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The impact of air pollution on labour productivity in France

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Abstract

This paper investigates the effect of air pollution on labour productivity in French establishments in both manufacturing and non-financial market services sectors from 2001 to 2018. An instrumental variable approach based on planetary boundary layer height and wind speed allows identifying the causal effect of air pollution on labour productivity. The finding shows that a 10% increase in fine particulate matter leads, on average, to a 1.5% decrease in labour productivity, controlling for firm-specific characteristics and other confounding factors. The analysis also considers different dimensions of heterogeneity driving this adverse effect. The negative impact of pollution is mainly driven by service-intensive firms and sectors with a high share of highly skilled workers. This finding is in line with the expectation that air pollution affects cognitive skills, concentration, headache, and fatigue in non-routine cognitive tasks. Compared to the marginal abatement cost of PM 2.5 reductions by the Air Quality Directive 2008/50/EC, the estimated gains only from the labour productivity channel could largely offset the abatement cost. All in all, these estimates suggest that the negative impact of air pollution is much larger than previously documented in the literature.[1]

Keywords: air pollution, labour productivity, planetary boundary layer height
JEL Codes: J24, O13, Q53, Q51, Q52

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1 Introduction

Air pollution is one of the major threats to human health in the 21^{st} century and dominates other principal causes of avoidable death.[2] Besides the impact on serious health problems (Chay and Greenstone, 2003; Anderson, 2009)[3], air pollution has been increasingly found to have subtle effects on concentration, fatigue, and cognitive skills (Kampa and Castanas, 2008; de Prado Bert et al., 2018; Sager, 2019; Shehab and Pope, 2019; Costa et al., 2020) as any deterioration in oxygen quality may impair brain functioning (Clark and Sokoloff, 1999). Air pollution might therefore have a direct impact on economic activity through its impact on labour productivity. However, despite increasing evidence on the link between air pollution and cognitive ability, concentration, and fatigue, there is limited evidence on how these affect aggregate labour productivity. What is the impact of air pollution by particles on labour productivity? Are different types of firms and sectors unevenly affected?

This paper provides a firm-level analysis using French microdata and geographical pollution data, analyzing the possible channels of air pollution on labour productivity. This estimation faces an endogeneity bias (Aguilar-Gomez et al., 2022). On the one hand, higher pollution can reduce labour productivity through weakened concentration and cognitive ability. On the other hand, the higher the produced output within a region, the higher the local pollution level. To address the underlying endogeneity bias, I propose an approach to identify the effect of air pollution on firm-level labour productivity using an instrumental variable (IV) strategy. I use wind speed and planetary boundary layer height (PBLH) to instrument air pollution. While both PBLH and wind speed are inversely related to air pollution, reverse causality can be plausibly ruled out, as PBLH and wind speed are neither affected by economic activity nor pollution. I include controls for temperature to account for the possibility that weather conditions affect productivity. Using these instruments in a fixed effects model, I estimate the causal effects of air pollution concentration on labour productivity within a firm. The results are robust to several robustness checks. They hold focusing on local labour markets with low population change, on firms that did not change location, using different pollutants, or on different levels of aggregation.

This study uses particulate matter 2.5 (PM 2.5) to measure air pollution. These particles with a diameter of less than 2.5 μm are tiny solid particles and liquid droplets found in the air that are small enough to enter the lungs and cause serious health problems (Underwood, 2017). Further, PM 2.5 can easily enter indoor working places and are therefore highly relevant for labour productivity in both indoor and outdoor workplaces (Thatcher and Layton, 1995; Vette et al., 2001; Chang et al., 2019). The World Health Organization (WHO, 2016) as well as other studies (amongst others Adhvaryu et al., 2019; Archsmith et al., 2018; Chang et al., 2016; Dechezleprêtre et al., 2019; Guo and Fu, 2019) commonly use PM 2.5 as a measure of air pollution.

The aim of this paper is twofold. First, the paper aims at testing whether, and to what extent, air pollution affects labour productivity, at a country-wide level, looking at single-establishment firms within both manufacturing and non-financial services sectors, as opposed to studies on specific firms (He et al., 2019; Adhvaryu et al., 2019; Chang et al., 2016, 2019; Graff Zivin and Neidell, 2012). This is possible through a country-wide applicable instrument and estimation method. The estimation strategy therefore allows to consider a broad variety of employment settings including both low-skilled and high-skilled labour.

Second, the empirical framework formally accounts for firm-specific time-invariant characteristics. Accounting for unobservable firm characteristics takes into account the health condition of the workforce, the composition of the workforce in general, but also the possible heterogeneity across firms in terms of policies protecting their workers from pollution. This firm-level approach allows for addressing the missing evidence on the heterogeneity of the effect of air pollution on productivity. The richness of the data allows comparing effects across locations, sectors, and share of services within the production.

[2]Causes of avoidable death include tobacco smoking, alcohol use, road accidents, and transmissible diseases such as AIDS, malaria, and tuberculosis.

[3]The impact of pollution on serious health problems is well documented in the epidemiological literature. Particulate matter can affect respiratory and cardiovascular conditions, and lead to asthma and heart attacks. For a review of this literature see Fuller et al. (2022) and Landrigan et al. (2018).

The results show that air pollution, instrumented by PBLH and wind speed, have significant negative effects on firm-level labour productivity. Over the observed period from 2001-2018, a 1 $\mu g/m^3$ increase in PM 2.5 concentration within a given local labour market, instrumented by PBLH and wind speed, is associated with a decrease of 1.5% of annual labour productivity, ceteris paribus. In practice, a 1 $\mu g/m^3$ increase in PM 2.5 concentration represents a 10% increase in PM 2.5 with respect to the sample average over the period. This effect is driven almost exclusively by firms with a high share of services within total production, as well as by firms operating in sectors with a high share of hours worked by high-skilled workers. This suggests that the negative effect might be driven by the impact on workers cognitive function in non-routine tasks. Further, the effect is also mostly driven by urban areas with higher levels of air pollution as well as a higher population density than rural areas, suggesting that up to certain levels of exposure, the effects on productivity might not be significant.

The importance of the findings goes beyond the literature on the effect of air pollution on productivity, and speaks to the economic geography literature studying the determinants of productivity within a given location. Labour productivity within a given region might be determined by the share of manufacturing, and agglomeration effects (Rosenthal and Strange, 2004; Martin et al., 2011; Combes et al., 2012). An estimation of the effect of agglomeration on productivity might be downward biased, as congestion and increased pollution might have an adverse effect on productivity.

This study also has important implications for policy-makers, as societal costs of air pollution may be substantially underestimated. This study presents evidence of sizeable costs of the labour productivity channel that go beyond healthcare and mortality costs. Compared to an estimation of the marginal abatement cost of PM 2.5 reductions by the Air Quality Directive 2008/50/EC (European Commission, 2008), gains only from the labour productivity channel are five times larger than the abatement cost over the implementation period. This cost-benefit study suggests that for France, the marginal cost of mitigating PM 2.5 emissions by about 25% would be 1,589 million € yearly. Thus, it is reasonable to assume that the cost of a 10% reduction in emissions would be less than 635 million €. In contrast, our estimates suggest that the benefit of a 10% reduction in emissions, considering only single establishment firms in manufacturing and services sectors from the sample, would be roughly five times larger (3,490 million €).

Also, this study focuses on a low pollution level setting (e.g., 10.49 $\mu g/m^3$ average PM 2.5 concentration in 2015). The sizeable costs of air pollution on labour productivity this study shows are therefore caused by acute exposure to air pollution at levels that are mostly below current European legal limits of 25 $\mu g/m^3$ average yearly PM 2.5 concentration.[4] The European legal limits are considerably higher than the WHO recommended guidelines of only 5 $\mu g/m^3$. Also, the costs estimated in this study relate to short-term exposure rather than to long-term air pollution exposure, and can therefore be considered as lower bound effect. This suggests that the current European legal limit is above the threshold that matters for workers, and that putting more stringent rules in place could bring substantial benefits in terms of productivity gains.

The paper proceeds as follows. Section 2 reviews the literature on the effect of air pollution on productivity. Section 3 describes the data on air pollution concentration, atmospheric variables, and firm-level productivity. Section 4 presents the underlying identification strategy. Section 5 presents the main results, as well as some heterogeneity of the effects based on sub-sample analyses. Section 6 discusses the various robustness checks included in the analysis. Section 7 concludes.

[4] https://www.eea.europa.eu/themes/air/air-quality-concentrations/air-quality-standards.

2 Literature

This paper contributes to the literature on the negative effects of air pollution. Prior evidence on the effect of the exposure to air pollution has mostly looked at health outcomes, in particular at extreme outcomes such as mortality (Dockery et al., 1993; Pope Iii et al., 2002; Chay and Greenstone, 2003; Deryugina et al., 2019) and hospitalization (Ward, 2015).

The paper speaks to two relevant channels through which pollution affects productivity. From a strictly economic perspective, pollution might reduce the supply of labour through increased absenteeism or reductions of hours worked (Hanna and Oliva, 2015; Aragon et al., 2017; Chang et al., 2019). Second, pollution might affect productivity of the employee conditional on being at work, consistent with the literature on air pollution and the impact on cognitive tasks (Stafford, 2015; Ebenstein et al., 2016; Archsmith et al., 2018; Zhang et al., 2018; Künn et al., 2019; La Nauze and Severnini, 2021).

There is a broad literature on the effect of pollution on labour supply through increased absenteeism (Aragon et al., 2017; Currie et al., 2009; Deryugina et al., 2019; Hanna and Oliva, 2015; Hansen and Selte, 2000). An advantage of absenteeism is the clear count of the number of absent people. Pollution has been found to affect total hours worked and increase absenteeism, closely linked to effect pollution has on health. Absences can be viewed as proxy for individual health that is more sensitive to subtle pollution-induced diseases than hospital related measures (Currie et al., 2009). There might be different illnesses that are not severe enough to be hospitalized. Absenteeism hence captures more serious health impacts than the effect of pollution that could be observed due to decreased level of productivity conditional on being at work.[5] Absences of adults can have two reasons: absence due to own illness or due to the care of ill relatives. There might be a heterogeneous effect of air pollution on absenteeism by gender, as women are more likely to take care of ill relatives at home.

Compared to the literature on the effect of pollution on absenteeism, the literature on the effect on labour productivity conditional from being at work is limited to specific settings. These studies typically focus on a narrow group of people, for which productivity is directly observable: worker-level output at two manufacturing sites in China (He et al., 2019), the number of garments sewn per hour in a Garment factory in India (Adhvaryu et al., 2019), boxes packed by pear packers in Northern California (Chang et al., 2016), calls handled by a worker in a Chinese call centre (Chang et al., 2019), or also at the daily harvest of agricultural workers at a berry and grape farm in California (Graff Zivin and Neidell, 2012). Besides having a focus on manufacturing and agricultural sectors, these very specific case studies raise a concern of external validity (A complete review of this literature can be found in Appendix A).

A related stream of literature looks at the effect of air pollution on the cognitive function. These studies include the impact on exam scores in high-school examination in Israel (Ebenstein et al., 2016) as well as in Texas (Stafford, 2015), stock market returns in New York (Heyes et al., 2016), the impact on the decision making of individual professional baseball umpires (Archsmith et al., 2018), the effect on chess player's probability of making an erroneous move (Künn et al., 2019), the impact on patenting activities (Bracht and Verhoeven, 2021), as well as the effect on brain-training games on adults (La Nauze and Severnini, 2021). A closely linked work has also shown that air pollution increases the likelihood of workers of making a mistake and as a consequence being more likely to experience work accidents (Depalo and Palma, 2020). Besides the short term impacts on productivity, Lavy et al. (2014) show that long term impacts of pollution exposure on productivity in young age can have a negative effect on human capital measured as productivity outcomes in the working age.

Dechezleprêtre et al. (2019) is the first cross-country study on the effect of air pollution on an economic output variable, regional GDP. The paper shows how pollution entails sizable

[5] There is a broad literature capturing the health impacts of increased air pollution concentration, often in form of hospitalizations (Arceo et al., 2016; Chay and Greenstone, 2003; Currie and Neidell, 2005; Hicks et al., 2016; Ward, 2015).

costs in terms of real GDP throughout the European Union. The paper estimates the effect of pollution through an IV approach with thermal inversions on real gross domestic product in the average NUTS3 region across Europe.

There is one exception of a broader studies of the effect of air pollution and productivity, to which this work is mostly related to. The work by Fu et al. (2021) is looking at the effect of air pollution on labour productivity across manufacturing plants in China. My paper adds two important contributions to these two studies. I contribute by controlling for firms characteristics and by including non-manufacturing sectors.

My productivity estimates capture all possible channels that affect labour productivity conditional on being at work (intensive margin) and hours worked (extensive margin) although I cannot distinguish them. With the underlying data labour productivity includes absenteeism, and I consider the aggregate effect of pollution on productivity including both mechanisms.

3 Data

Air pollution data.

The key explanatory variable of the empirical framework is air pollution. There are various air pollutants. Health concerns are particularly related to particulate matter (PM), ground-level ozone, nitrogen oxides, and sulfur oxides. In this paper, I consider PM 2.5 as measure for air pollution, due to the following reasons. First, PM 2.5 has the largest estimated impact on mortality and health outcomes (WHO, 2016) compared to other pollutants. PM 2.5 can affect the lung function and worsen medical conditions such as asthma and heart diseases. This can lead to increased respiratory and cardiovascular hospital admissions, emergency department visits and deaths. Effects of PM 2.5 also include short-term and less harmful health effects, which include eye, nose, throat and lung irritation, coughing, sneezing, runny nose and shortness of breath. Further, PM 2.5 has been increasingly found to have subtle effects on concentration, fatigue, and cognitive skills (Kampa and Castanas, 2008; de Prado Bert et al., 2018; Sager, 2019; Costa et al., 2020). Second, as PM 2.5 is the most harmful pollutant to affect cognitive function and physical health, it is seen as a reference indicator to track air pollution globally by for example the WHO (2016). Being the most widely used measure of pollution, the use of PM 2.5 ensures comparability of the results with most prior studies. Third, the level of indoor and outdoor PM 2.5 concentration is highly correlated as PM 2.5 easily enters buildings. Penetration ranges from 70 to 100% (Thatcher and Layton, 1995; Vette et al., 2001). Other pollutants can less easily penetrate indoor spaces, or do rapidly break down once indoors.

The various air pollutants are likely to be correlated with each other as their main sources (e.g. industrial activity) are very similar. Therefore, the estimates from the model using PM 2.5 might confound the effect with the one from other pollutants. The resulting estimates should therefore cautiously be interpreted as effect of air pollution in general on productivity, rather than of PM 2.5 only. In the robustness section, I estimate the baseline regression with particulate matter 10 (PM10), to see how the effect varies according to the pollutant used.

The air pollution data used in the empirical analysis stems from Van Donkelaar et al. (2016)[6]. The data is available on an annual basis and on a fine (0.01 degree) resolution grid, i.e., approximately 1.1 km × 1.1 km at the equator. Yearly PM 2.5 concentrations for France[7] is obtained from 2001 to 2018. I aggregate the time series up at the zip code level, and then at the local labour market level.

This data merges satellite air quality measurements with a geo-chemical transport model, and uses geographically-weighted regression based on surface air monitoring stations in order to obtain an improved match with surface air quality measures. This approach provides

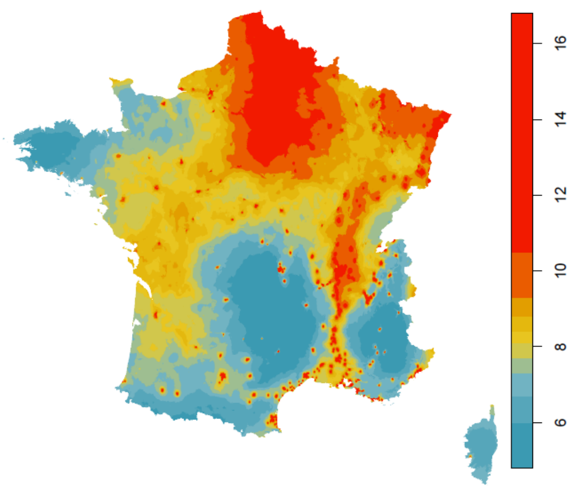
[6] This data set is widely-used in the literature, e.g. the WHO uses the data to produce the Global Burden of Disease report, the OECD uses it to measure exposure to poor levels of air quality.

[7] For France the latitude ranges from 42°20' N to 51°05' N, while longitude ranges from 4°47' W to 8°13' E.

consistent values of the magnitude and spatial distribution of air pollution. The alternative to satellite data is data collected from monitoring stations. Measurements in such settings might be very location specific, and therefore prone to bias if for example the station is located close to a polluting street. Satellite data has the advantage to provide more consistent data over a large territory, however might be subject to measurement error not being directly measured at the ground level, as well as to lower variation in air pollution.

According to the data, average exposure to fine particulate matter is equal to 10.49 µg/m3 in 2015, which complies with the European limit value of 25 µg/m3 but is above the WHO 2021 guideline of 5 µg/m3, on average. In that year, the distribution of PM2.5 concentration in France ranges from 5.59 to 15.73 µg/m3 at the zip code level.

Figure 1: PM 2.5 Distribution in France, 2015



Note: The figure shows PM 2.5 distribution in $\mu g/m^3$ across France for the year 2015. Source: Authors own calculation based on data from Van Donkelaar et al. (2016).

Boundary Layer Height and Wind Speed data.

The data to construct the instruments comes from the dataset ERA 5 from the European Centre for Medium-Term Weather Forecasting (ECMWF) [8], a consolidation and interpolation of all weather station data across Europe available at a 0.25 degree resolution grid.

The atmospheric variables are aggregated from an hourly to a yearly measure through the count of the number of days in each year in which the variables fall into certain bins. For PBLH, I consider days in which the value falls into the lowest percentile. Boundary layer height has an effect on pollution in "extreme" cases, i.e. when the PBLH is particularly low. I chose the bottom percentile as robust and extreme case, in which the PBLH is the most strongly linked the pollution. Results hold and are statistically significant using different thresholds.[9] The variable based on wind speed is calculated as count of the number of days each year in which the daily average wind speed falls into the lowest of 12 wind speed bins (defined using the Beaufort wind scale). Consequently, this means that one looks at the inverse of PBLH as well as the inverse of wind speed - both events that increase air pollution. I first aggregate the time series up to the zip code level, and then in a second step up to the local labour market level.

Firm-level balance sheet data.

French firm-level balance sheet data on economic outcomes is obtained from the FICUS/ FARE databases on balance sheet and income statement information and linked by means of the unique firm identifier (SIREN). This data provides production and financial information for all firms operating in France. The main indicator variable is gross value added[10] over

[8]For the source see: https://cds.climate.copernicus.eu/cdsapp!/dataset/reanalysis-era5-pressure-levels?tab=overview

[9]Results are statistically significant using the bottom decile of PBLH.

[10]Since I abstract from intermediate inputs, I use value added as the measure of output. Using value added requires that prices do not reflect market power in either the primary or downstream input markets. I cannot guarantee that prices are independent of market power.

total employment (labour productivity) at current prices at the firm level. Nominal values are not deflated with sector-level prices since the price effects are captured by the sector-time fixed effects (Foster et al., 2008). Price differences across firms (due e.g. to product quality leading to different markups) cannot be disentangled from productivity differentials. However, permanent differences are captured through firm fixed effects. In order to exactly identify the location of the firm, I consider only single establishment firms. While this choice considerably reduces the sample, it enables to track down the exact location of the firm in order to link it to the pollution exposure within that given location - an important condition for the estimation strategy.

The underlying measure of productivity is revenue based in contrast to quantity based and can therefore not disentangle the effect driven by supply side factors (the effect I am interested in understanding in this paper) from the one driven by the demand side. This would be a concern if consumers would take pollution into account in their decision making and for instance systematically avoid leaving the house during high pollution events. As France has a relatively low average pollution level, I assume that few consumption decisions are sensitive to pollution events.

Yearly data on firm-level productivity is matched to the relevant zip code and local labour market (INSEE) over the period 2001 to 2018 for both firms operating within manufacturing and non-financial market services. The sample includes 285 local labour market across metropolitan France, and 5.507 zip codes.[11] The firms refer to 54 different industries in both manufacturing and non-financial business services sectors. Additional details relating to the construction of all the variables used in the analysis are provided in Appendix B (Table 19).

Table 1 provides sample statistics for the main variables for the year 2015.[12] One can see from the table that an important caveat focusing on single establishment firms is that this reduces the sample towards smaller and slightly less productive firms. In the robustness tests, I expand the analysis to multi-plant firms through a weighted approach.

Table 1: Sample statistics single establishment firm in manufacturing and non-financial market services sectors - 2015

	Mean	Std. Dev.	p25	p50	p75
Value added					
(Single-establishment sample)	393.7	2,071.2	76.2	150.5	322.2
(Full sample)	264,261.3	1,539,992	108.6	289.7	1,889.4
Sales					
(Single-establishment sample)	1,643.3	25,716.8	116.8	319.4	918.9
(Full sample)	167,263.8	1,128,940	190.7	694.8	4,148.4
N. employees					
(Single-establishment sample)	13	354	1	3	6
(Full sample)	1,459	15,173.2	2	4	19
(Labour productivity log)					
(Single-establishment sample)	3.7	0.6	3.5	4.0	4.4
(Full sample)	4.1	0.7	3.8	4.1	4.5
PM 2.5	12.04	3.10	9.75	11.67	13.84
PBLH	843.54	282.73	722.51	773.34	846.55
Wind speed	1.83	2.04	1.42	2.04	2.72

Note: Financial variables (value added, sales, and labour productivity) are in thousands of euro.

[11] Metropolitan and overseas France has a total of 306 local labour markets and 6.328 zip codes.
[12] See Appendix C for additional descriptives on the pollution variable.

4 Identification strategy

Consider the following equation characterising the relationship between firm-level productivity and air pollution concentration for the establishment i, the sector s, the local labour market l, and time t:

$$LPROD_{i,s,l,t} = \beta_1 P_{l,t} + \gamma_l + \gamma_i + \gamma_{s,t} + \epsilon_{i,s,l,t}, \tag{1}$$

where $LPROD_{i,s,l,t}$ captures labour productivity (log) of firm i, and $P_{l,t}$ the average air pollution concentration within the local labour market at time t, and γ_l are local labour market fixed effects, γ_i are establishment fixed effects and $\gamma_{s,t}$ are sector - time fixed effects.

The level of aggregation at the local labour market level ("Zone d'emploi"[13]) is chosen to take into account both, the location of work and the location of home. Local labour markets are defined based on the commuting times of people and is a geographic area where most of the residents lives and works. As workers are exposed to pollution not only at the work place but also on their daily commute or at their home, these are also potential zones in which cognitive abilities and concentration can be impacted.

The coefficient β_1 can be interpreted as the contemporaneous impact of pollution on firm-level productivity from a one-unit increase in the pollution concentration (1 $\mu g/m^3$).

4.1 Endogeneity Air Pollution and Productivity

Such estimation of the effect of air pollution on productivity cannot be performed with OLS because of the simultaneity bias within the relationship. On the one hand, higher pollution can reduce labour productivity through weakened concentration and cognitive ability. This is the effect this study focuses on. On the other hand, labour productivity and economic activity might also affect pollution levels. The higher the produced output within a region, the higher is the pollution level. Consequently, simple regression estimates of the effect of pollution on productivity will confound these two effects.

In order to address this endogeneity, one solution is to implement an IV approach that provides a quasi-random variation in pollution and affects productivity only through the pollution channel. In this study, two instruments are used, which are PBLH and wind speed.

Instrument validity requires that the chosen instruments — PBLH and wind speed — do influence the concentration of air pollution (Instrument Relevance), should not be affected by pollution or economic activity (Instrument Exogeneity), and only affect firm-level labour productivity through the influence on pollution (Exclusion Restriction).

The PBLH is the area where most vertical exchange of heat, water vapor, and pollution between the earth's surface and the atmosphere takes place. The air above a particular area contains both locally emitted and transported pollutants. The lower atmosphere has substantial vertical mixing capacities that dilute local emissions into the air above. This mixing mostly disappears above a certain elevation, called the PBLH (Finlayson-Pitts and Pitts Jr, 1986). Consequently, the PBLH captures the distance between the earth's surface and this elevation which is the troposphere, the lowest layer of the atmosphere. This elevation varies over time.

The PBLH is inversely related to air pollution concentration. Lets assume that in time 1, PBLH is very high, and ventilation can take place. In time 2 however, the PBLH is low and less ventilation can take place, which increases the pollution compared to time 1. Another advantage of this instrument is that it is a continuous measure that is directly available from the data. The PBLH is commonly used in the atmospheric literature to proxy for pollution levels (e.g. Godzinski and Castillo (2021) using the LMDZ model, an atmospheric general circulation model developed by the "Laboratoire de meteorologie dynamique").

[13]The classification is defined by INSEE. For more information, see https://www.insee.fr/fr/metadonnees/definition/c1361.

PBLH has an important advantage in comparison to the use of thermal inversions, used by a large amount of papers to proxy for air pollution (Dechezleprêtre et al., 2019; Fu et al., 2021). Thermal inversions do happen only over night (Palarz et al., 2020). This limited time frame does not take into account pollution during the rest of the day. If for example, a thermal inversion takes place at night but its effect on pollution vanishes during the day, the effect on pollution is likely to be underestimated. PBLH in contrast is a continuous measure throughout the day, and is therefore a better suited instrument.

The PBLH is influenced by climatic processes (Xiang et al., 2019) and varies according to different factors.

1. Heating flux between the sun and the earth (diurnal pattern)

2. Unpredictable large-scale air movements (free atmosphere wind speed)

3. Subsidence, which brings the top of the layer downward in a high pressure diverging area

4. Horizontal movement of cold air brings it under a warmer layer of air (frontal inversion at the top of the planetary boundary layer)

Variations in PBLH are therefore not assumed to affect worker's productivity directly, as these processes happen in the atmosphere on average 2km above the ground.

One concern is that pollution could affect the PBLH. As Dechezleprêtre et al. (2019), I refer to the atmospheric physics literature, that confirms that aerosols can cause thermal inversions and thus a reduction in the PBLH by reflecting sunlight. However, this happens only at extremely high levels of pollution, at about 100 times larger than the sample average and at around 50 times larger than the sample maximum (Rémy et al., 2015). Within the French setting, reverse causality can therefore plausibly be ruled out.

Lastly, one concern might be that PBLH is also affected by temperature, which might in turn affect productivity. In order to address this possible violation in the exclusion restriction, I test the baseline specification including a control for high temperatures.

The IV should only affect the dependent variable through their effect on pollution, the endogenous variable. While the exclusion restriction cannot be directly tested for, I am not aware of any known effect of PBLH on other determinants of labor productivity such as capital investment, R&D, economies of scale or financial constraints. Due to the above mentioned reasons, I consider PBLH as an attractive option for an IV.

The second instrument I use in the analysis is wind speed. Wind has the capacity to carry particulate matter (and other air pollutants). Wind speed is inversely related to pollution. This means that the higher the wind speed, the lower the pollution within a given location, through the ventilation capacity of wind. There are a number of papers that use wind as an instrument for predicting pollution concentrations (Herrnstadt and Muehlegger, 2015; Ward, 2015; Bondy et al., 2020; Anderson, 2020). Both, the wind speed as well as the wind direction are hereby relevant. In this study, I focus on wind speed that is sufficiently low to concentrate pollution within a particular local labour market. I decide to use wind speed instead of wind direction, as I am focusing on low wind speed events. Low wind speed within a given location is likely to increase pollution within that location, but is at the same time not likely to carry pollution away from that location.

To be a valid instrument, wind speed should not be caused by pollution or economic activity. Wind patterns are highly variable within short time frames and are generated by atmospheric pressures. These processes are unlikely to be associated with worker productivity, and therefore, wind speed is an attractive option for a second instrumental variable.

For the exclusion restriction to hold, wind should only affect productivity through pollution. Very high wind speed could affect the input of production for certain firms, if for example traffic or construction is reduced or even blocked. However, in this exercise I consider events with particularly low wind speed. No wind, or a very low wind speed is not likely to affect economic activity in any way except through air pollution.

4.2 Empirical model

In the empirical approach, I rely on the panel structure of the data to estimate models with local labour market and time fixed effects. The first stage estimation estimates the effect of the instruments, the inverse of PBLH and the inverse wind speed, on air pollution, where l indexes the local labour market, and t the year.

$$P_{l,t} = \alpha_1 B_{l,t} + \alpha_2 W_{l,t} + \gamma_l + \gamma_{s,t} + \phi_{l,t}, \tag{2}$$

with $P_{l,t}$ capturing $PM2.5$ concentration at the local labour market level. The instruments are computed as $B_{l,t}$, the number of days in which the PBLH falls into the bottom percentile within each year across the local labour markets (national level), and $W_{l,t}$ as the number of days in which the wind speed falls into the lowest bin of 12 within each year across the local labour markets (national level). The estimation further includes local labour market fixed effects, γ_l, and sector-time fixed effects, $\gamma_{s,t}$. Local labour market fixed effects capture if a firm moves over the time span. Sector-time fixed effects also account for varying number of days within bissextile years.

I then define the second-stage model, where i indexes the establishment based on single-establishment firms, s the sector, l the local labour market, and t the time.

$$LPROD_{i,s,l,t} = \alpha_1 \widehat{P_{l,t}} + \gamma_i + \gamma_l + \gamma_{s,t} + \epsilon_{i,s,l,t} \tag{3}$$

with $LPROD_{i,s,l,t}$ as log labour productivity, and $\widehat{P_{l,t}}$ as instrumented air pollution based on the first-step estimation. Establishment fixed effects γ_i control for time-invariant differences across firms, such as for example the year of creation of the firm, or the average year of birth of the workers (health does change over time), while sector-time fixed effects control for any macro-economic shocks or changes in economic activity within a given sector over the observed period of time.

Through the inclusion of local labour market fixed effects our identification relies on the comparison of labour productivity levels between days with higher and days with lower pollution levels within a local labour market. This approach removes any potential confounding from time-invariant structural differences between local labour markets that could lead to selection of entrepreneurs and employees, which, as mentioned above, is a prime concern. The fixed effects capture any time-invariant differences between local labour markets, such as differences in human capital, firm composition, health composition, or even average pollution stock within the local labour market.

5 Results

5.1 First Stage Results

Table 2 reports the results of equation (2), the first stage estimation of the two-stage approach to estimating the effect of pollution on labour productivity. In this stage, I estimate the impact of the instrumental variables on PM 2.5 concentration, after conditioning on sector-year fixed effects and local labour market fixed effects. The identification is therefore based on within local labour market variability over time. In the baseline regressions, the instrumental variable based on PBLH ($B_{l,t}$) is defined as the number of days in a year in which the PBLH falls into the lowest percentile across France. The instrument based on wind speed ($W_{l,t}$) is in a similar way defined as the number of days within a year in which the wind speed falls into the lowest bin of the 12 wind speed categories. The two variables therefore capture events in which air pollution concentration is the highest.

High temperature might also have a negative effect on labour productivity, through cognitive skills (Addoum et al., 2020; Borg et al., 2021; Flouris et al., 2018; Zhang and Shindell, 2021). In order to address this issue, I control for temperature adding a dummy for extreme heat periods ($C_{l,t}$), "Canicule", defined as number of days in which temperature raises above 31 °C during the day, and stays above 21 °C at night time. This temperature control is included in the first and second stage estimation and is therefore also reported in Column (2).

Table 2: First stage estimation on the effect of the instruments on air pollution

	(1) $P_{l,t}$	(2) $P_{l,t}$
$B_{l,t}$	0.043***	0.037***
	(0.01)	(0.01)
$W_{l,t}$	0.039***	0.032***
	(0.01)	(0.01)
$C_{l,t}$		0.021*
		(0.00)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.89	0.91
F-statistics	71.51	86.43

Note: Robust standard errors clustered at the local labour market-year and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. The instruments are defined as follows: $B_{l,t}$ is the number of days in which the PBLH falls into the bottom percentile, $W_{l,t}$ is the number of days in which the wind speed falls into the lowest bin of 12. $C_{l,t}$ captures the number of days in which temperature raises above 31 °C during the day, and stays above 21 °C at night time. Air pollution $P_{l,t}$ refers to PM 2.5 concentration. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Within the estimation, I use two sets of instruments, wind direction and PBLH in order to generate exogenous variation in pollution. The instruments are not highly correlated with one another. The correlation between the number of days within the percentile with the lowest PBLH and the lowest bin of the 12 wind speed categories is 0.2 after controlling for year and local labour market fixed effects. This suggests that the two instrument capture different elements of high pollution concentration.

As expected, both events of low PBLH and inverse (low) wind speed are positively related to air pollution. Considering Column (1), one additional day with the lowest PBLH within a given local labour market, leads to an average increase in PM 2.5 concentration of approximately 4.3 $\mu g/m^3$. One additional day with the lowest wind speed bin within a given local labour market, would lead to an average increase in PM 2.5 concentration of 3.9 $\mu g/m^3$, ceteris paribus. The table shows that both PBLH and low wind speed are highly statistically significant and large, suggesting that both chosen instruments are relevant. Instrumentation is not weak according to the F statistic (Angrist and Pischke, 2008).[14] This again confirms the relevance of the selected set of instruments. Further, the results hold controlling for extreme temperature events (Table 2, column 2).

Both columns are used for the second-stage estimation. The first-stage estimation in column (1) refers to the second stage in Table 3 column (1), and column (2) refers to the second-stage results in Table 3 column (2).

[14]The reported test refers to the Cragg-Donald Wald F statistic.

5.2 Second Stage Results

Table 3 presents the main results of the paper, where equation (3) is estimated. This main equation regresses labour productivity on instrumented pollution using PBLH and wind speed, as well as controls. The organization of the table is as follows. Column (1) presents the baseline equation with both instruments simultaneously, while column (2) additionally controls for extreme high temperature events ("canicule") (from the first stage estimation in Table 2, column (2)).

Table 3: IV estimation of the effect of predicted air pollution on labour productivity

	(1) $LPROD_{i,s,l,t}$	(2) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.015***	-0.014***
	(0.00)	(0.01)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
Temperature control	no	yes
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.63	0.72
Weak id. stat.	25.42	26.58
Hansen J stat. p-value	0.51	0.42
Hausman Test	0.04	0.04

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log terms as value added over total number of employees. $C_{l,t}$ captures the number of days in which the temperature falls into the "canicule" definition. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

In column (1), in which I control for establishment fixed effects as well as time invariant local labour market characteristics and sector-time fixed effects, the estimates suggest that over the 2001-2018 period, a 10% increase in PM 2.5 concentration with respect to the sample average over the period within a given local labour market (equal to an increase of 1μ g in PM 2.5 concentration) is on average associated with a decrease of 1.5% of the mean labour productivity within that given local labour market, ceteris paribus. The effect is statistically significant irrespective of whether or not including a control for extremely high temperature events. These deliver nearly identical results in magnitude and significance. In order to quantify the effect size, one standard deviation increase in pollution concentration (3.10 $\mu g/m^3$ of PM 2.5) decreases the mean productivity by 4.6%.

In order to simplify the interpretation of the results, let's think of a more concrete example. Consider the year 2015 and the results from Column (1). If Lille with an average pollution concentration of $14.0\mu g/m^3$ of PM 2.5, would reduce its pollution concentration to the level of Montpellier ($12.0\mu g/m^3$ PM 2.5 in 2015), the mean log productivity in Lille would increase by 2.96% through the decrease of air pollution in that specific year.

I perform different statistical tests to look at the (1) endogeneity of the regressor (Hausman test), (2) at the over-identification of instruments (Hansen J Test), and (3) the weak identification statistic (Stock and Yogo Test). In order to test the endogeneity of the regressor, I consider the Hausman Test. The null hypothesis is that the regressor is exogenous, meaning that the OLS estimation would be good and an IV approach would not be needed.[15] The small p value of 0.042 indicates that the regressor is endogenous and IV is needed. The

[15]To do so, one can run the first stage regression and save the residual $\hat{v}$. Then run an auxiliary regression $y = x\beta + d\hat{v}$ and test H0 : d = 0.

second test I consider, is the over-identification or Hansen J Test. The key coefficient is over-identified if the number of IV exceeds the number of endogenous regressors.[16] The null hypothesis is rejected, but is so not very strongly. This does not make doubt the validity of the estimates. Lastly, the weak identification statistic refers to the Stock and Yogo Test. For this test, the null hypothesis is that the IV is irrelevant (weak IV). I reject the null hypothesis, as the F statistic exceeds 10, the rule-of-thumb. Results hold controlling for a time-varying firm-level variables, capital (see Appendix D, Table 21), as well as implementing the estimation as log-log specification ((see Appendix D, Table 24)). Also, results hold replicating the baseline estimation at the zip code level (See Appendix D, Table 23).

5.3 Heterogeneity

The second step of the analysis consists of exploring some heterogeneity across firms and sectors to understand some of the underlying mechanisms driving the negative effect of air pollution on labour productivity. Certain types of firms and sectors might be more affected by air pollution. PM 2.5 penetrates deep into the lungs and brains and has been found to affect cognitive skills, concentration, headache, and fatigue through inflammatory reactions (Kampa and Castanas, 2008; de Prado Bert et al., 2018; Sager, 2019; Shehab and Pope, 2019; Costa et al., 2020) and a reduction the transportation of oxygen to the brain (Bernstein et al., 2008). These effects might therefore have particular implications for high-skilled office workers executing non-routine cognitive tasks, mainly represented in professional, managerial, technical, and creative occupations (Autor and Price, 2013) in contrast to lower skilled workers.

To start with, I consider heterogeneity across firms, based on the service intensity of output sold. Each establishment has information about the share of output sold consisting of services ("total de la production vendue de services"). I augment the baseline equation with an interaction term of the predicted air pollution with the share of services output.[17].

Table 4 shows the results of this exercise. The predicted effect of pollution on labour productivity becomes statistically insignificant for manufacturing-intensive firms with a share of output sold in services of zero. Interestingly, one can see that the negative effect of pollution is significant for service-intensive firms. A $1\mu g/m^3$ increase in air pollution concentration would cause a decrease of approximately 2.3% on average labour productivity across high service-intensive firms within a given local labour market, ceteris paribus. The results hold for different definitions of service intensive vs. manufacturing intensive establishments.[18]

[16]Hansen test of overidentifying restrictions should be performed routinely in any overidentified model estimated with instrumental variables techniques. If a strong rejection of the null hypothesis of the Hansen test is encountered, one should strongly doubt the validity of the estimates.

[17]I add an interaction term in both the first and the second stage estimation.

[18]I tested the same regression with different definitions of service intensive vs. manufacturing intensive establishment with a share of services of 50%, 60%, and 70% of output.

Table 4: Firm-level heterogeneity in the effect of air pollution on labour productivity: Share of services within total production

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.009
	(0.00)
$ServiceIntensity_{i,s,l,t}$	0.017**
	(0.01)
$\widehat{P_{l,t}} * ServiceIntensity_{i,s,l,t}$	-0.023***
	(0.00)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	yes
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.58

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. $ServiceIntensive_{i,s,l,t}$ captures the share of total output generated by services. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Second, I look at industry-level characteristics related to the skill-intensity at the sector-level. To do so, I perform a Rajan and Zingales type of exercise and use US sector-level data for the share of hours worked by high skilled workers over the years 1995 to 2000. $HighSkilled_s$ is absent from the right hand side variables as they drop out due to establishment fixed effects.

Table 5 shows that within sectors with a share of hours worked by high skilled workers equal to zero, an increase in pollution concentration has on average no significant effect on labour productivity. In contrast, a $1\mu g/m^3$ increase in pollution concentration would cause a statistically significant decrease of 0.7% on average across firms in sectors with the median share of hours worked by high skilled workers. This is in line with what one would expect from the impact of air pollution on cognitive skills and concentration, which might be in particular crucial for high-skilled workers executing non-routine tasks. The result hold, using a dummy variable for the lower and upped median sectors based on their share of hours worked by high skilled workers (Appendix D, Table 25).

Table 5: Sector-level heterogeneity in the effect of air pollution on labour productivity: Share of hours worked by high skilled

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	0.004
	(0.03)
$\widehat{P_{l,t}} * HighSkilled_s$	-0.025***
	(0.00)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	yes
Sector-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.69

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$. The estimation includes year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. $HighSkilled_{s,l}$ is the share of hours worked by high skilled workers over the years 1995 to 2000 for the US. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Next, I look at location based heterogeneity with the aim to see how the effect differs according to the pollution individuals are exposed to. In urban areas, workers are more likely to be exposed to higher pollution levels not only at work, but also at home and during their leisure time. For this exercise, I refer to the INSEE definition of urban and rural units at the zip code level. The concept of urban unit is based on the continuity of the built environment and the number of inhabitants. The urban unity is defined as a commune with a continuous built-up area (no more than 200 metres between two buildings) with at least 2,000 inhabitants.[19] The measure ($Urban_{z,t}$) is equal to 1 if the unit is measured as urban unit, and 0 referring to a rural unit.

Impacts of air pollution are unsurprisingly concentrated in urban areas where pollution concentration is typically higher than elsewhere. In urban areas, a $1\mu g/m^3$ increase in air pollution concentration reduces labour productivity by an average of 3.53%. Interestingly, for rural areas the coefficient becomes less significant. This does follow the reasoning that as pollution concentrations are typically lower in rural areas and that even though the high pollution events take place (low PBLH and low wind speed), these might not raise pollution enough to reach a relevant level.[20] Nevertheless, the results show that in rural areas, a $1\mu g/m^3$ increase in air pollution concentration reduces labour productivity by an average of 1.43%. The results hold using population density, measured as 100 people per km^2 (See Appendix D, Table 26), and using a pollution stock measure (See Robustness, Table 22).

This result could also be explained by the fact that rural areas have a lower share of skill intensive cognitive service industries than in urban areas. In order to control for this confounding factor, I add the share of services in firm output to the estimation (Column 2). One can see that accounting for the higher share in services, the effect is reduced but still significant. It is therefore not only a story of service-intensity, but also of a higher likelihood to be exposed to pollution in urban areas.

[19] In order to capture the effect, I modify the first stage estimation adding the urban unit measure. In the baseline equation (3), I add an interaction term with estimated air pollution and population density, and drop establishment fixed effects from the estimation. The other elements of the estimation however, remain the same.

[20] The Air Quality Index categorises unhealthy PM 2.5 concentration, as a concentration above $35\mu g$. This threshold might be less likely to be reached in rural areas.

Table 6: Location based heterogeneity in the effect of air pollution on labour productivity: Urban vs. rural

	(1) $LPROD_{i,s,z,l,t}$	(2) $LPROD_{i,s,z,l,t}$
$\widehat{P_{l,t}}$	-0.012*	0.014
	(0.02)	(0.01)
$Urban_{z,l,t}$	0.336**	0.559*
	(0.02)	(0.03)
$\widehat{P_{l,t}} * Urban_{z,l,t}$	-0.021**	-0.015**
	(0.03)	(0.03)
$ServiceIntensity_{i,s,z,l,t}$		0.094***
		(0.02)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	no	no
Sec-Time FE	yes	yes
Establishment FE	no	no
Robust SE	yes	yes
Adjusted R2	0.34	0.46

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. The estimation includes sector-year fixed effects. Labour productivity is measured in log as value added over total number of employees. The measure ($Urban_{z,t}$) is equal to 1 if the zip code is measured as urban unit, and 0 referring to a rural unit. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

6 Robustness

Next, I discuss possible challenges to the estimation and conduct a number of robustness checks to ensure that similar results are delivered by alternative choices within the model.

6.1 Geographical Sorting

Geographical sorting might be a potential challenge to the estimation of the desired effect. Including local labour market fixed effects in the estimation framework controls for omitted variable bias at the regional level that are constant over time. There might still be a bias in the case regional characteristics vary over time. Even though individuals are unlikely to consider random variations in air pollution in their location decision, geographical sorting can happen at the level of firms, but also at the level of employees.

Location sorting of firms takes place if high productivity firms systematically decide to locate to areas due to their pollution level. The most productive firms might be the ones that can afford to locate in more expensive and less polluted areas, impacting the firms and regional productivity (close to suppliers, customers). What is observed as location at time t is the outcome of this choice by the firms.

Within the estimation framework, this should not be a concern as the variation comes from random variation in pollution within a local labour market in contrast to average pollution levels within a given year.

As robustness check, the analysis is restricted to firms that have been located for a long while within a given location, as one can observe the year of creation of the firm in the data. I estimate equation (3) for different subsets of old firms only, first only for firms older than 10 years (Column (1)), and second only for firms older than 7 years (Column (2)). This approach allows to avoid the bias within the estimation that arises through young firms choosing their location dependent on a particular level of pollution. Table 7 shows that the estimated results hold focusing only on the subsample of old firms.

Table 7: The effect of predicted air pollution on labour productivity - Old firms

	(1) $LPROD_{i,s,l,t}$ $Age > 10$	(2) $LPROD_{i,s,l,t}$ $Age > 7$
$\widehat{P_{l,t}}$	-0.019***	-0.021***
	(0.00)	(0.00)
Parameters of the regressions:		
N of observations	1,271,255	1,565,171
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.74	0.74

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018. Column (1) refers to establishments older than 10 years, while column (2) refers to establishments older than 7 years.

As a further robustness, I also consider a regression that estimates the effect of average pollution in the previous (next) five years and the probability of a firm moving. I check if firms with perfect information would move if they would know that air pollution is going to increase in future, or if they moved following the information they had on past pollution. To do so, I generate the probability of reallocation to another local labour market in 2010. I then generate a variable that captures average pollution levels in the years following 2010, i.e. 2011 to 2018, and another variable that captures the average pollution level by local labour market over the years 2001-2009.

Table 8 shows that neither the information of the past pollution nor speculative information about future levels of pollution have an effect of the probability of firm reallocation. This evidence therefore rules out that geographical sorting is an issue for the underlying estimation.

The finding on limited geographical sorting of firms is confirmed by Fu et al. (2021). Their paper confirms that air pollution is not linked to firm entry or exit in a given location in the short run. Nevertheless, I do acknowledge the possibility that over long time periods of sustained high pollution levels, firms might take pollution into their location choice.

Table 8: The effect of past and future air pollution on the probability of firm reallocation

	(1) $Prob.Exit_{l,2010}$	(2) $Prob.Exit_{l,2010}$
$\bar{P}_{l,2011-2018}$	-0.002	
	(0.00)	
$\bar{P}_{l,2001-2009}$		-0.003
		(0.00)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.01 0.01	

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. The dependent variable $Prob.Exit_{l,2010}$ refers to the probability of exit of firms within a local labour market from 2010 to 2011. $\bar{P}_{l,2011-2018}$ refers to the average pollution concentration (PM 2.5) over the years 2011 to 2018, while $\bar{P}_{l,2001-2009}$ refers to the one from 2001 to 2009. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

One further concern is residential sorting of employees. Individuals choose their residential location based on characteristics of the specific area, which leads to a non-random assignment of pollution. Preferences might depend on employment opportunities, commuting time and cost, and the quality of public facilities, such as schools, parks, hospitals, and environmental quality (Tiebout, 1956). These characteristics are bundled in a location (e.g. urban areas might have worse air quality but high quality schools, while some suburban areas might have better air quality but schools with lower quality). Therefore, the overall direction of the bias introduced by income is theoretically ambiguous. Individuals therefore optimize along multiple dimensions based on their intensity of their preferences for each local characteristic. This implies that the choice of the neighbourhood, including the choice of pollution levels, are endogenously determined. Further, sorting can be an issue if within a given location people are better equipped to deal with higher pollution.

As an additional robustness check, I exclude locations which have either lost or increased population by a significant amount over the period, to see if these results change significantly. The results in Table 9 estimate equation (3) but restrict the sample to local labour markets with relative constant population. The constant population sample is defined as local labour markets that experienced a population change less than +10%/-10%. The results are robust to a change in the sample.

Table 9: The effect of predicted air pollution on labour productivity - Local labour markets with constant population

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.028**
	(0.00)
Parameters of the regressions:	
N of observations	1,144,747
LLM FE	yes
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.74

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018 within local labour markets with constant population (population change of less than +/- 10%).

All in all, I find little evidence of such sorting in the results. One has to note that the underlying estimation focuses on short-term impacts of air pollution on productivity, and does not aim to estimate long-run effects. For example, firms may take action in order to respond to air pollution, i.e. protecting indoor workers, installing air filters. In this sense, sorting might not be an issue for the estimation on the short-run, but might still occur over longer periods.

6.2 Pollution accumulation

Another challenge of the identification is the temporal effect of pollution on annual firm-level productivity. As summarized in Graff Zivin and Neidell (2012), the impact of the pollutant might vary depending on the duration of the exposure of the individual. PM 2.5 can have short-term impacts in as quickly as 1 to 2 hours, while also having more long term effects (Keet et al., 2018). Short and long term effects of PM 2.5 might differ significantly. As an example, short-run exposure of PM 2.5 can lead to decreased lung function, irregular heartbeat, increased respiratory problems, non-fatal heart attacks and angina. Shehab and Pope (2019) also stress the impact on short-term cognitive performance. On the other hand, long-run exposure may lead to cardiopulmonary diseases, respiratory infections, lung cancer (EPA, 2004) and asthma (Neidell, 2004), and might therefore be significantly more important. These long-run health effects can manifest themselves in the short run if high levels of pollution (pollution accumulation) trigger conditions resulting from previously accumulated exposure.

In my estimation, the measure of interest counts the number of extreme days within the year, which can then be matched to the yearly financial data. The mechanism in mind is that one day of extremely low PBLH or wind speed, i.e. short-term exposure to air pollution, has an impact on average yearly productivity. This implicitly assumes the daily effects to be linear. Suppose there are only two days in a year. If pollution in the first day lowers productivity in that day by 10%, and by 20% in the second day, then annual average will be lowered by 15%. One challenge is that this main estimation does not directly allow to distinguish between the pollution stock within a given location. I address this issue through a robustness check, augmenting the baseline estimation with an interaction of the estimated pollution and the pollution stock, in order to take into account differences in actual pollution accumulation.

I augment the baseline estimation by an interaction term of estimated pollution variation and of a pollution stock within a given local labour market - year. I compute a dummy variable equal to 1 if the pollution concentration within a given local labour market - year is in the upper quartile, and 0 otherwise.

Table 22 shows that within local labour market-years with a high pollution concentration, the negative effect of air pollution on labour productivity is particularly strong. Within local labour market with a high pollution stock a 1 $\mu g/m^3$ increase in PM 2.5 leads on average to a 12% decrease in labour productivity, controlling for firm specific characteristics and other fixed effects. In contrast, within local labour market with a low pollution stock a 1 $\mu g/m^3$ increase in PM 2.5 leads on average to a 0.1% decrease in labour productivity.

Table 10: The effect of predicted air pollution on labour productivity by pollution stock

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.006**
	(0.05)
$Stock_{l,t}$	-0.032***
	(0.63)
$\widehat{P_{l,t}} * Stock_{l,t}$	-0.110***
	(0.05)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	no
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table refers to the estimation $LPROD_{i,s,l,t} = \alpha_1 \widehat{P_{l,t}} + \alpha_2 Stock_{l,t} + \alpha_3 \widehat{P_{l,t}} * Stock_{l,t} + \gamma_i + \gamma_{s,t} + \epsilon_{i,s,l,t}$, with $LPROD_{i,s,l,t}$ as log labour productivity, and $\widehat{P_{l,t}}$ estimated air pollution based on the first-step estimation. $Stock_{l,t}$ is a dummy variable that refers to stock of actual pollution within a given local labour market - year. If the stock of pollution falls into the highest 75% percentile, the dummy has the value of one, zero otherwise. The estimation includes sector-year, local labour markets, and establishment fixed effects. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

6.3 Summer vs. Winter Inversions

As variations in PBLH might be seasonally heterogeneous, I separately measure the number of days in the lowest PBLH percentile by winter and summer. This is possible, as PBLH data is available at a high frequency (daily). I define summer as 16 April to 15 October and winter as 16 October to 15 April each year.

Table 11 Column (1) and (2) present the first stage estimation with a separate measure for summer and winter PBLH. The findings show a strong impact for the summer PBLH instrument. In contrast, the winter PBLH instrument appears to be less significant. Evidence shows that in winter, inversions lowering the PBLH happen early in the morning and dissipating quickly as the sun starts shining (Janhäll et al., 2006).

For completeness, Table 11 Column (3) presents the second stage results, based on the first stage estimation presented in column (2). Even though smaller in size, the main result holds.

Table 11: The effect of seasonal BLH and wind speed on air pollution

	(1)	(2)	(3)
Estimation	First stage	First stage	Second stage
Dependent variable	$P_{l,t}$	$P_{l,t}$	$LPROD_{i,s,l,t}$
$B_{l,t}^{Summer}$	0.154***	0.153***	
	(0.00)	(0.00)	
$B_{l,t}^{Winter}$	0.060*	0.065*	
	(0.00)	(0.00)	
$W_{l,t}$		-0.090***	
		(0.00)	
$\widehat{P_{l,t}}$			-0.010***
			(0.00)
Parameters of the regressions:			
N of observations	2,491,151	2,491,151	2,491,151
LLM FE	yes	yes	yes
Sec-Time FE	yes	yes	yes
Establishment FE	no	no	yes
Robust SE	yes	yes	yes
Adjusted R2	0.88	0.88	0.63
Weak id. stat.			24.32
Hansen J stat. p-value			0.73

Note: Robust standard errors clustered at the local labour market-year and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018. Summer is defined from the 16 April to the 15 October and winter from the 16 October to the 15 April each year.

6.4 Different Pollutants

Different air pollutants might have different effects on humans (see for example Godzinski and Castillo (2021)). Further, there might be a correlation between different pollutants. In order to validate the results, I replicate the baseline estimation using a different pollutant, particulate matter 10 (PM 10), to see how the relative effect varies according to the pollutant used.[21]

The results in Table 15 confirm the negative effect on pollution using another pollutant, despite being less statistically significant. This might be due to the fact that PM 2.5 is known for its strong effect on short-term cognitive performance compared to other pollutants (WHO, 2016).

Table 12: The effect of predicted air pollution on labour productivity based on different pollutants

Dependent variable	(1) First stage $PM10_{l,t}$	(2) Second stage $LPROD_{i,s,l,t}$
$B_{l,t}$	0.003^{**}	
	(0.01)	
$W_{l,t}$	0.002^{**}	
	(0.01)	
$\widehat{PM10}_{l,t}$		-0.038^{*}
		(0.51)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	no	yes
Robust SE	yes	yes
Adjusted R2	0.85	0.70
F-statistics	10.28	

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. $PM10_{l,t}$ refers to normalized PM 10 values. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

6.5 Non-linear effect of air pollution on productivity

In the next robustness check, I want to explore the potential non-linearity of the effect on air pollution on labour productivity.

The findings in Table 13 show that the marginal damage increases as pollution increases. The non-linear results should be interpreted cautiously as instruments are less strong in some cases. Nevertheless, the results are consistent with findings of non-linear effects in the health literature (Pope III et al., 2009; Burnett et al., 2014). Burnett et al. (2014) shows that at low PM 2.5 levels ($< 100\mu g/m^3$) mortality risk is rapidly increasing, and reaching a plateau at higher levels of air pollution ($> 300\mu g/m^3$). In the French setting, an increasing marginal damage is therefore in line with expectations for low polluting regions. This can help reconcile the finding that air pollution causes significant damages in relatively low-pollution regions of the world with similar results in high-pollution regions.

[21] Data for the other pollutants is retrieved from the CAMS European air quality reanalyses available from 2003 to 2018, slightly reducing the panel dimension of the data.

Table 13: The non-linear effect of air pollution on labour productivity

	(1)	(2)	(3)
Estimation	First stage	First stage	Second stage
Dependent variable	$P_{l,t}$	$P^2_{l,t}$	$LPROD_{i,s,l,t}$
$B_{l,t}$	0.032^{**}	0.014^{**}	
	(0.21)	(0.14)	
$W_{l,t}$	0.021^{**}	0.013^{**}	
	(0.14)	(0.11)	
$\widehat{P_{l,t}}$			0.010^{**}
			(0.11)
$\widehat{P^2_{l,t}}$			-0.008^{**}
			(0.00)
Parameters of the regressions:			
N of observations	2,491,151	2,491,151	2,491,151
LLM FE	yes	yes	yes
Sec-Time FE	yes	yes	yes
Establishment FE	no	no	yes
Robust SE	yes	yes	yes
Adjusted R2	0.88	0.88	0.70

Note: Robust standard errors clustered at the local labour market-year and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

6.6 Further Topics

Measure of Labour Productivity: The measure of labour productivity as value added per employee in year t measures the impact of pollution on value added per worker rather than value added per hour worked. Air pollution might affect productivity through the intensive margin, output per hour worked, and through the extensive margin the number of hours worked. The measure of productivity makes it not possible to disentangle these channels, and I focus on measuring the aggregate effect of these two possible channels.

The chosen measure of labour productivity might raise another concern. A reduction in productivity due to air pollution on a specific day might lead to some adaptation, either by the employee or the firm. In Korea, a study by Eom et al. (2020) finds that a pollution increase leads to an energy intensive adaption behaviour[22]. Another adaptation behaviour could arise from increasing productivity on low pollution days to counterbalance low productivity days in the event of high pollution. In fact, these adaptation behaviours go in the opposite direction of the estimated coefficient and would therefore only lead to an underestimation of the underlying effect.

Indoor vs. outdoor pollution: Air pollution is expected to primarily affect outdoor workers. These are in general more exposed to unfiltered air pollution, and do often hold more physical jobs, than office workers do. However, one important characteristic of PM2.5 is that it can easily enter indoor areas (Vette et al., 2001), and therefore also affect high skilled indoor workers. Penetration rates range from 70 to 100% (Thatcher and Layton, 1995; Vette et al., 2001). Concentrations tend to follow outdoor trends, although there may be some delay due to mixing and dilution. Indoor workers can therefore hardly avoid air pollution, unless their employers installs pollution filters. The estimates of the analysis capture both, the effect of indoor and outdoor workers as well as their exposure during commuting.

[22]Households respond by using various pollution-adaptive measures that required the use of energy, such as air purification, and additional lighting measures.

Input-output relations: Another concern is that high pollution events might lead to disruptions in input. This could be a concern through (i) input-output linkages, whereby a firm cannot deliver intermediate goods due to reduced productivity; and (ii) government restrictions, which apply directly and indirectly along the supply chain.

First, there is the concern that material input from a firm cannot deliver intermediate goods due to reduced productivity to its clients. Such a reduction in supply due to high pollution levels in a certain location could therefore indirectly also affect the productivity of other firms in other locations as well. The underlying estimations captures cannot disentangle this effect.

Second, in France, government restrictions introduce traffic controls and limitations in case of high polluting events within certain cities, which could have an impact along the supply chain. However, one has to note that traffic limitations due to high pollution events are extremely rare in France. The government implemented the "Crit'Air" stickers, allowing only cars with low pollution stickers into certain areas on high-pollution days. Within the metropolitan area of Paris, these restriction are binding for 'heavy goods vehicles' every day. Therefore, one could expect that freight forwarding vehicles must have adapted to this policy and that supply disruptions due to high pollution events might be minimal.

6.7 Reduced-form Model

For completeness, I also report the reduced-form model in the aim to address the relevance of the chosen instrumental variables. In line with the baseline results from Table 3, the reduced form results confirm that the atmospheric variables used as IVs and causing an increases in pollution have a negative impact on economic activity. The estimates suggest that over the 2001-2018 period, one more day in the average number of extreme PBLH events within a given local labour market is associated with a decrease of 0.3% of the mean labour productivity within that given local labour market, ceteris paribus. In contrast, one additional day in the lowest wind speed bin results into a 0.2% reduction in labour productivity. The reduced-form model confirms the direct link and relevance of both PBLH and wind speed on labour productivity.

Table 14: Reduced-form results: The effect of PBLH and wind on labour productivity

	(1) $LPROD_{i,s,l,t}$	(2) $LPROD_{i,s,l,t}$	(3) $LPROD_{i,s,l,t}$
$B_{l,t}$	-0.003***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)
$W_{l,t}$	-0.002***	-0.003*	-0.003*
	(0.00)	(0.00)	(0.00)
$C_{l,t}$			-0.00
			(0.00)
Parameters of the regressions:			
N of observations	2,491,151	2,491,151	2,491,151
LLM FE	no	yes	yes
Sec-Time FE	yes	yes	yes
Establishment FE	yes	yes	yes
Robust SE	yes	yes	yes
Adjusted R2	0.70	0.70	0.70

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The results refer to the estimation $LPROD_{i,s,l,t} = \alpha_1 B_{l,t} + \alpha_2 W_{l,t} + \gamma_l + \gamma_i + \gamma_{s,t} + \epsilon_{i,s,l,t}$, with $LPROD_{i,s,l,t}$ as log labour productivity, as well as sector-year, local labour markets, and establishment fixed effects. The instruments are defined as follows: $B_{z,t}$ is the number of days in which the PBLH falls into the bottom percentile, $W_{l,t}$ is the number of days in which the wind speed falls into the lowest bin of 12. Labour productivity is measured in log as value added over total number of employees. $C_{l,t}$ captures the number of days in which the temperature falls into the "canicule" definition. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

6.8 Placebo Test

As an additional robustness check, I estimate a placebo model where I randomly assign pollution and atmospheric variables from each local labour market to a different local labour market and estimate the model with these placebo variables. The placebo estimation ensures that our econometric specification is not delivering the coefficients we are obtaining. The coefficient from the placebo regression is zero, suggesting that the results are not driven by the empirical approach but by the data.

Table 15: Placebo Test - The effect of randomized air pollution on labour productivity

	(1)	(2)
	First stage	Second stage
Dependent variable	$P_{l,t}$	$LPROD_{i,s,l,t}$
$B_{l,t}$	0.082	
	(0.05)	
$W_{l,t}$	0.0113	
	(0.07)	
$\widehat{P_{l,t}}$		-0.003
		(0.01)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	no	yes
Robust SE	yes	yes
Adjusted R2	0.90	0.73
F-statistics	6.77	0.26

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

7 Discussion

7.1 Overall magnitude of finding

One advantage of focusing on labour productivity, is the straightforward quantification of the monetary size of the effect. The following part discusses the monetary size of the benefits from a 1 $\mu g/m^3$ reduction in air pollution concentration and compares these benefits to the marginal PM 2.5 abatement cost.

In 2015, the total value added of the firms considered in the single-establishment firms sample summed up to 235,843 million €. In this setting, a decrease in the average concentration of fine particulate pollution of 1 $\mu g/m^3$ (corresponding to an decrease of approximately 10% in average pollution concentration) would lead to a yearly benefit of 3,490 million euro in terms of productivity gains among manufacturing and non-financial services firms.

How does this relate to marginal abatement costs of PM2.5 concentration? To compare both, I refer to the Air Quality Directive 2008/50/EC (European Commission, 2008). The 2008 directive develops two scenarios for the European level of (1) PM 2.5 reductions of 20% and (2) PM 2.5 reductions of 25% (See Appendix E, Table 29 for more information).

Focusing on the more ambitious scenario B of PM 2.5 reductions of 25%, marginal abatement costs for France amount to 23.87 € per person per year. The total yearly cost amounts to 1,588.7 million €. Thus, one can assume that the cost of a 10% reduction in emissions would be less than 635.4 million €. At the same time, a decrease in PM 2.5 levels of 10% could result in around 3,490 million € of benefits through gains in productivity, considering only single establishment firms in the manufacturing and services sectors. The estimates suggest that the benefit of a 10% reduction in emissions would be roughly five times the abatement costs. Gains from reducing PM 2.5 concentration from the labour productivity channel in manufacturing and services sectors among only single establishment firms can largely offset the related abatement cost.

Also, it is interesting to note that focusing on France, this study focuses on a low pollution level setting (e.g. 10.49 $\mu g/m^3$ average PM 2.5 concentration in 2015). The sizeable costs of air pollution on labour productivity this study shows are therefore caused by acute exposure to air pollution at levels that are primarily below current EU directive (Directive 2008/50/EC[23]) of 25 $\mu g/m^3$ average yearly PM 2.5 concentration. Also, the costs estimated in this study relate to short-term exposure rather than to long-term air pollution exposure and can therefore be considered a lower-bound effect. In line with these adverse effects of pollution at low levels, the WHO Air quality guideline[24] recommends a PM 2.5 concentration limit of 5 $\mu g/m^3$. This suggests that implementing a lower air pollution limit at the European level could bring more productivity gains than the current one.

7.2 Comparison with existing studies

I now compare my findings with the ones in other papers (a graphical comparison can be found in Appendix F, Table 3).

Table 16: Comparison with other studies on air pollution and productivity

Author	Country	Productivity measure	Effect of $1\mu g/m^3$ increase in PM2.5 concentration
Adhvaryu et al. (2019)	India	Number of garments sewn / hour	0.08%
Borgschulte et al. (2022)	USA	Reduction in income of workers	2.5%
Chang et al. (2016b)	USA	Number of pear boxes packed (indoor)	0.8%
Dechezlepretre et al. (2019)	Europe	Regional GDP	1.1%
Ebenstein et al. (2016)	Israel	Student's Bagrut composite score	0.164 unit decline
Fu et al. (2017)	China	Labour productivity manufacturing plants	1.08%
Fu et al. (2021)	China	Labour productivity across manufacturing plants	0.82%
Fu and Guo (2019)	China	Marathon running time	0.270%
He et al. (2018)	China	labour productivity in two textile plants	from 0.04 to 0.3%
Heyes et al. (2016)	USA	NY Stock Exchange returns	1.19%
Künn et al. (2019)	Germany	Chess player's probability of making an erroneous move	2.63%

The estimated coefficient in my study is slightly larger compared to other studies. This might be due to different reasons. First, previous estimates of the studies cited above apply only to particular worker types, or to specific firms. The estimates of this study take into account a considerably broader set of firms located. Further, in contrast to other studies focusing only on manufacturing sectors, this study also includes non-financial services sectors for which the estimated coefficient is higher than for manufacturing sectors. Third, previous studies measure daily or monthly effects while we capture annual cumulative effects. In contrast to some of the studies (an exception is for example Fu et al., 2021), the estimates of this study include not only the intensive margin (productivity per hour worked) but also the extensive one (hours worked). Lastly, another possible reason for a slightly larger estimated effect is that I estimate annual cumulative effects rather than those of shorter duration.

Even though the level of pollution between certain countries might be difficult to compare (i.e. China and France), it is interesting to see that air pollution matters even at much lower concentration levels than those observed in China.

[23] https://environment.ec.europa.eu/topics/air/air-quality/eu-air-quality-standards$_en$

[24] https://www.who.int/publications/i/item/9789240034228)

8 Conclusion

In this paper I match establishment-level balance sheet data to geographical data on air pollution and weather conditions to estimate the causal effect of air pollution on labour productivity in France. I use data on productivity for French single establishments firms over the years 2001 to 2018. To overcome the problem of reverse causality, my identification strategy relies on quasi-random variation in PBLH and wind strength as instruments for air pollution. PBLH determines the mixing height of air pollution, and wind blowing carries pollution away from a certain location. Both are consequently inversely related to air pollution. With this, I provide causal evidence on the impact of air pollution on labour productivity in France.

I find that increases in air pollution cause substantial reductions in labour productivity. The baseline model shows that increasing the average concentration of fine particulate pollution PM 2.5 by 1 $\mu g/m^3$ (approximately by 10%) reduces labour productivity by 1.5%. I explore the heterogeneity of this impact across firms and economic sectors, and find that this effect is driven almost exclusively by firms with a high share of services within total production, as well as by firms operating in sectors with a high share of hours worked by high-skilled workers. This suggests that the negative effect might be driven by the impact on workers cognitive function in non-routine tasks. Further, the effect is also mostly driven by local labour markets with high levels of air pollution as well as high population density, suggesting that up to certain levels of exposure, the effects on productivity might not be significant.

Future research on the topic could disentangle the impact of pollution along the value chain. Which type of workers, i.e. blue vs white collar jobs, might be stronger impacted by air pollution? Which types of occupations are particularly impacted even within a narrowly defined sector? In order to answer this question, the main challenge is to define a comparable productivity measure at the employee level. Also, it would be important to validate the results with other pollutants, and other countries, in order to further validate the generalizability of the results. Another direction of research could be to consider the pollution mix, the interacting effects of different pollutants. Expanding the analysis to other sectors could further help to provide an insight in potential sector-level heterogeneity of the effect of pollution on labour productivity.

These results are of paramount importance for evaluating the benefits of reducing air pollution, which is crucial when comparing the costs to the benefits of air pollution regulations. This study's findings suggest that air pollution's impact is larger than previously estimated, considering only the effect on hospitalisations and mortality. Compared to an estimation of the marginal abatement cost of PM 2.5 reductions by the Air Quality Directive 2008/50/EC (European Commission, 2008), gains only from the labour productivity channel are five times larger than the abatement cost over the implementation period. Therefore, the study provides relevant information on the additional costs of air pollution for cost-benefit evaluations of air pollution reduction policies. Stronger air quality regulations are therefore needed.

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Appendix

Appendix A. Literature Review

In addition to the literature review, some further details related to the literature on air pollution and productivity are provided in the table below.

Table 17: Summary table - Literature on Pollution and Productivity

Authors	Country	Productivity measure	Pollutant	Findings
Adhvaryu et al. (2019)	India	Number of garments sewn / hour	$PM_{2.5}$	Indicate that a one SD increase in fine PM reduces worker productivity by roughly 1/3 to 1/2 %
Archsmith et al. (2018)	US	Incorrect calls of MLB (Baseball) umpires	CO, $PM_{2.5}$	Indicate that a 1 ppm increase in 3-hour CO causes an 11.5% increase in the propensity of umpires to make incorrect calls, while a $10\mu g/m^3$ increase in 12-hour $PM_{2.5}$ causes a 2.6% increase in the propensity to make incorrect calls
Borgschulte et al. 2022	US	Workers Income	$PM_{2.5}$	Show that one additional day of smoke exposure reduces earnings by about 0.1 percent
Chang et al. (2016b)	US	Number of boxes packed by pear-packers	$PM_{2.5}$	Indicate that a 10-unit change in $PM_{2.5}$ significantly decreases worker productivity by roughly 6 percent
Dechezleprêtre et al. (2019)	EU	Real GDP (by capita)	$PM_{2.5}$	Indicate that a $1\mu g/m^3$ increase in $PM_{2.5}$ concentration causes a 0.8% reduction in real GDP that same year
Ebenstein et al. (2016)	Israel	Exam scores in high-school examinations; Post-secondary education, earnings	$PM_{2.5}$	Indicate that a ten unit increase of $PM_{2.5}$ is associated with a 0.55 % decrease in test score
Fu and Guo (2019)	China	Marathon running time	$PM_{2.5}$	Indicate a increase 0.270% in times (for 1% increase in PM)
Graff Zivin and Neidell (2012)	US	Daily harvest of agricultural workers Berry and grape farm	ozone	10 ppb decrease in ozone concentration increases workers productivity by 5.5 %

Table 18: Summary table - Literature on Pollution and Productivity (continued)

Authors	Country	Productivity measure	Pollutant	Findings
Heyes et al. (2016)	US	Stock market returns	$PM_{2.5}$	One standard deviation increases in ambient $PM_{2.5}$ reduces same-day returns by 11.9%
Holub et al. (2016)	Spain	Propensity to take sick leave	PM_{10}	Estimate that a $13.38\mu g/m^3$ increase in PM_{10} concentration increases propensity to take sick leave by 0.005 %
He et al. (2019)	China	Day-to-day fluctuations in worker-level output (2 textile plants)	$PM_{2.5}$, SO	Increase in $PM_{2.5}$ concentration sustained over 25 days reduces labour productivity by 0.38% to 3%
Künn et al. (2019)	Germany	chess player's probability of making an erroneous move	$PM_{2.5}$, $CO2$	A 10 µg/m3 increase in $PM_{2.5}$ concentration increases a player's probability of making an erroneous move by 26.3%

Appendix B. Variables of interest

Additional details relating to the construction of the variables used in the analysis are provided in the table below.

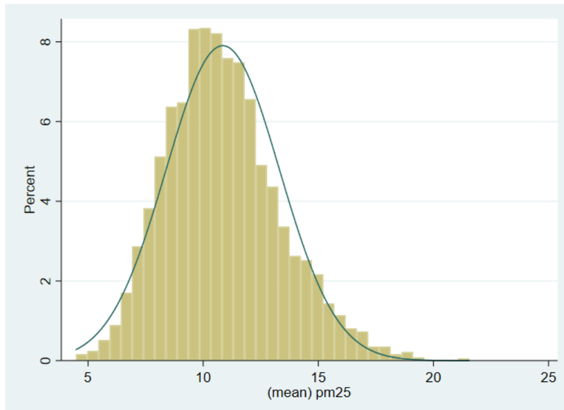
Table 19: Details on the main variables

Variable	Data source
PM 2.5	I obtain daily mean PM 2.5 concentration for each grid cell from the Van Donkelaar et al. (2016) data, ranging from January 1, 2001 to December 31, 2018. I obtain a daily measure for each local labour market as mean of all grid cells within that local labour market. I then compute a yearly PM 2.5 measure, calculated as mean over all days of the year.
PBLH	I obtain hourly mean PBLH within each grid cell from the ERA 5 data provided by the ECMWF, ranging from January 1, 2001 to December 31, 2018. I obtain daily measures for each grid cell as average over the total of hours. I then obtain a daily measure for each local labour market as mean of all grid cells within that local labour market. I then compute a yearly PBLH measure, counting the number of days the value falls into the lowest percentile of that year.
Wind speed	I obtain hourly mean wind speed within each grid cell from the ERA 5 data provided by the ECMWF, ranging from January 1, 2001 to December 31, 2018. I obtain daily measures for each grid cell as average over the total of hours. I then obtain a daily measure for each local labour market as mean of all grid cells within that local labour market. I then compute a yearly wind speed measure, counting the number of days the value falls into the lowest of 12 bins corresponding to the Beaufort wind scale.
PM 10	I obtain hourly mean concentration within each grid cell from the ERA 5 data provided by the ECMWF, ranging from January 1, 2001 to December 31, 2018. I obtain daily measures for each grid cell as average over the total of hours. I then obtain a daily measure for each local labour market as mean of all grid cells within that local labour market. I then compute a yearly PM 10 measure, calculated as mean over all days of the year.
Heat wave ("canicule")	I obtain hourly mean temperature within each grid cell from the ERA 5 data provided by the ECMWF, ranging from January 1, 2001 to December 31, 2018. I obtain measures for day and night time for each grid cell as average over the total of hours. I then obtain a day and night time measure for each local labour market as mean of all grid cells within that local labour market. I define a heat wave, as number of days in which temperature raises above 31°C during the day, and stays above 21°C at night time. I then compute a yearly heat wave measure, counting the number of days with heat waves.

Appendix C. Additional Descriptives

The following histogram shows the distribution of PM 2.5 concentration across local labour markets in France.

Figure 2: PM 2.5 Distribution across Local Labour Markets in France, 2001-2018



Note: The figure shows PM 2.5 distribution across Local Labour Markets in France over the period of 2001-2018.
Source: Authors own calculation.

Appendix D. Additional Results

OLS estimates

For completeness, I include results from an ordinary least squares specification without instrumental variables, i.e., equation (1). The OLS regression coefficient indicates a statistically negative relationship between particulate matter and firm-level productivity.

As explained above, this regression coefficients fails to estimate the causal effect of pollution on labour productivity, due to the underlying simultaneity bias.

Table 20: OLS estimates: The relation between air pollution on labour productivity

	(1) $LPROD_{i,s,l,t}$
$P_{l,t}$	-0.0274***
	(0.04)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	yes
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.08

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates with time-varying firm-level controls

Even though I control establishment fixed effects, some time-varying firm-level variables could affect the productivity of the firm within a given year. I therefore add to the baseline estimation in column (1) a firm-level measure of total capital. The table shows that the results are robust.

Table 21: The effect of predicted air pollution on labour productivity controlling for time-varying firm-level variables

	(1) $LPROD_{i,s,l,t}$	(2) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.0148***	-0.146***
	(0.00)	(0.00)
$K_{i,s,l,t}$		0.005**
		(0.00)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.63	0.54
Weak id. stat.	25.42	25.42
Hansen J stat. p-value	0.60	0.60

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. $K_{i,s,l,t}$ refers to the capital of the firm at time t. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates with regional sub samples

The negative effect of air pollution on labour productivity might be different depending on regional characteristics, population density, or average level of pollution. As additional step, I estimate the model excluding Ile de France area and focusing only on the Ile de France area. The results confirm that the negative effect holds, even after excluding the Ile de France area.

Table 22: The effect of predicted air pollution on labour productivity without and only with Ile de France

	(1) Excluding Ile de France $LPROD_{i,s,l,t}$	(2) Only focusing on Ile de France $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.013**	-0.038***
	(0.01)	(0.02)
Parameters of the regressions:		
N of observations	1,689,001	802,150
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.70	0.64

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table refers to the estimation $LPROD_{i,s,l,t} = \alpha_1 \widehat{P_{l,t}} + \alpha_2 Stock_{l,t} + \alpha_3 \widehat{P_{l,t}} * Stock_{l,t} + \gamma_i + \gamma_{s,t} + \epsilon_{i,s,l,t}$, with $LPROD_{i,s,l,t}$ as log labour productivity, and $\widehat{P_{l,t}}$ estimated air pollution based on the first-step estimation. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates at the zip-code level

In the baseline estimation, the level of aggregation of the variables is set at the local labour market l, in order to control for the fact that the pollution at the individuals home might differ from the pollution at work, but might still impact the effect on the individual. At the same time, there might be a considerable heterogeneity of air pollution within a given local labour market (e.g. industrial area vs. residential area). To account for this, I compute the baseline equation at the zip code level z.

Table 23 shows that the negative effect holds, even though it is smaller than the baseline estimate. The reason might be that indeed few individuals live and work within the same zip code, contrarily to the local labour market. Differences in air pollution between the work and home location might therefore explain the difference in the effect sizes between the estimates aggregated at the zip code level vs. the ones at the local labour market level.

Table 23: Effect of predicted air pollution on labour productivity at the zip-code level

	(1)	(2)
	First stage	Second stage
Dependent variable	$P_{z,t}$	$LPROD_{i,s,z,t}$
$B_{z,t}$	0.018**	
	(0.01)	
$W_{z,t}$	0.027**	
	(0.01)	
$\widehat{P_{z,t}}$		-0.008***
		(0.01)
Parameters of the regressions:		
N of observations	8,641,091	8,641,091
Zip-code	yes	yes
Sec-Time	yes	yes
Establishment FE	no	yes
Robust SE	yes	yes

Note: Robust standard errors clustered at the zip code -year and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, zip code, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates in log-log form

As robustness check, I also replicate the baseline results in log-log form, where I transform the two instruments as well as air pollution as natural log.

Table 24: The effect of predicted air pollution on labour productivity: Log-log specification

	(1) First stage $P_{l,t}$ (log)	(2) Second stage $LPROD_{i,s,l,t}$ (log)
$B_{l,t}$ (log)	0.016***	
	(0.01)	
$W_{l,t}$ (log)	0.028***	
	(0.01)	
$\widehat{P_{l,t}}$		-0.248***
		(0.15)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	no	yes
Robust SE	yes	yes
Adjusted R2	0.89	0.63
Weak id. stat.		25.42
Hansen J stat. p-value		0.60

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Heterogeneity estimates based on dummy variables

As a robustness to the heterogeneity exercise, I create a dummy variable, splitting the variable into lower median and upper median share of hours worked by high skilled workers. As a reference, the mean share of hours worked by high skilled workers for the lower median is 17.11%. For the upper median the mean share is 37.36%.

Table 25: Sector-level heterogeneity in the effect of air pollution on labour productivity: Low vs. high share of hours worked by high skilled (> 50%)

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.007
	(0.01)
$\widehat{P_{l,t}} * HighSkilled_s$	-0.013***
	(0.00)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	yes
Sector-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.69

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level in parentheses $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. The estimation includes year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. $HighSkilled_{s,l}$ is a sector-level dummy variable capturing the share of hours worked by high skilled workers over the years 1995 to 2000 for the US. The dummy is equal to 1 if the share of hours worked by high skilled workers is higher than 80%, and 0 otherwise. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Table 26: Local labour market level heterogeneity of population density: The effect of air pollution on labour productivity

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.015*
	(0.01)
$PopulationDensity_{l,t}$	0.601**
	(0.22)
$\widehat{P_{l,t}} * PopulationDensityl, t$	-0.005**
	(0.02)
Parameters of the regressions:	
N of observations	2,491,151
LLM FE	no
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.63

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. The estimation includes sector-year fixed effects. Labour productivity is measured in log as value added over total number of employees. $PopulationDensity_{l,t}$ measures the density of the population within a given local labour market, as 100 people per km^2. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates: Input vs output channel

The labour productivity measure is composed of the input channel (log number of employees) and on the output channel (log value added). In this step, I look at the effect of pollution on each of this channel. The results show that the effect is mainly driven by the output channel, reductions in value added, and not by the input channel, the number of employees.

Table 27: The effect of predicted air pollution on value added vs. labour input

	(1) $VA_{i,s,l,t}$	(2) $L_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.0335***	-0.0050
	(0.01)	(0.00)
Parameters of the regressions:		
N of observations	2,491,151	2,491,151
LLM FE	yes	yes
Sec-Time FE	yes	yes
Establishment FE	yes	yes
Robust SE	yes	yes
Adjusted R2	0.88	0.90

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. The sample focuses on single establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Baseline estimates: Multi-plant firms

In this step, I expand the analysis to multi-plant firms. Expanding the analysis underlies a trade-off. Considering multi establishment firms is interesting to overcome the limitation to focus on single establishment firms only, as well as to avoid the related selection bias in terms of smaller size and productivity of firms. Considering multi-establishment firms also allows including the largest and most productive firms in the sample. Including them is an important step for comparing the overall costs and benefits of pollution abatement policies. On the other hand, looking at all plants might increase measurement error as I weight labour productivity, air pollution, as well as the instruments (PBLH and wind speed) by the number of employees.

The estimates suggest that over the 2001-2018 period, a 1μ g increase of PM 2.5 within a given local labour market is on average associated with a decrease of 2.8% of the mean labour productivity, ceteris paribus. The difference in effect size to the estimates on single-establishment firms might be driven by econometric reasons, in particular as the variables are weighted by number of employees. Further, including multi-establishment firms does also include headquarters, where most knowledge intensive services within a firm are located. Within these occupations, the impact on cognitive skills through an increase in air pollution might matter more.

Table 28: The effect of predicted air pollution on labour productivity - Multi plant firm sample

	(1) $LPROD_{i,s,l,t}$
$\widehat{P_{l,t}}$	-0.028***
	(0.00)
Parameters of the regressions:	
N of observations	5,345,407
LLM FE	yes
Sec-Time FE	yes
Establishment FE	yes
Robust SE	yes
Adjusted R2	0.004

Note: Robust standard errors clustered at the local labour market-year level and at the establishment level are reported in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The estimation includes sector-year, local labour markets, and establishment fixed effects. Labour productivity is measured in log as value added over total number of employees. All variables are weighted by employees in the specific location. The sample focuses on multi establishment firms in manufacturing and non-financial services sectors over the period 2001-2018.

Appendix E. Implications for cost-benefit analyses of air pollution control

The last part of the analysis focuses on a simple cost-benefit analysis of air pollution control policies in order to compare the costs with the benefits from the productivity channel. In order to calculate the marginal abatement cost (€/person/year) for France, I refer to the population count of 66.55 million in 2015 (INSEE).

Table 29: 2008 Air Quality Directive 2008/50/EC - Abatement costs for France

2025 Scenario (EU 25)	Scenario A	Scenario B
Reduction in average urban PM 2.5 concentration	-20%	-25%
Marginal abatement cost (Million €/year)	878.4	1,588.7
Marginal abatement cost (€/person/year)	13.20	23.87

Source: European Commission (2008).

Appendix F. Comparison with existing studies

Figure 3: Comparison with existing studies