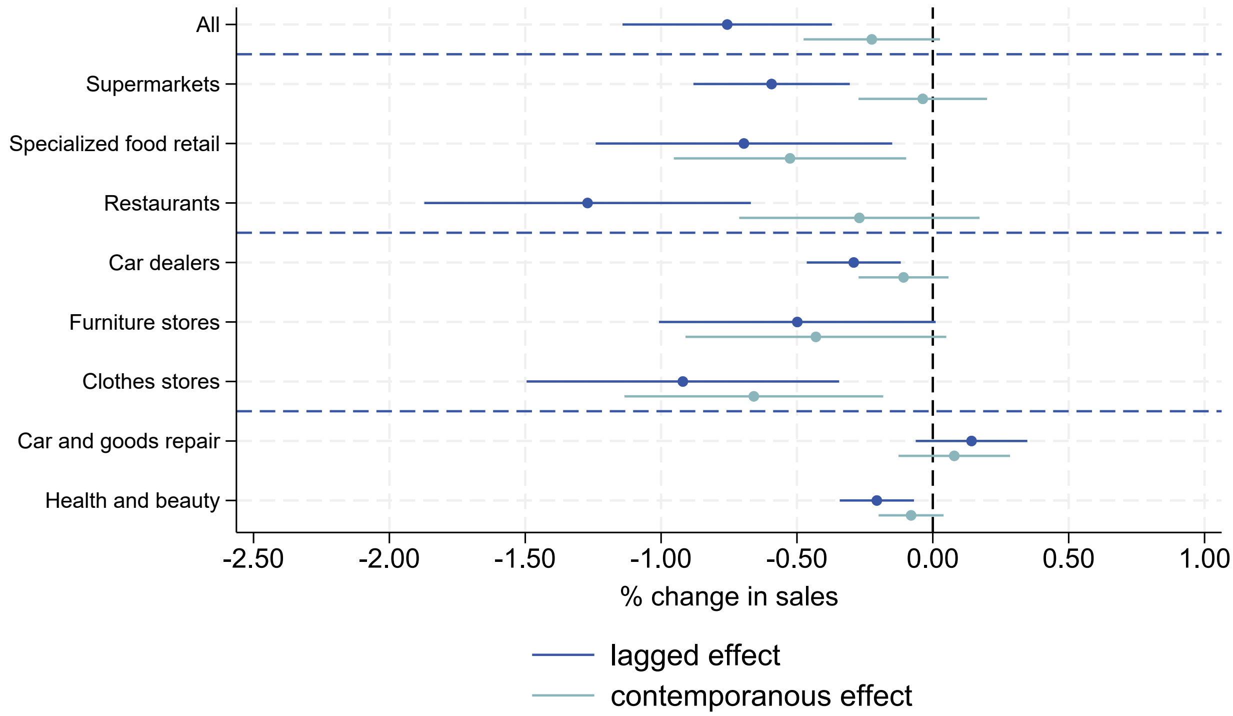


Figure 5: Effect of a one-unit increase in $PM_{2.5}$ on firms' sales by industry in the next two months within the business-to-consumer retail and services sector

Notes: Figure shows IV point estimates and 95% confidence intervals for the effect of $PM_{2.5}$ at $t-1$ (lagged effect) and t (contemporaneous effect) on firms' sales outcome at t by industry, based on equation (7). All regressions include month-by-year-by-industry fixed effects, firm-by-year fixed effects, quarter-by-county fixed effects, weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at $t+1$. The confidence intervals are based on standard errors clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability.

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 retail 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 retail 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: Data from panel a) is based on the firm-level dataset. Data from panel b) is based on the establishment-level dataset, with weights corresponding to the number of workers for whom we observe sick leave within each establishment.

Table 2: First stage results

	PM$_{2.5}$ exposure	
	Municipality aggregation	Firm aggregation
	(1)	(2)
$\mathrm{Z}_{\mathrm{South}\,gyt}$	1.432***	1.468***
	(0.097)	(0.152)
$\mathrm{Z}_{\mathrm{West}\,gyt}$	0.529***	0.575***
	(0.0635)	(0.148)
$\mathrm{Z}_{\mathrm{North}\,gyt}$	1.112***	1.231***
	(0.0484)	(0.055)
$\mathrm{Z}_{\mathrm{East}\,gyt}$	1.645***	1.610***
	(0.0481)	(0.0748)
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
N	391,234	6,322,128
R-squared	0.93	0.93

Notes: Table reports the first stage results based on equation (10), using municipality-month data (column (1)), and single establishment firm-month data (column (2)). Holiday and weather controls and quarter by-county-fixed effects are included. We report standard errors in parentheses, clustered at the Copernicus grid cell. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table 3: The effect of $PM_{2.5}$ on firms' sales, all sectors

	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
PM_{t-1}	0.00766	-0.448***	0.0250	-0.490***
	(0.0207)	(0.108)	(0.0231)	(0.110)
PM_t	0.0813***	-0.151**	0.0949***	-0.116*
	(0.0254)	(0.0675)	(0.0279)	(0.0694)
K-P F-stat of first stage				167
N	9,411,781	9,411,781	6,072,012	6,072,012
R-squared	0.9469	0.9469	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 $t-1$ and t on the sales outcome at t based on 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 firm-by-year fixed effects, month-by-year-by-industry fixed effects, quarter-by-county fixed effects, weather and holidays controls at $t-1$, t and $t+1$, as well as (instrumented) pollution at $t+1$. 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. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Panel A: Manufacturing				
PM_{t-1}	0.00665	-0.180**	-0.0101	-0.149*
	(0.0210)	(0.0717)	(0.0247)	(0.0779)
PM_t	0.0588***	-0.0527	0.0475**	0.00173
	(0.0201)	(0.0528)	(0.0221)	(0.0556)
K-P F-stat of first stage				150
N	1,880,380	1,880,380	1,233,990	1,233,990
R-squared	0.9641	0.9641	0.9535	0.9535
Panel B: Construction				
PM_{t-1}	-0.0201	-0.232***	-0.0226	-0.283***
	(0.0219)	(0.0633)	(0.0248)	(0.0685)
PM_t	-0.0174	-0.158***	-0.0231	-0.132*
	(0.0216)	(0.0584)	(0.0240)	(0.0679)
K-P F-stat of first stage				131
N	1,531,685	1,531,685	1,074,583	1,074,583
R-squared	0.9353	0.9353	0.9165	0.91625
Panel C: Business-to-Business Trade and Services				
PM_{t-1}	-0.0443**	-0.288***	-0.0146	-0.258***
	(0.0217)	(0.0726)	(0.0273)	(0.0858)
PM_t	0.0491**	-0.0195	0.0505*	-0.00856
	(0.0214)	(0.0573)	(0.0266)	(0.0651)
K-P F-stat of first stage				104
N	2,875,213	2,875,213	1,498,367	1,498,367
R-squared	0.9338	0.9338	0.9155	0.9155
Panel D: Business-to-Consumer Retail and Services				
PM_{t-1}	0.0840**	-0.757***	0.113***	-0.788***
	(0.0404)	(0.196)	(0.0419)	(0.186)
PM_t	0.190***	-0.225*	0.226***	-0.113
	(0.0462)	(0.128)	(0.0488)	(0.136)
K-P F-stat of first stage				108
N	3,124,500	3,124,500	2,265,070	2,265,070
R-squared	0.9457	0.9457	0.9342	0.9342

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ and t on the sales outcome at t based on equation (7) by sector , including all firms in columns (1) and (2) or single-establishment firms in columns (3) and (4). All regressions include firm-by-year fixed effects, month-by-year-by-industry fixed effects and quarter-by-county fixed effects, as well as weather and holidays controls at $t-1$, t and $t+1$ and (instrumented) pollution at $t+1$. The instruments are either the predicted firm-level pollution measure (column 2) or the 4 wind directions (column 4). Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability. 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	Manufact.	Construction	Business-to-business trade and services	Business-to-consumer trade and services
PM_{t+2}	-0.0197	-0.0839	0.000437	-0.0323	-0.0196
	(0.0441)	(0.0527)	(0.0607)	(0.0498)	(0.101)
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 based on equation (7) for all firms and by sector. All regressions include firm-by-year fixed effects, month-by-year-by-industry fixed effects and quarter-by-county fixed effects, as well as weather and holidays controls at t. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

	(1) Baseline	(2) AQI	(3) No AQ alerts	(4) Winsorized outcome	(5) Linear + quadratic weather controls	(6) Weather incl. humidity	(7) Flu incidence control
PM_{t-1}	-0.448***		-0.459***	-0.431***	-0.677***	-0.396***	-0.453***
	(0.108)		(0.111)	(0.114)	(0.148)	(0.111)	(0.108)
PM_{t}	-0.151**		-0.166**	-0.155**	-0.344***	-0.170**	-0.150**
	(0.0675)		(0.0796)	(0.0721)	(0.0920)	(0.0830)	(0.0685)
AQI_{t-1}		-6.14***					
		(1.81)					
AQI_{t}		-2.08*					
		(1.15)					
N	9,411,781	9,411,781	9,048,811	9,460,260	9,411,787	9,411,764	9,411,781

Notes: Table reports the IV estimates of the effect of a one-unit increase in $PM_{2.5}$ (or AQI) at $t - 1$ and t on the sales outcome at t based on equation (7) for all firms. All regressions include weather and holidays controls at $t-1$, t and $t+1$, instrumented pollution at $t+1$, 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. Coefficients (and standard errors) have been multiplied by 100 for readability. 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_t	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 for the effect of $PM_{2.5}$ at t 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 observed in the Hygie dataset 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 Channel: Heterogeneous effects of air pollution on sales and worker absenteeism in the manufacturing sector, by stock level

	Sales effect			Absenteeism effect		
	(1)	(2)	(3)	(4)	(5)	(6)
	All firms	Low stock	High stock	All firms	Low stock	High stock
PM_{t-1}	-0.180**	-0.314***	-0.00625			
	(0.0717)	(0.0971)	(0.103)			
PM_t	-0.0527	-0.132*	0.0673	0.313*	0.316	0.378*
	(0.0528)	(0.0691)	(0.0895)	(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	1,880,380	1,151,685	629,076	1,351,931	865,271	486,658
R-squared	0.9640	0.9708	0.9530	0.1273	0.1279	0.1271

Notes: Columns 1-3 report the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ and t on the sales outcome at t based on equation (7) for manufacturing firms (excluding extraction and utilities). All regressions include weather and holidays controls at $t-1$, t and $t+1$, as well as instrumented pollution at $t+1$, 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 at t, controlling for weather and holidays controls at t and industry-by-month-of-sample, establishment, and quarter-by-county fixed effects. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter (1-3) or of the establishment (4-6). Coefficients (and standard errors) have been multiplied by 100 for readability for the sales outcome. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

References

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

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

Almunia, M., P. Antràs, D. Lopez-Rodriguez, and E. Morales (2021). Venting out: Exports during a domestic slump. *American Economic Review 111*(11), 3611–62.

Andrews, I., J. H. Stock, and L. Sun (2019). Weak Instruments in Instrumental Variables Regression: Theory and Practice. *Annual Review of Economics* (Volume 11, 2019), 727–753.

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

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

Borgschulte, M., D. Molitor, and E. Y. Zou (2024). Air Pollution and the Labor Market: Evidence from Wildfire Smoke. *Review of Economics and Statistics 106*(6), 1558–1575.

Borusyak, K., P. Hull, and X. Jaravel (2025). A Practical Guide to Shift-Share Instruments. *Journal of Economic Perspectives 39*(1), 181–204.

Bruyneel, L., W. Kestens, M. Alberty, G. Karakaya, R. Van Woensel, C. Horemans, E. Trimpeneers, C. Vanpoucke, F. Fierens, T. S. Nawrot, and B. Cox (2022). Short-Term exposure to ambient air pollution and onset of work incapacity related to mental health conditions. *Environment International 164*, 107245.

Calderón-Garcidueñas, L., A. Mora-Tiscareño, E. Ontiveros, G. Gómez-Garza, G. Barragán-Mejía, J. Broadway, S. Chapman, G. Valencia-Salazar, V. Jewells, R. R. Maronpot, C. Henríquez-Roldán, B. Pérez-Guillé, R. Torres-Jardón, L. Herrit, D. Brooks, N. Osnaya-Brizuela, M. E. Monroy, A. González-Maciel, R. Reynoso-Robles, R. Villarreal-Calderon, A. C. Solt, and R. W. Engle (2008). Air pollution, cognitive deficits and brain abnormalities: a pilot study with children and dogs. *Brain and Cognition 68*(2), 117–127.

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

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

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

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

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

Dahl, G. B. and L. Lochner (2012). The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit. *American Economic Review 102*(5), 1927–1956.

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

Dechezleprêtre, A. and V. Vienne (2025). The impact of air pollution on labour productivity: Large-scale micro evidence from Europe. *OECD Science, Technology and Industry Working Papers 24*.

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

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

European Commission (2013). Comission staff working document: Impact assessment on the proposal for a directive of the european parliament and of the council on the reduction of national emissions of certain atmospheric pollutants and amending directive 2003/35/ec.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Lee, S. and S. Zheng (2025). Extreme Temperatures, Adaptation Capacity, and Household Retail Consumption. *Journal of the Association of Environmental and Resource Economists*.

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

Meyer, S. and M. Pagel (2024). Fresh air eases work—the effect of air quality on individual investor activity. *Review of Finance 28*(3), 1105–1149.

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

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

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

Prost, J.-M. and J.-P. Villetelle (2018). Rapport annuel de l'Observatoire des delais de paiement 2017. Contre les retards de paiement: Les entreprises inegalement mobilisees. Technical report, Banque de France.

Real, E., F. Couvidat, A. Ung, L. Malherbe, B. Raux, A. Gressent, and A. Colette (2022). Historical reconstruction of background air pollution over France for 2000–2015. *Earth System Science Data 14*(5), 2419–2443.

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

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

Shen, S., C. Li, A. van Donkelaar, N. Jacobs, C. Wang, and R. V. Martin (2024). Enhancing Global Estimation of Fine Particulate Matter Concentrations by Including Geophysical a Priori Information in Deep Learning. *ACS EST Air 1*(5), 332–345.

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

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

van Donkelaar, A., M. S. Hammer, L. Bindle, M. Brauer, J. R. Brook, M. J. Garay, N. C. Hsu, O. V. Kalashnikova, R. A. Kahn, C. Lee, R. C. Levy, A. Lyapustin, A. M. Sayer, and R. V. Martin (2021). Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty. *Environmental Science and Technology 55*(22), 15287–15300.

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

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

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

Appendix – For online publication only

A Additional Figures and Tables

A.1 Figures

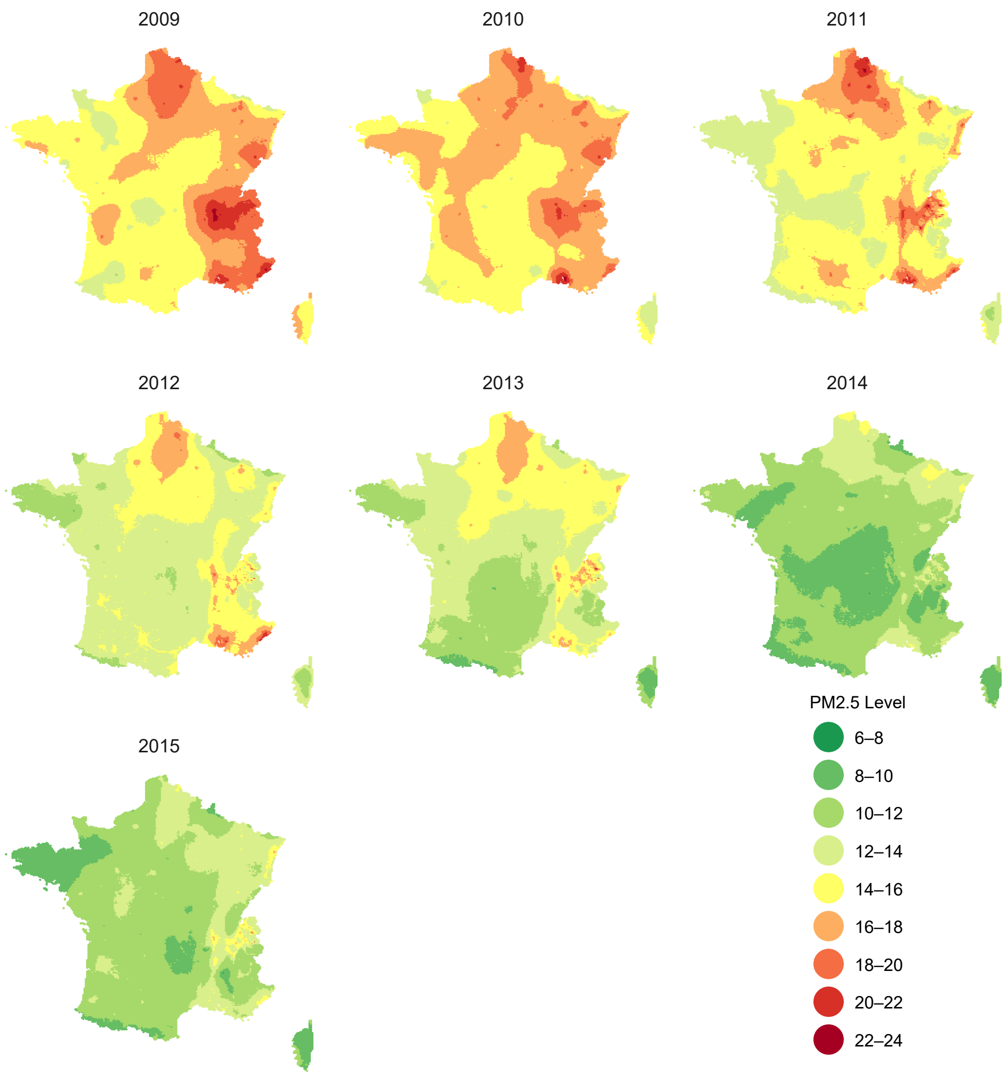
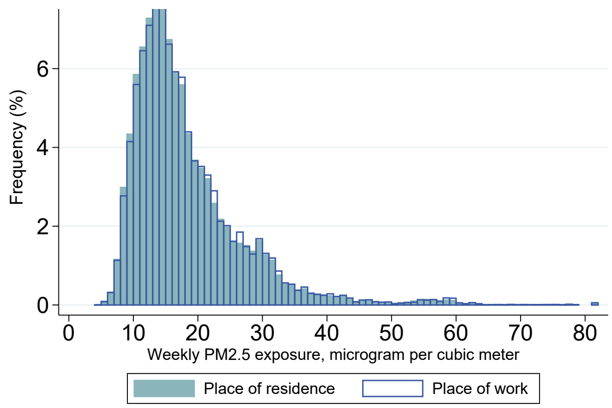
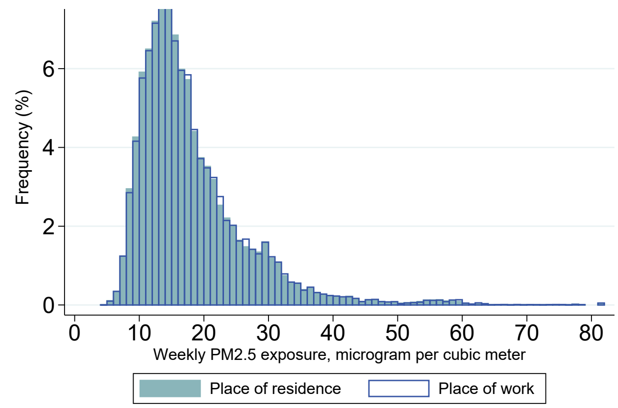


Figure A.1: Average annual concentrations of $PM_{2.5}$ (µg/m^3)

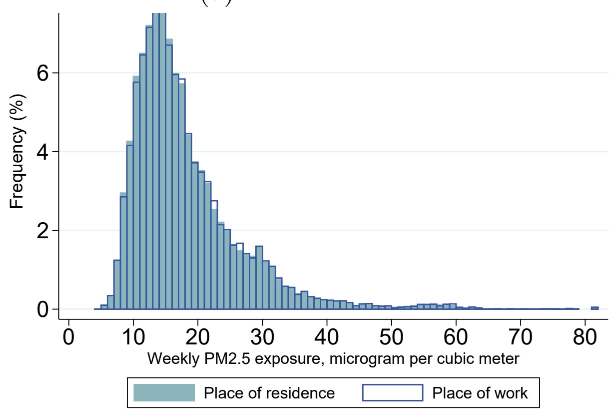
Notes: Figure shows the average annual concentration of $PM_{2.5}$ measured at the 4km x 4 km grid cell level using the reanalysis pollution data. There are 33,252 such grid cells in metropolitan France.



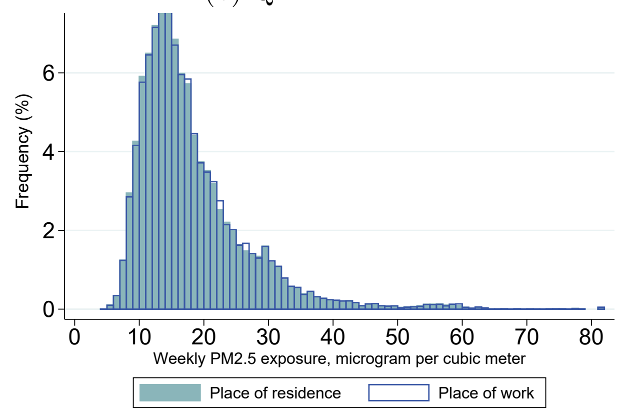
(a) All



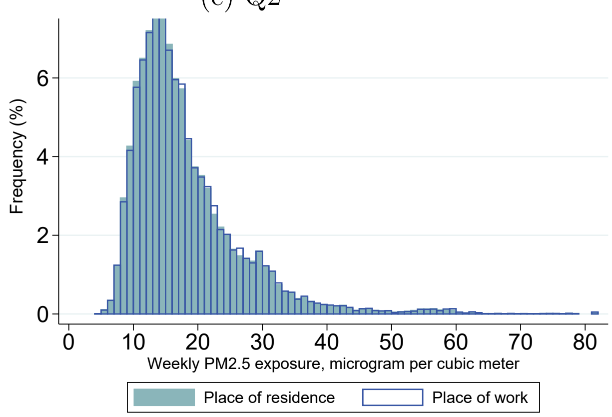
(b) Q1



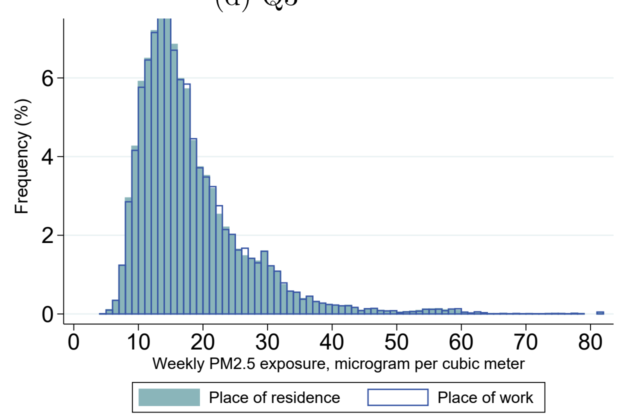
(c) Q2



(d) Q3



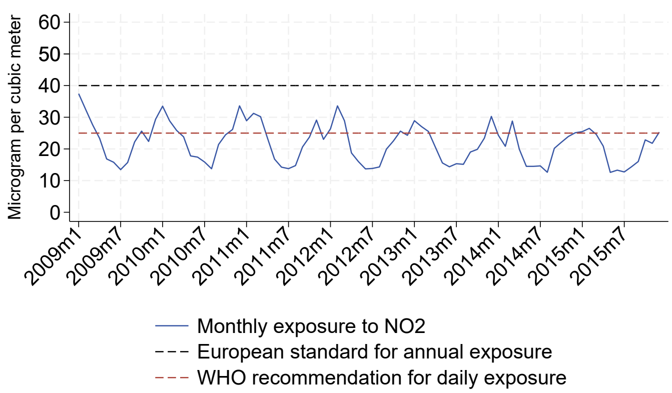
(e) Q4



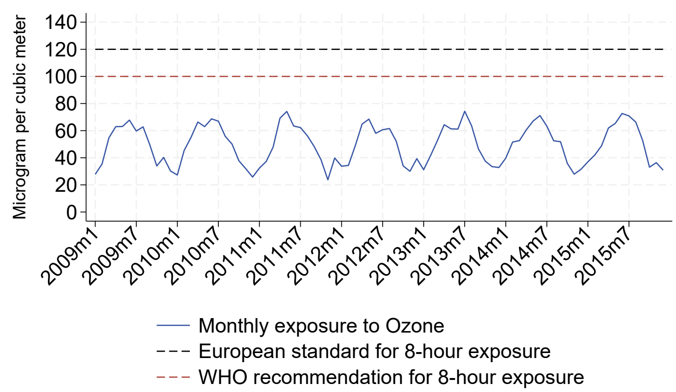
(f) Q5

Figure A.2: Distribution of $PM_{2.5}$ pollution exposure at the municipality of residence and at the municipality of workplace in 2009, for all private sector workers and by wage quintile

Notes: Data source: exhaustive matched-employer employee data for all private sector workers in 2009.



(a) NO_2



(b) Ozone

Figure A.3: Average monthly exposure to nitrogen dioxide (NO_2 and ozone

Notes: Figure shows the monthly average of workers' exposure to $PM_{2.5}$ at the municipality of their workplace. 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 employed in each municipality in the absenteeism dataset.

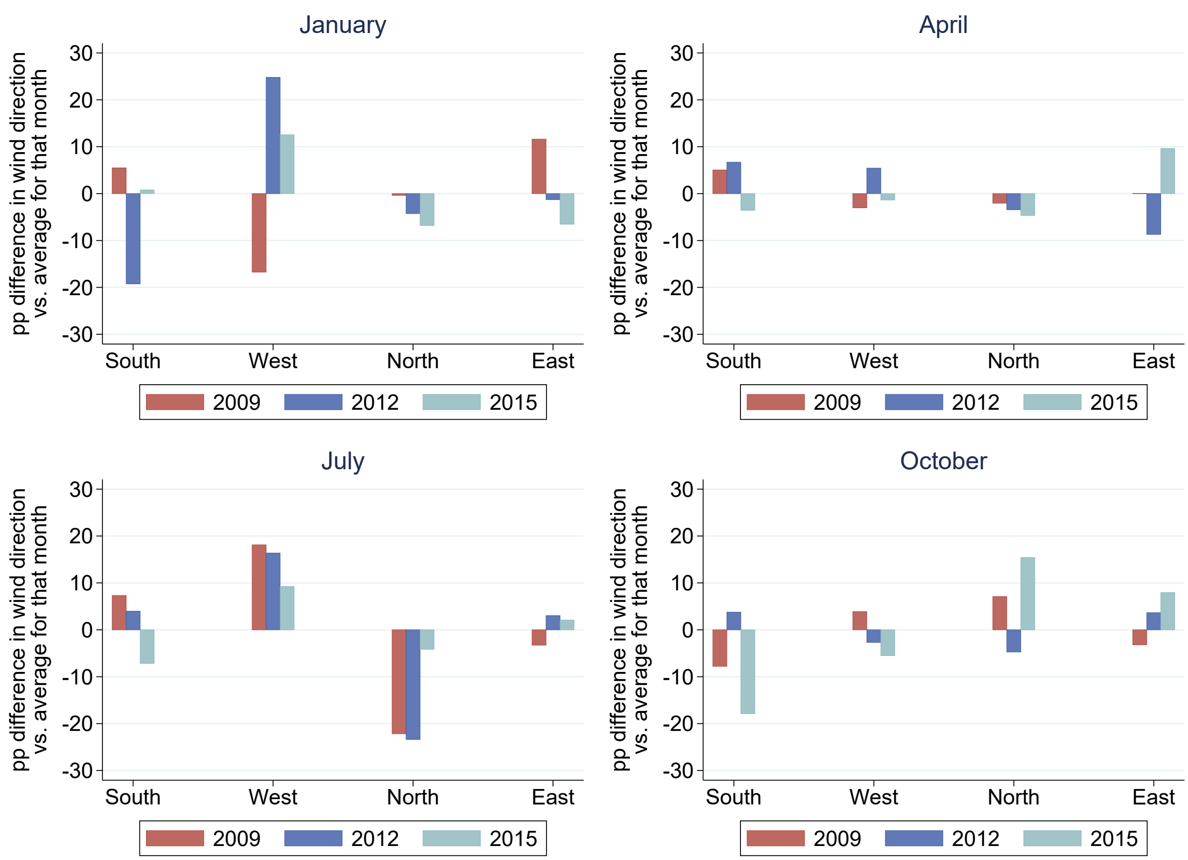


Figure A.4: Within-calendar month variation in wind direction, Paris

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).

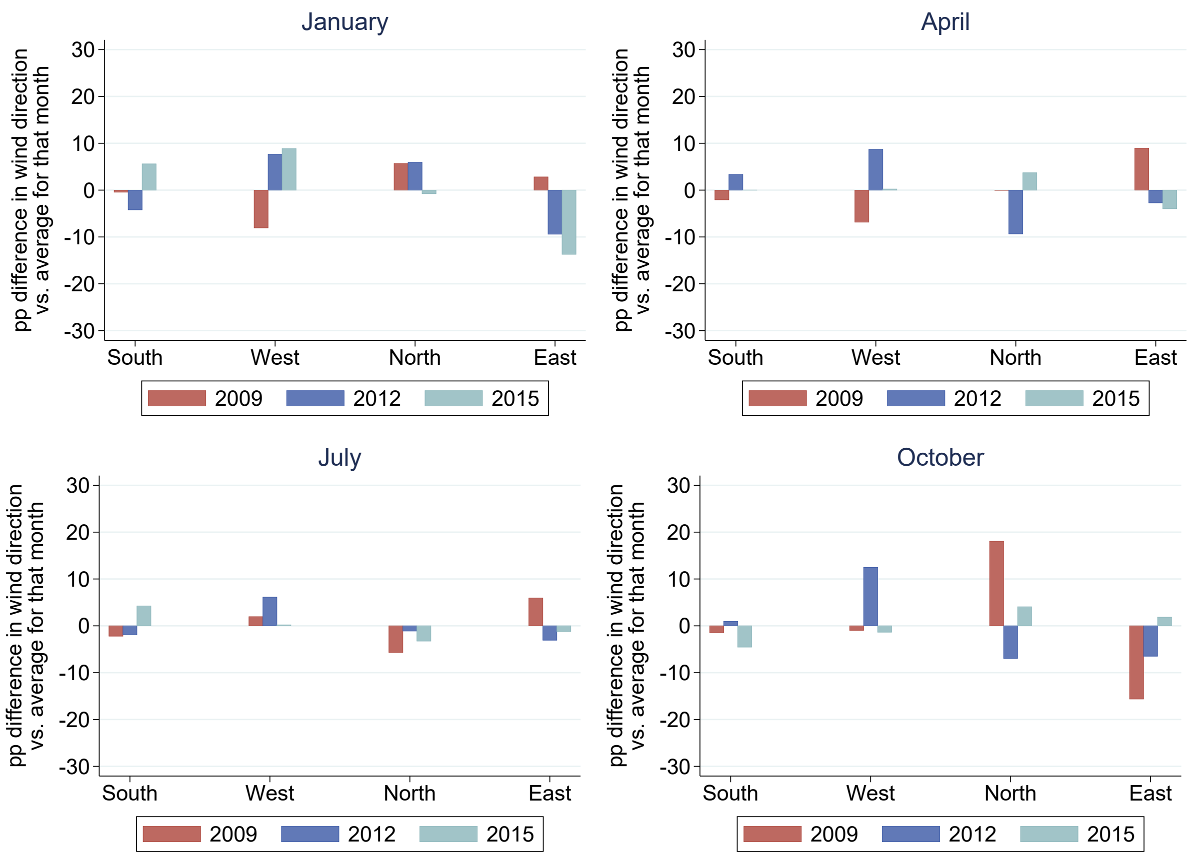
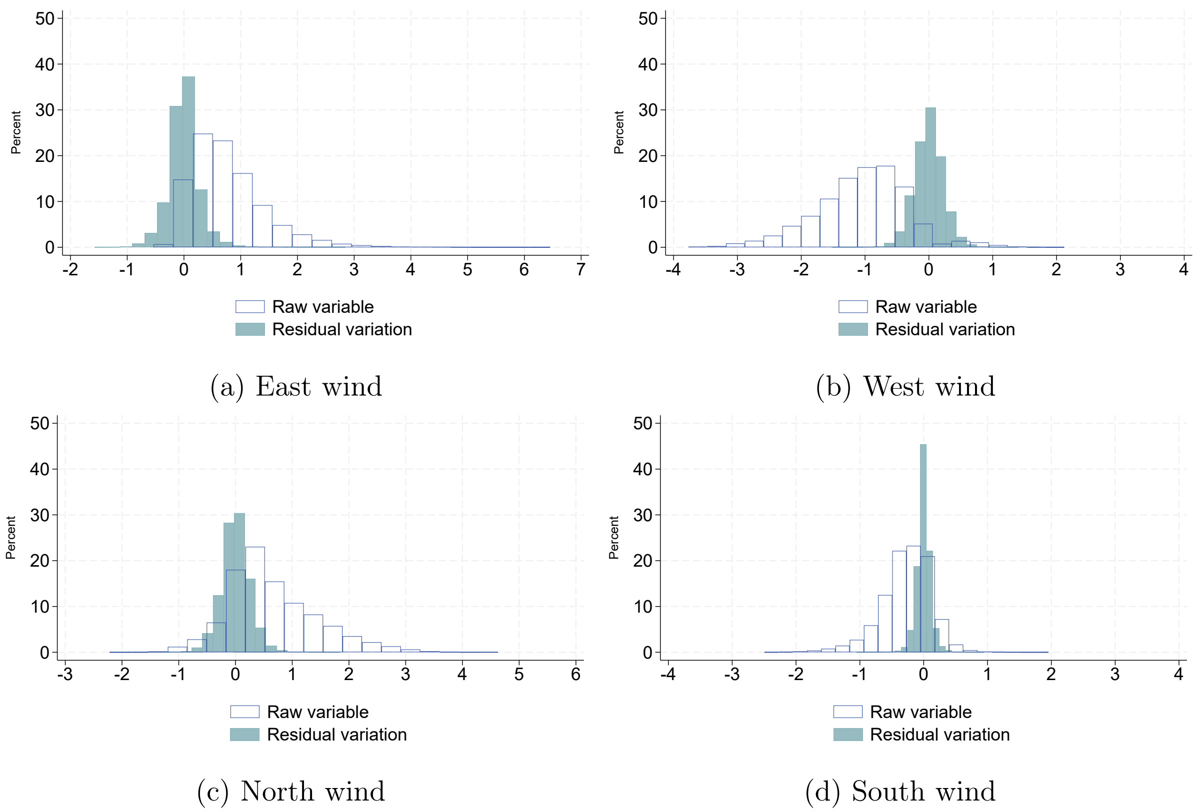


Figure A.6: Within-calendar month variation in wind direction, Marseille (South-East of France)

Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, de-meaned 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

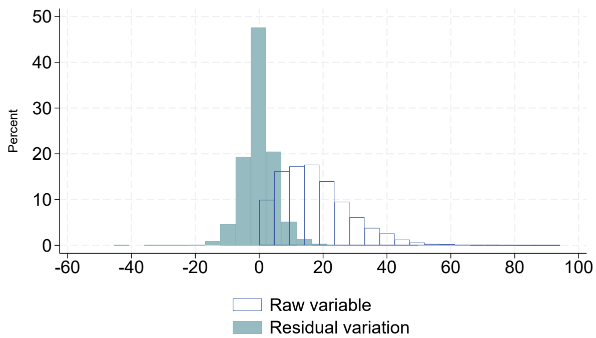
(b) West wind

(c) North wind

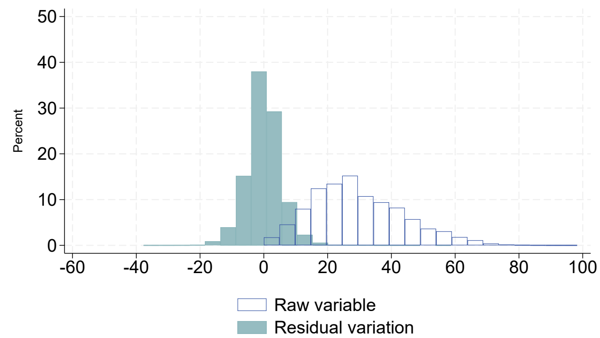
(d) South wind

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

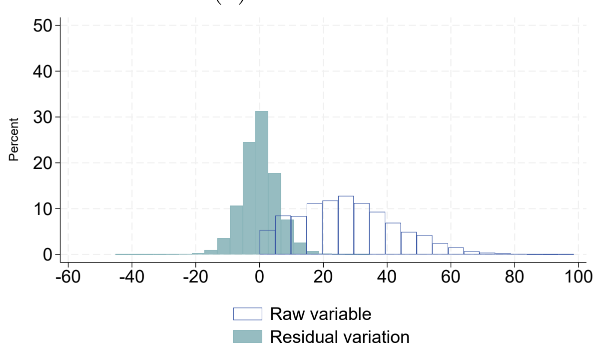
Notes: Residualized variables are obtained by regressing each wind instrument value on the right-hand side variables of equation (10) for the sample of single-establishment firms: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-county fixed effects, and firm-by-year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



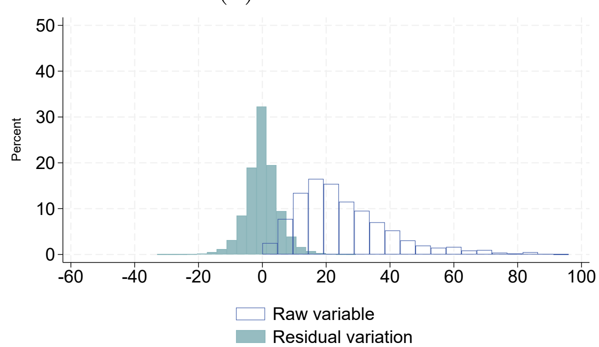
(a) East wind



(b) West wind



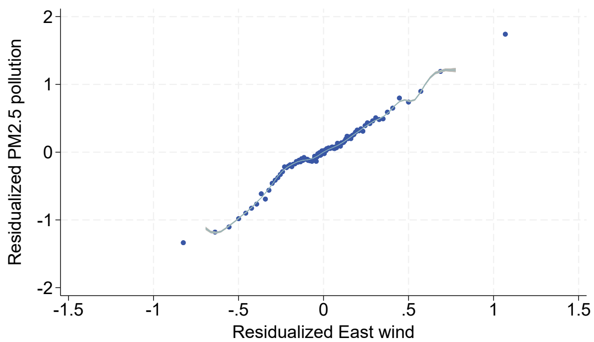
(c) North wind



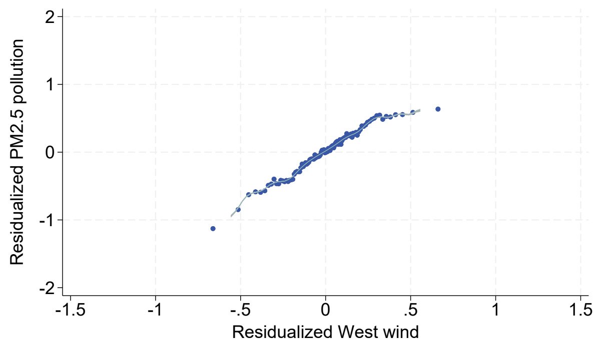
(d) South wind

Figure A.10: Identifying variation - Distribution of raw and residualized share of each wind's direction

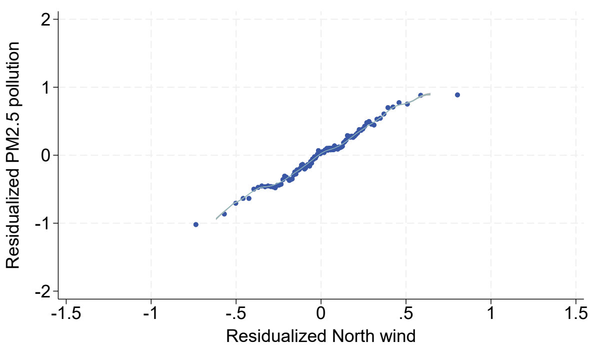
Notes: Residualized variables are obtained by regressing monthly shares of each wind direction on the right-hand side variables of equation (10) for the sample of single-establishment firms: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-county fixed effects, and firm-by-year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



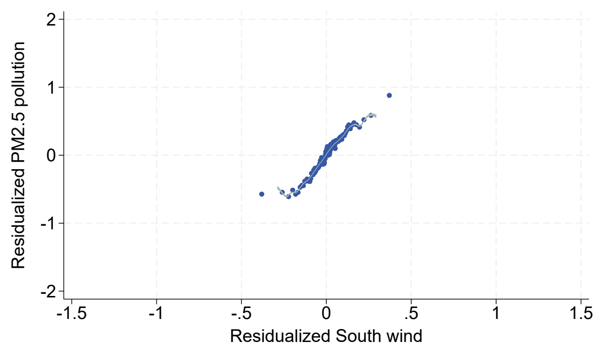
(a) East wind



(b) West wind



(c) North wind



(d) South wind

Figure A.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 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).

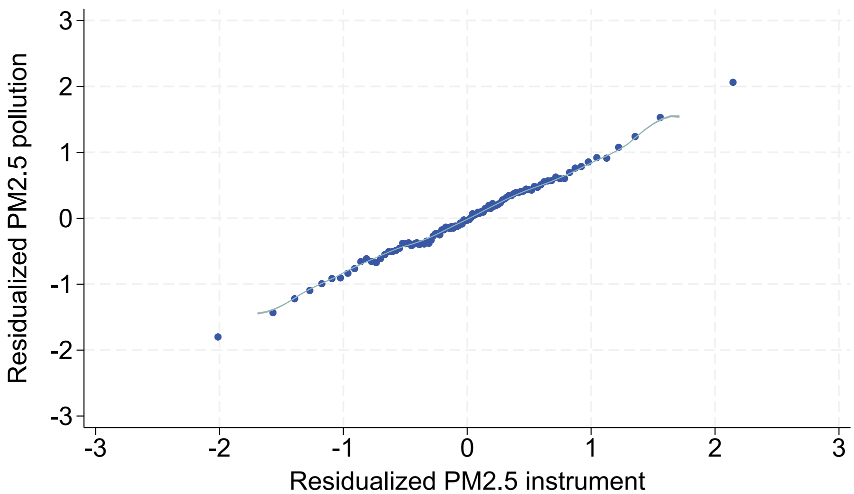
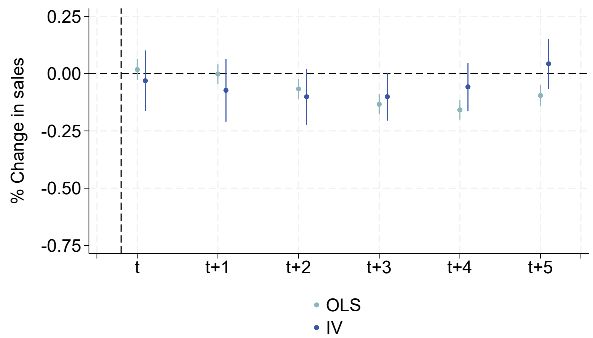
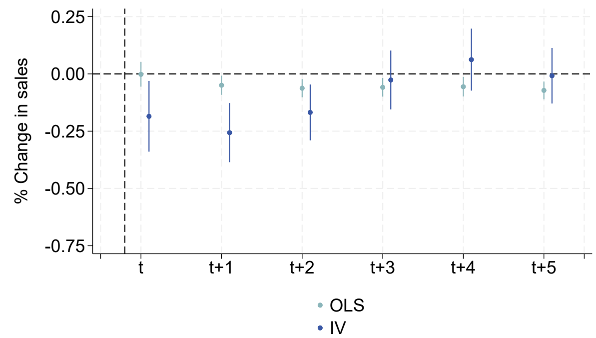


Figure A.14: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

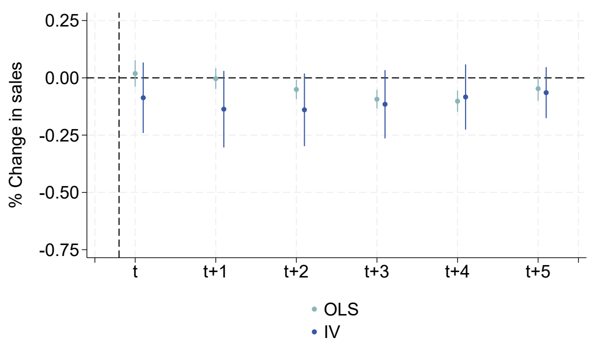
Notes: Figure is based on the sample of all firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing the predicted $PM_{2.5}$ variable $\widehat{PM_{fyt}}$ (resp. the endogenous $PM_{2.5}$ variable) on the right-hand side variables of equation 10: weather and holiday controls, industry-by-month-by-year 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).



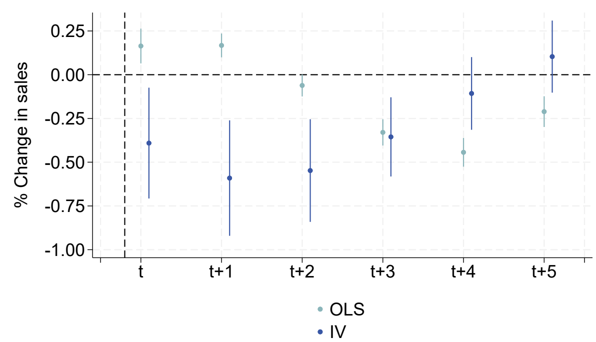
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Retail & Services

Figure A.15: 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 $t-5$) on firms' sales outcome 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 from $t-1$ to $t+1$. Standard errors are clustered at the Copernicus grid cell level. Coefficients (and standard errors) have been multiplied by 100 for readability.

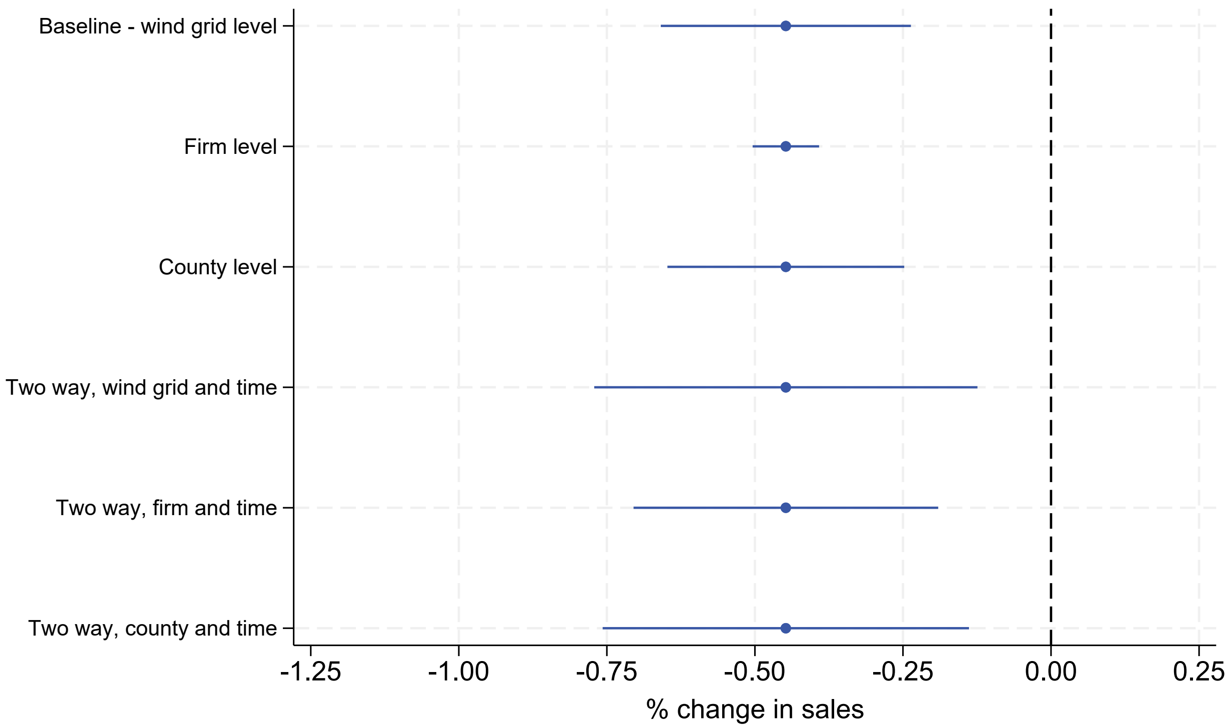


Figure A.16: Sensitivity of the results to the level of clustering for standard errors

Notes: Figure shows IV point estimates and 95% confidence intervals for the effect of $PM_{2.5}$ at $t-1$ and t on firms' sales at t, based on equation (7). All regressions include month-by-year-by-industry fixed effects, firm-by-year fixed effects, quarter-by-county fixed effects, weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at $t+1$. Coefficients (and standard errors) have been multiplied by 100 for readability.

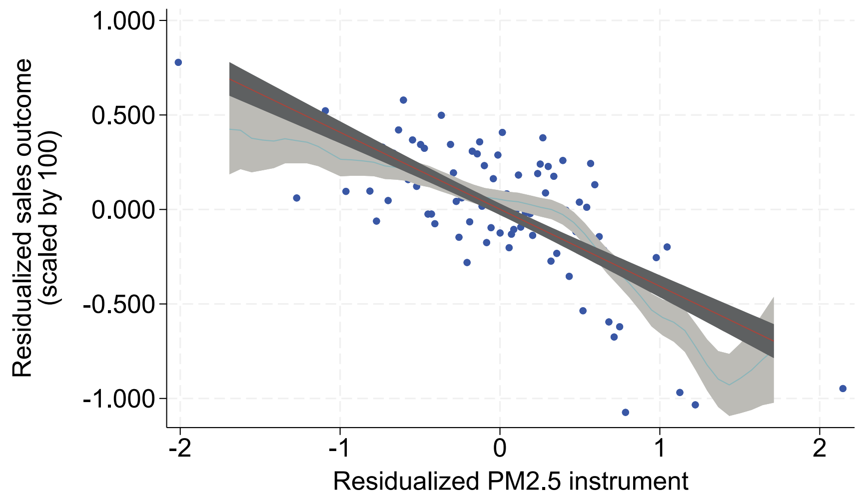


Figure A.17: Residualized binned scatter plot between sales and $PM_{2.5}$ instrument and local polynomial fit

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 (the predicted $PM_{2.5}$ variable, $\widehat{PM_{fyt}}$) 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). The solid red line shows a linear regression fit, with the dark grey area around showing 95% confidence bands.

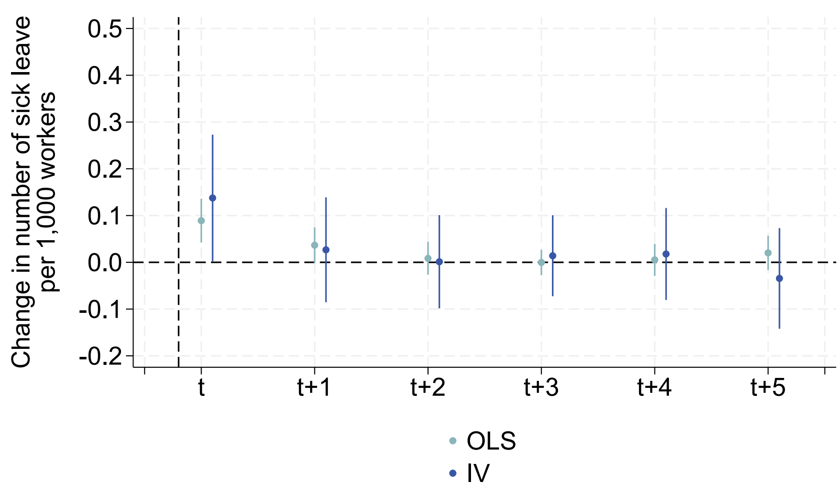


Figure A.18: Dynamic effects of $PM_{2.5}$ on absenteeism

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals based on 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 from $t-1$ to $t+1$. Standard errors are clustered at the Copernicus grid cell level.

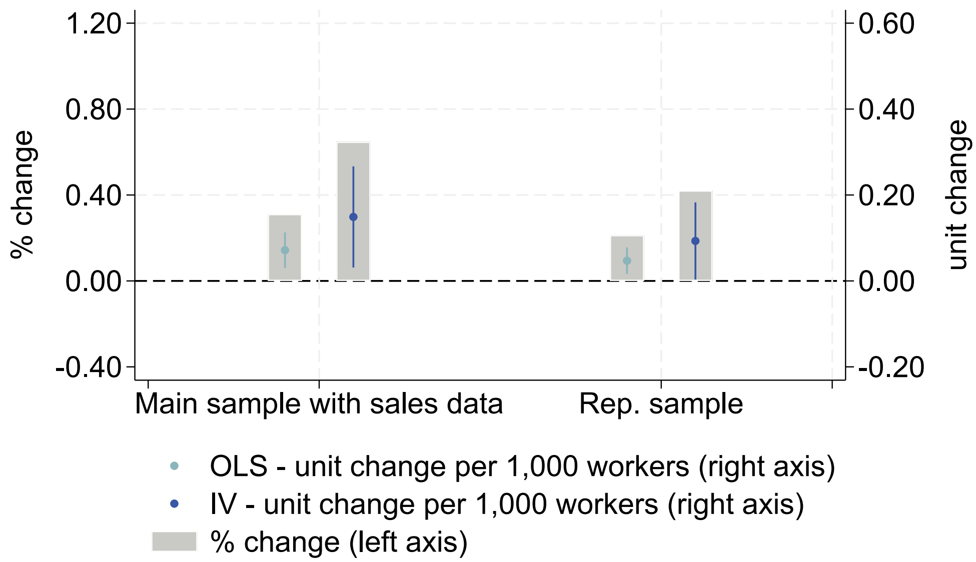


Figure A.19: Absenteeism results for our main sample, only including workers employed in the firms of our sales sample (left), vs. the representative sample including all workers (right)

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals for the effect of contemporaneous $PM_{2.5}$ on the number of workers entering sick leave at t per 1,000 workers, based on equation (8). All regressions include month-by-year-by-industry, establishment, and quarter-by-county fixed effects, as well as weather and holidays controls. Standard errors are clustered at the Copernicus grid cell level.

A.2 Tables

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

Sample	Main sample establishments with sales data		All establishments with absenteeism	
	Mean	Sd	Mean	Sd
Age	40.2	8.7	40.4	8.9
Annual wage	28,542.0	20,576.1	25,911.0	20,547.4
Annual total medical expenditures	442.0	809.8	462.5	819.8
Works in a single-establishment firm	41%	0.49	-	-
Works in: Manufacturing	28%	0.45	17%	0.37
Construction	12%	0.32	7%	0.26
Business-to-business services	33%	0.47	20%	0.40
Business-to-consumer services	27%	0.39	16%	0.32
Others	0%	-	40%	0.49
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)	24.7	113.4	23.9	111.3
incl: for <93 days	**23.0**	109.2	**22.1**	107.0
N	8,233,440		16,409,124	

Notes: Table reports descriptive statistics on workers included in the absenteeism dataset, aggregated at the establishment level applying worker weights. The left panel is based on our main sample of analysis for whom we have sales data and the right panel on the entire representative sample of private sector employees.

Table A.2: The Effect of $PM_{2.5}$ on Firm-level Sales, Adding Fixed Effects progressively

	(1)	(2)	(3)	(4)	(5)
Panel A: OLS results					
PM_{t-1}	-0.0404*	0.0335	0.0325	0.00147	0.00766
	(0.0216)	(0.0258)	(0.0251)	(0.0213)	(0.0207)
PM_t	0.111***	0.145***	0.137***	0.0786***	0.0813***
	(0.0228)	(0.0284)	(0.0297)	(0.0235)	(0.0254)
N	9,412,076	9,411,967	9,403,047	9,411,967	9,403,047
R-squared	0.9208	0.9456	0.9468	0.9459	0.9470
Panel B: IV results					
PM_{t-1}	-0.582***	-0.576***	-0.539***	-0.461***	-0.448***
	(0.131)	(0.114)	(0.116)	(0.103)	(0.108)
PM_t	-0.266***	-0.275***	-0.257***	-0.154**	-0.151**
	(0.0832)	(0.0827)	(0.0791)	(0.0673)	(0.0675)
N	9,412,076	9,411,945	9,411,781	9,411,945	9,411,781
R-squared	0.9208	0.9456	0.9467	0.9458	0.9469
Firm FE	Yes	No	No	No	No
Firm-by-year FE	No	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	No	Yes	No
Month-by-year-by-industry FE	No	No	Yes	No	Yes
Quarter-by-departement FE	No	No	No	Yes	Yes

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ and t on the sales outcome at t based on 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 $t+1$. Standard errors are clustered at the Copernicus grid cell level. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.3: The Effect of adding lags of $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS results						
PM_t	0.0527*	0.0819***	0.0949***	0.0851***	0.0791***	0.0680***
	(0.0286)	(0.0253)	(0.0259)	(0.0239)	(0.0247)	(0.0246)
PM_{t-1}		0.00794	0.0275	0.0220	0.00412	-0.00419
		(0.0207)	(0.0202)	(0.0214)	(0.0224)	(0.0238)
PM_{t-2}			-0.0198	0.00382	-0.0150	-0.0290
			(0.0179)	(0.0183)	(0.0175)	(0.0185)
PM_{t-3}				-0.165***	-0.154***	-0.162***
				(0.0235)	(0.0222)	(0.0223)
PM_{t-4}				-0.165***	-0.154***	-0.162***
				(0.0235)	(0.0222)	(0.0223)
PM_{t-5}						-0.105***
						(0.0203)
N	9,585,132	9,403,025	9,220,160	9,036,731	8,853,170	8,669,685
R-squared	0.9461	0.9470	0.9476	0.9480	0.9485	0.9489
Panel B: IV results						
PM_t	-0.175***	-0.148**	-0.163**	-0.200**	-0.210***	-0.190**
	(0.0640)	(0.0672)	(0.0728)	(0.0798)	(0.0806)	(0.0810)
PM_{t-1}		-0.447***	-0.423***	-0.425***	-0.448***	-0.444***
		(0.107)	(0.101)	(0.100)	(0.105)	(0.110)
PM_{t-2}			-0.243***	-0.245***	-0.257***	-0.250***
			(0.0788)	(0.0774)	(0.0764)	(0.0763)
PM_{t-3}				-0.207***	-0.225***	-0.213***
				(0.0633)	(0.0629)	(0.0637)
PM_{t-4}					-0.129***	-0.139***
					(0.0464)	(0.0497)
PM_{t-5}						0.00373
						(0.0458)
N	9,585,132	9,403,025	9,220,160	9,036,731	8,853,170	8,669,685
R-squared	0.9461	0.9470	0.9476	0.9480	0.9485	0.9489
Weather and holiday controls at t and $t+1$	Yes	Yes	Yes	Yes	Yes	Yes
Weather and holiday controls at $t-1$	No	Yes	Yes	Yes	Yes	Yes

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $\text{PM}_{2.5}$ at different lags on the sales outcome at t based on 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 $t+1$. Standard errors are clustered at the Copernicus grid cell level. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.4: Heterogeneous sales responses to $PM_{2.5}$, by firm size

	(1) Below 15 workers	(2) Above 15 workers
Panel A: All firms		
PM_{t-1}	-0.499***	-0.367***
	(0.119)	(0.0957)
PM_t	-0.133	-0.151**
	(0.0846)	(0.0606)
N	4,518,389	4,884,519
R-squared	0.8527	0.9386
Panel B: Manufacturing		
PM_{t-1}	-0.367***	-0.0546
	(0.123)	(0.0644)
PM_t	-0.0229	-0.0496
	(0.0964)	(0.0587)
N	603,306	1,272,780
R-squared	0.8395	0.9559
Panel C: Construction		
PM_{t-1}	-0.363***	-0.0659
	(0.0906)	(0.0737)
PM_t	-0.135	-0.159**
	(0.0835)	(0.0679)
N	837,109	693,235
R-squared	0.8026	0.9253
Panel D: Business-to-Business Trade and Services		
PM_{t-1}	-0.304***	-0.260***
	(0.0972)	(0.0870)
PM_t	-0.0458	0.000512
	(0.0735)	(0.0701)
N	1,226,875	1,646,457
R-squared	0.8492	0.9281
Panel E: Business-to-Consumer Retail and Services		
PM_{t-1}	-0.665***	-0.872***
	(0.186)	(0.216)
PM_t	-0.149	-0.320**
	(0.140)	(0.132)
N	1,847,214	1,275,900
R-squared	0.8737	0.9377

Notes: Table reports the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ and t on the sales outcome at t based on (7) for firms with fewer than 15 workers on average (column 1) and those with at least 15 workers (column 2). All regressions include firm-by-year, month-by-year-by-industry and quarter-by-county fixed effects, weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at $t+1$. The confidence intervals are based on standard errors clustered at the Copernicus grid cell level. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for

Table A.5: Sensitivity of the results to the choice of instrument

	(1) Baseline 2009-2015	(2) Early-period B component 2009-2015	(3) Wind share A component only 2009-2015	(4) Baseline 2010-2015	(5) Early-period B component 2010-2015
PM_{t-1}	-0.448***	-0.357***	-0.217***	-0.311***	-0.435***
	(0.108)	(0.110)	(0.0752)	(0.108)	(0.107)
N	9,411,781	9,381,735	9,411,781	8,146,573	8,172,701

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 based onequation (7) for all firms in all sectors. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, instrumented pollution at $t+1$, firm-by-year fixed effects, quarter-by-county fixed effects and industry-by-month-by year fixed effects. Column (1) shows the baseline result. Column (2) shows the result with a modified instrumental variable where component B of each instrument is calculated using data from the first period only, 2009. Column (3) shows the result with an alternative instrumental variable leveraging only variation in wind shares. Column (4) shows the baseline result restricting the sample to 2010-2015, and column (5) shows the result using the same modified instrumental variable as in columns (2), but restricting the sample to the 2010-2015 period. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.6: Sensitivity of the results to the source of pollution data

	(1) Reanalysis Baseline	(2) Satellite -based	(3) Reanalysis 2011-2015	(4) Monitor -based inv. distance 2011-2015	(5) Monitor -based nearest 2011-2015
PM_{t-1}	-0.448***	-0.553***	-0.318***	-0.278***	-0.267***
	(0.108)	(0.162)	(0.0987)	(0.0923)	(0.0892)
N	9,411,781	9,411,781	6,797,845	6,693,030	6,489,037

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 $t+1$ based on 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. Column (3) shows the baseline result when the sample is restricted to the 2011-2015 period to enable comparison with columns (4) and (5), where the $PM_{2.5}$ data is based on observations from monitoring stations only, which are more readily available starting in 2011. The median distance to the nearest $PM_{2.5}$ monitoring station is 16 kilometers and the average is 25 kilometers. Standard errors are clustered at the Copernicus grid cell level of the firm's headquarter. Coefficients (and standard errors) have been multiplied by 100 for readability. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.7: The contemporaneous effect of $PM_{2.5}$ on the number of sick days in manufacturing

	OLS	IV
	(1)	(2)
PM_t	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 based on equation (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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

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.

Column (1) of table B.2 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 index increases 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 $PM_{2.5}$ is 0.93, a similar order of magnitude. Columns (3) to (6) 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, changing the specification of weather controls and controlling for flu incidence.

Column (2) of table B.3 shows that the order of magnitude of the effect holds if we use satellite-derived $PM_{2.5}$ data instead of reanalysis $PM_{2.5}$ data. Columns (3) and (4) show that the results are the same if we use monitoring station data only (restricting the period of analysis to 2011-2015).

Table B.1: 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_t	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 based on equation (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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table B.2: The Effect of $PM_{2.5}$ on worker absenteeism, all sectors, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	AQI	No AQ alerts	Winsorized outcome	Linear and quadratic weather controls	Weather incl. humidity	Flu incidence control
PM_t	0.147^{**}		0.156^{**}	0.157^{***}	0.155^{**}	0.117^{*}	0.131^{**}
	(0.0603)		(0.0650)	(0.0496)	(0.0611)	(0.0637)	(0.0604)
AQI index_t		2.151^{**}					
		(0.868)					
N	8,238,888	8,238,888	7,890,564	8,238,888	8,238,888	8,238,887	8,238,888

Table reports IV estimates based on 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 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 $p < 0.01$.

Table B.3: Sensitivity of the results on sick leave to the source of pollution data

	(1) Reanalysis Baseline	(2) Satellite -based	(3) Reanalysis 2011-2015	(4) Monitor -based inv. distance 2011-2015
PM_t	0.147**	0.191**	0.189***	0.189***
	(0.0603)	(0.0818)	(0.0605)	(0.0612)
N	8,238,888	8,238,888	5,796,540	5,796,540

Notes: Table reports the IV estimates of the effect of a one-unit increase in $PM_{2.5}$ at t on the number of workers starting a sick leave at t per 1,000 workers, based on equation (8). 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.19), 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.1 shows the geographic distribution of the employees' workplaces in 2009, which is consistent with the distribution of the French population across the territory.

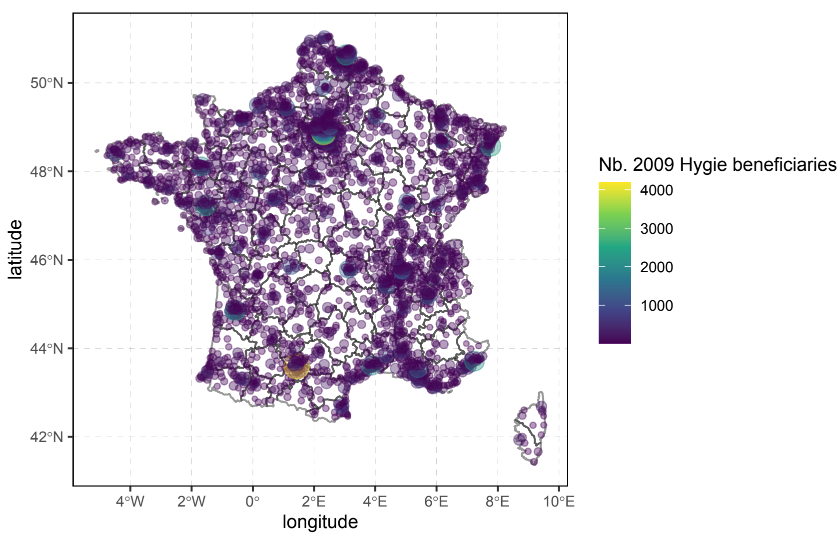
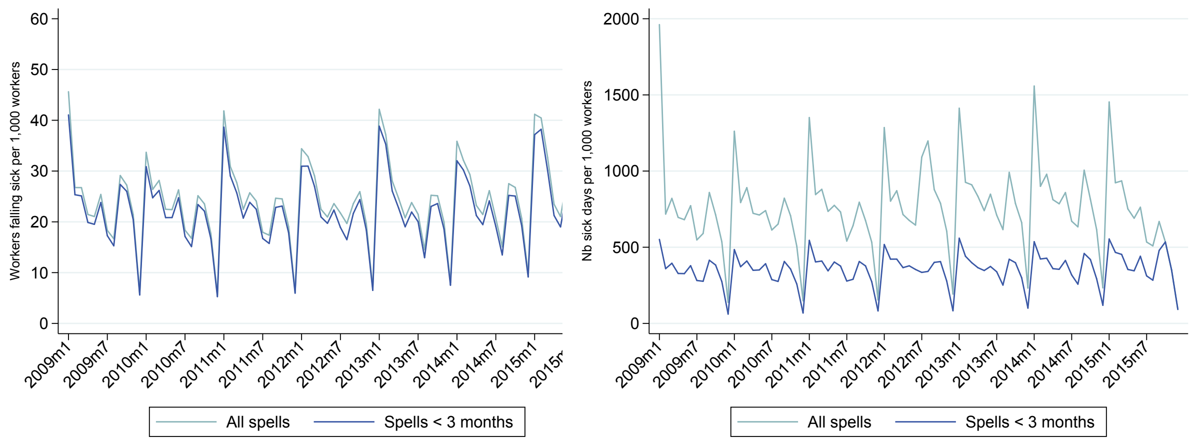


Figure C.1: Location of workers from the Hygie dataset based on the workplace municipality, in 2009

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,[49] we find that those workers representing the population from which our sample is drawn are 55% male, 41 on average, and earn an average annual gross wage of €26,204. Thus, the average individual in our final worker sample – as shown in Table 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.2: 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.[50] Our measure of sales includes both domestic sales and exports to EU and non-

[49]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.

[50]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

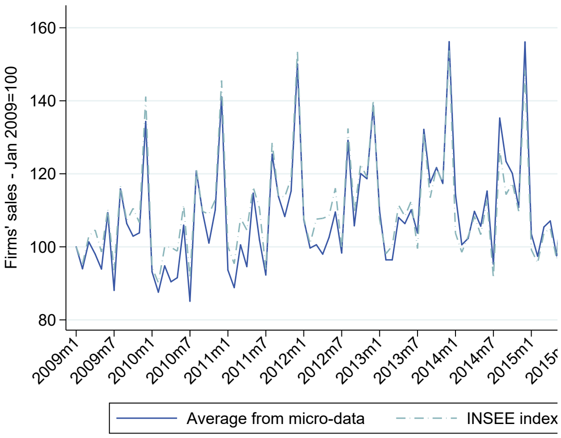
EU countries. The French tax administration imposes monthly declarations to firms with annual sales above €818,000 for the manufacturing sector and the hospitality industry and to those with annual sales above €247,000 for the other sectors. Firms below this threshold are allowed to fill declarations on a quarterly basis.

We discard the entire firm-year series for firms not reporting sales each month within a year. However, we make one exception for zero sales records in July since it is a relatively common pattern in the data. A large number of French firms close for vacation during some weeks in August, the month where the July VAT declaration is expected (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.[51] 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.

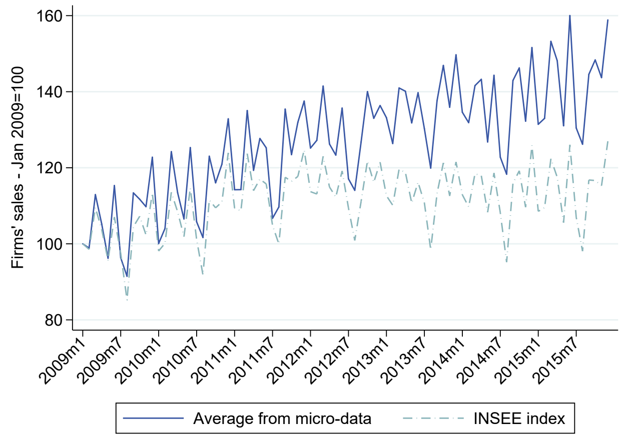
We determine sectors of activity based on the sectoral classification available at the establishment level and we use the mode of sector categories across establishments for multi-establishment firms. We define 4 sectors of interest: manufacturing, construction, business-to-consumer retail and services, 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.3c shows the time series of monthly sales in construction (C.3a), manufacturing (C.3b) and all services (C.3c) 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.

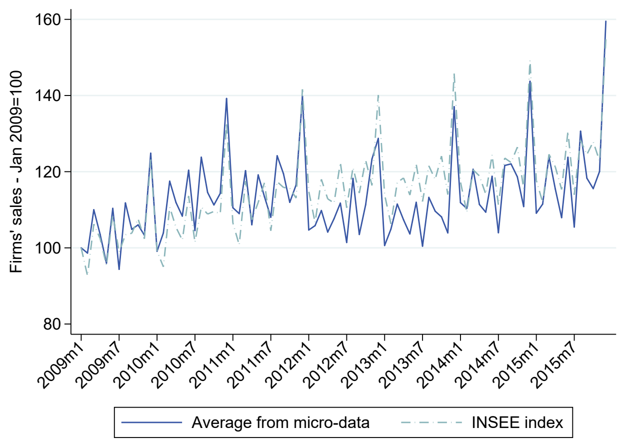
[51] See https://shorturl.at/TAZjH.



(a) Construction



(b) Manufacturing



(c) Services

Figure C.3: 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.