

Bad for business? The impact of air quality on firm outcomes in Germany*

Roman Eric Sieler[†] Beat Hintermann[†] Corrado Di Maria[‡]

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Abstract

Whereas economic activity and environmental quality have traditionally been seen as substitutes, recent scientific evidence contexts increasingly points towards a complementary relationship. Using administrative microdata at the plant level from Germany, we analyze the causal effect of PM2.5 air pollution in terms of production value, hours worked, and salaries paid. We find that air pollution has a negative impact on both the value of production and the number of hours worked. When combining our estimates with a model of production, we find that the most important mechanism behind the pollution-related reduction in output is a decrease in workers' hourly productivity.

Keywords: Air pollution; productivity; firm-level effects; Germany; manufacturing; absenteeism.

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[†]University of Basel, Switzerland; E-mail: romaneric.sieler@unibas.ch

[‡]University of East Anglia, UK.

1 Introduction

Pollution has long been viewed as an unavoidable by-product of economic activity and thus a price that society must pay in its pursuit of economic growth. This price can be very high: In the wake of the industrial revolution, for example, bronchitis became the leading cause of death in British industrial towns (Mosley, 2014). Fortunately, the relationship between economic development and air pollution is not monotonic, instead following a so-called environmental Kuznets curve: emissions of local pollutants initially increase and later decrease with economic development (Selden and Song, 1994; Cole et al., 1997). Despite significant advances in pollution control technologies, air pollution persists almost everywhere and continues to adversely affect human health. Among the different air pollutants, particulate matter with an aerodynamic diameter of less than 2.5 micrometers ($\text{PM}_{2.5}$) has been shown to be particularly harmful to human health (e.g. Kampa and Castanas, 2008).

The effects of air pollution go beyond our health. Several recent studies suggest that high levels of air pollution can have negative impacts on production and productivity and therefore actually hinder economic progress (Adhvaryu et al., 2022; Chang et al., 2019; He et al., 2019). However, a detrimental effect of air pollution on economic activity has also been established for more developed countries that, in principle, have decoupled economic growth and pollution (e.g., Dechezleprêtre et al., 2019; Dechezleprêtre and Vienne, 2025).

In this paper, we use administrative data from German manufacturing firms between 2003 and 2018 to analyze the impacts of $\text{PM}_{2.5}$ air pollution on production, the number of hours worked as well as salaries paid. Our data allow us to measure the impact of air pollution on output and to identify separate mechanisms, specifically absenteeism and labor productivity, within a unified framework. Following the recent literature, we use temperature inversions (i.e. meteorological events that change the layering of the atmosphere and essentially trap polluted air) as an instrument to address the potential endogeneity issue arising from the two-way relationship between economic activity and pollution (e.g. Dechezleprêtre et al., 2019; Krebs and Luechinger, 2024).

We find that an increase in average air pollution of one standard deviation (corresponding to about $0.9 \mu\text{g}/\text{m}^3$ in our setting) reduces the value of production by 1.6% and hours worked by 1.1%. Restricting the analysis to the subsample of plants for which both production value and hours worked are available, we obtain estimates of -1% for production and -0.6% for hours worked. Drawing on a simple structural model and the aggregate elasticity of output with respect to labor estimated by Hintermann et al. (2020) using the same data ($\beta = 0.4$), we find a labor productivity effect of 1.9%. This points to labor productivity as the key transmission channel, a conclusion that remains robust across all plausible values of β . The

absenteeism channel is also important, but smaller in magnitude. The effects are confined to air pollution on weekdays, suggesting that the negative impacts materialize on the time scale of a few days. Sub-sample regressions indicate differences between small and large firms: While the productivity effect increases with firm size, small firms suffer more through absenteeism, possibly due to the imperfect substitutability of individual workers. Changes in air pollution lead to larger effects for firms located in areas with higher ex-ante pollution and with a higher share of female employees (presumably due to caring responsibilities). Our results are robust to changing air pollution data, instruments, level of aggregation, and other air pollutants, and do not change significantly over the timeframe of our analysis.

Our paper contributes to the literature on the effect of air pollution on economic outcomes. Apart from Yamada and Narita (2025), who focus on working hours, we are not aware of any previous published work using plant-level data, which is relevant as our work shows that aggregating data at the firm level can lead to significant biases. Most of the previous literature has focused on emerging economies characterized by high levels of air pollution, and in particular on China (e.g., Fu et al., 2021; Hao et al., 2018). Studies on sector-wide effects in low-pollution contexts are rare and include Dechezleprêtre et al. (2019) on regional GDP in Europe, Dechezleprêtre and Vienne (2025) on production in Europe, as well as Kögel (2022) and Leroutier and Ollivier (2025) on labor productivity and sales in France, respectively.

The combination of plant-level data on outputs and inputs allows us to identify the two main mechanisms that underlie the detrimental effect of air pollution: (i) Air pollution makes workers less productive, and (ii) it prevents some workers from coming to work (absenteeism). Both pathways have been the subject of previous research, albeit usually in isolation from each other and without linking them to aggregate outcomes. As far as we know, our paper is the first to use a unified framework to separately gauge both mechanisms for a large sector. Additionally, our data allow us to study the effect on salaries paid, adding a new dimension to the literature on labor market effects of air pollution, as most previous work focused on earnings lost rather than the costs incurred by firms (see, e.g. Borgschulte et al., 2024).

The remainder of the paper is structured as follows. Section 2 provides a brief overview of the relevant literature. Section 3 introduces a theoretical model and outlines the empirical setup, Section 4 describes the data used, Section 5 presents the results of the analysis, and Section 6 offers concluding remarks.

2 Literature

Graff Zivin and Neidell (2012) and Chang et al. (2016) show that ozone and $\text{PM}_{2.5}$, respectively, reduce the productivity of agricultural workers in California. Since then, a growing literature has focused on the effect of air pollution on productivity in a wide range of tasks. For example, $\text{PM}_{2.5}$ has been found to affect the error rate of baseball umpires (Archsmith et al., 2018) and the performance of subjects taking part in cognitive tasks (Laurent et al., 2021; Zhou et al., 2023). Similar results were obtained for other types of air pollution, for example the impact of NO_x on performance in online arithmetic games (Krebs and Luechinger, 2024). $\text{PM}_{2.5}$ has also been found to impair attention and reduce test scores in children (Saenen et al., 2016; Wen and Burke, 2022), and to negatively affect the performance of investment bankers (Heyes et al., 2016).

The productivity impacts found in economic studies are consistent with findings from medical research. Air pollution, and in particular $\text{PM}_{2.5}$, has been shown to impair the functioning of the nervous system (e.g. Ferreira et al., 2022) and potentially affect general cognition, verbal fluency, and executive function at the personal level (Thompson et al., 2023; Zhang et al., 2018; La Nauze and Severnini, 2025). The effects of air pollution go beyond cognitive abilities, as studies have shown impacts on the physical performance of healthy adults (Oliveira et al., 2006), which was also demonstrated for football players specifically (Lichter et al., 2017; Li et al., 2024). This can further undermine productivity.

Recent papers indicate that the detrimental effects on individual-level productivity scale up to firms, sectors, and aggregate measures of economic performance, such as firm production or regional GDP. Air pollution-related reductions in firm-level productivity have been found for textile firms (Adhvaryu et al., 2022; He et al., 2019), prison workers (Chen and Zhang, 2021) and call centers (Chang et al., 2019) in both China and India. For both countries, there is also growing evidence of overall production effects (Fu et al., 2021; Majumder et al., 2024; Ye et al., 2024; Jiang et al., 2024). Detrimental effects have also been reported for regions with relatively low pollution levels. At an aggregated level, Dechezleprêtre et al. (2019) measure a significant causal relationship between air pollution and regional GDP in Europe. Similar to our approach, they use satellite-based air pollution data as well as an instrumental variable approach relying on thermal inversions and find that a $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ leads to a 0.8% reduction in GDP on NUTS-3 level, mostly due to reductions in agricultural output. At the firm level, Kögel (2022) and Dechezleprêtre and Vienne (2025) identify a reduction in output per worker in France and across Europe, respectively. The former use an instrumental variable approach based on boundary layer height and wind speed to analyze the impact of $\text{PM}_{2.5}$ on labor productivity, defined as gross value added over

total employment, for French single-plant firms in manufacturing and non-financial services. They find that a $1 \mu\text{g}/\text{m}^3$ increase reduces annual labor productivity by 1.5%. These effects are found to be driven by firms with a high services share and a high share of hours worked by high-skilled workers. The latter also use boundary layer height as an instrument to analyze $\text{PM}_{2.5}$ air pollution impacts on value added per worker for firms across Europe. The authors' data gives them comprehensive annual coverage, but allows them to only allocate air pollution based on the location of a firm's headquarters; despite trying to mitigate this through filtering, they cannot distinguish between multi- and single-plant firms. They find a reduction of 0.55% in labor productivity for $1 \mu\text{g}/\text{m}^3$ $\text{PM}_{2.5}$ and confirm both non-linear effects and that services and construction drive the overall results.

Air pollution can reduce economic production through two main effects: A reduction in worker productivity per hour, as discussed above, and a drop in the number of hours worked. Exposure to high levels of $\text{PM}_{2.5}$ air pollution has been linked to acute respiratory diseases (Kurt et al., 2016) and sleeplessness (Heyes and Zhu, 2019), which may keep workers at home. Research on the impacts of air pollution on labor supply generally confirms that pollution can cause absenteeism (Fernando M. Aragón et al., 2017; Kim et al., 2017; Fernando Rodrigues-Silva et al., 2012; Hanna and Oliva, 2015; Holub et al., 2020; Borgschulte et al., 2024; Fan and Grainger, 2023; Zhou and Zhang, 2023; Hoffmann and Rud, 2024; Yamada and Narita, 2025; Beshir and Fichera, 2025). Absenteeism can be linked to the workers' own health, but also to the health of their children, for example, who are particularly affected by the acute effects of short-term $\text{PM}_{2.5}$ air pollution (Darrow et al., 2014; Schwartz et al., 1994). Park et al. (2002) find that particulate air pollution can be linked to school absenteeism, which may force parents of young children to stay at home. This is consistent with findings that pollution-related effects on labor supply are stronger for women than for men, specifically for mothers (Han et al., 2023; Montt, 2018; Gu et al., 2020). Worker absenteeism via children's health may be highly relevant in our setting, since German employees with public insurance may stay home for up to 10 days per child, with their pay covered by their health insurance, if their children are ill. Note, however, that pollution-related absenteeism may be partially offset by firms paying for overtime (see, e.g., Zhang et al., 2017; Allen, 1983), implying that any observed change in hours worked, which includes overtime, could understate actual absences. Employers in Germany are required to continue paying sick workers their full salaries for a period of six weeks, which is longer than the typical duration of an episode of acute respiratory disease. Therefore, any air-pollution-related overtime or replacement adds to salary costs, beyond the regular labor expenditures. In contrast, insurance covers sickness that lasts longer than six weeks, or when workers stay at home due to their children's

sickness. In these cases, labor expenditures would remain constant if the workers are replaced with workers of similar skills, and decrease if no significant replacement takes place.

Additional dimensions of the air pollution effect discussed in the literature include the timing of the effect, its linearity, and how it differs across firms of different sizes. Studies using short-term air pollution have addressed the question of how quickly air pollution effects materialize, such as Graff Zivin and Neidell (2012), who find that impacts of ozone on farm worker productivity materialize almost immediately, during the same workday, and studies on activity-loss days discussed in Orellano et al. (2023), which also indicate short-term effects. This is supported by the medical literature indicating both acute respiratory symptoms (Kurt et al., 2016) – which could lead to absences – and reductions in physical performance (Li et al., 2024) as well as impacts on cognitive ability (Thompson et al., 2023) within a few days. There is also some discussion around the linearity of air pollution effects, with previous studies finding non-linear effects of air pollution on productivity of German football players (Lichter et al., 2017), while Behrer et al. (2023) observe no difference based on base-level pollution. Regarding firm size, there is some disagreement in the literature. Ye et al. (2024) for instance show that productivity effects are stronger for large firms than for small firms, while Ali and Burhan (2024) show that larger firms are more likely to adopt air pollution protection measures, which would suggest the opposite.

Papers most related to our work include an unpublished working paper by Leroutier and Ollivier (2025), who study the impact of air pollution on sales as well as the onset of sick leave episodes in the context of French firms, and as Borgschulte et al. (2024), who focus on the effects of wildfire smoke in the USA and find that a $1 \mu\text{g}/\text{m}^2$ increase in quarterly $\text{PM}_{2.5}$ lowers per-capita quarterly earnings by about \$ 103. He and Ji (2021) use Chinese household survey data to analyze air pollution effects on wages as a measure of productivity, and on working hours.

Our study is the first to estimate the effect of air pollution on firm/plant production and absenteeism within the same framework – meaning using the same approach and sample, which allows us to separately identify the absenteeism and productivity channels and compare them. This is a direct consequence of the richness of our data, as we have information not only about the value of production but also about the number of hours worked. Our data also includes information on labor expenditure, which allows us to assess the importance of overtime. Additionally, we are one of the first papers to implement the analysis on plant instead of firm level and we directly estimate the effect of pollution on the overall production value and on the labor costs directly incurred by firms. This allows us to bridge the gap between these studies and analyses of firm-level outcomes such as Dechezleprêtre and Vienne (2025) and Kögel (2022), putting previous findings in a comparable context with one another.

3 Methodology

We start by illustrating the theoretical relationship between labor productivity, labor quantity, and output in a stylized analytical framework, before describing the empirical methodology we use to identify the effect of air pollution on each of these outcomes.

3.1 Analytical Framework

Let Y_{ft} refer to the value of the production by plant f , in year t . Output is produced with capital, K , labor, L , and materials (including energy), M , according to the following Cobb-Douglas production function:

$$Y_{ft} = \Omega_{ft} K_{ft}^{\alpha} (\omega_{ft} L_{ft})^{\beta} M_{ft}^{\gamma} \quad (1)$$

Labor enters production as efficiency units, i.e. the quantity of labor (in hours worked) times a firm-time specific efficiency factor ω_{ft} . The elasticities α , β and γ determine the extent to which inputs are transformed into output, given a firm-specific total factor productivity (TFP), Ω_{ft} .

The efficiency factor ω_{ft} is not directly observable, so that we need to resort to a more indirect approach to measure the effect of air pollution on labor productivity. The key assumption in equation (1) is that changes in both L and ω map into changes in output via the same elasticity parameter, β :

$$\beta = \frac{\partial Y_{ft}}{\partial \omega_{ft}} \frac{\omega_{ft}}{Y_{ft}} = \frac{\partial Y_{ft}}{\partial L_{ft}} \frac{L_{ft}}{Y_{ft}} \quad (2)$$

Taking logs of (1) and differentiating with respect to air pollution P , we obtain:

$$\frac{\partial \ln Y_{ft}}{\partial P} = \frac{\partial \ln \Omega_{ft}}{\partial P} + \alpha \frac{\partial \ln K_{ft}}{\partial P} + \beta \left(\frac{\partial \ln \omega_{ft}}{\partial P} + \frac{\partial \ln L_{ft}}{\partial P} \right) + \gamma \frac{\partial \ln M_{ft}}{\partial P}.$$

Assuming that, in the short run, changes in pollution do not directly affect Ω_{ft} , K_{ft} , or M_{ft} ,¹ the above expression may be simplified and rearranged to give

$$\frac{\partial \ln \omega_{ft}}{\partial P} = \frac{\frac{\partial \ln Y_{ft}}{\partial P}}{\beta} - \frac{\partial \ln L_{ft}}{\partial P} \quad (3)$$

Therefore, the proportional change in productivity, $\partial \ln \omega_{ft}$, driven by a change in air pollution can be recovered by dividing the proportional change in output by the elasticity

¹We believe that this is a reasonable assumption to make, given that investment and purchasing decisions are typically fixed in the short term, and considering our analysis is framed within a low-pollution context.

parameter β , and subtracting the proportional, air-pollution-induced change in the labor input. To estimate the effect of air pollution on ω , it therefore suffices to know the effect of pollution on output Y and on the actual labor input, L , provided that β is known. In terms of theoretical priors, we would expect a negative effect of air pollution on output, labor and ω . A priori, we do not have expectations about the relative magnitudes of the changes in ω and L . Because there is empirical uncertainty surrounding the true value of β , which furthermore varies by industry, we present the main results as a function of this parameter.

3.2 Identifying Assumptions and IV

The central identification problem in estimating the impact of air pollution on productivity is reverse causality, because increases in manufacturing output are also expected to increase local pollution. Following an extensive literature that was originally pioneered by Arceo et al. (2016), we use temperature inversions as an instrument for air pollution. Temperature inversions are meteorological phenomena that disrupt the layering of the troposphere, which usually exhibits a negative vertical temperature gradient. If a temperature inversion occurs, the layering in a part of the troposphere switches to a positive vertical temperature gradient, which restricts the circulation of air and effectively puts a ‘lid’ on lower atmospheric layers. This lack of circulation traps air in lower layers and leads to an increase in the concentration of air pollutants. Wallace and Hobbs (2006) define temperature inversions as layers of air in which temperatures increase with height. These can occur throughout the troposphere and beyond, with a capping inversion usually marking the top of the troposphere. Relevant in our setting is the lowest inversion. This can be identified by its base layer, the bottom of the lowest layer of the atmosphere with a positive vertical temperature gradient, and its top layer, the first subsequent layer with a negative temperature gradient (Kahl, 1990). The ability of an inversion to trap pollution depends on its characteristics, such as its height and strength (Ferrario et al., 2008; Largeron and Staquet, 2016; Stryhal et al., 2017; Xu et al., 2019; Liu et al., 2019; Palarz et al., 2020).

While the meteorological literature generally favors a dynamic definition of inversions as in Kahl (1990), most of the previous economic papers have used simplified definitions of inversion events, for instance by comparing temperatures between two individual layers of the atmosphere (Chen et al., 2022; Fu et al., 2021; Chen et al., 2018; Dechezleprêtre et al., 2019) or air temperatures at a given layer with the surface (Jans et al., 2018; Sager, 2019; Dechezleprêtre et al., 2019). This approach has the advantage of clearly identifying inversions at lower layers, which are most relevant for trapping pollution. It, however, does not properly account for inversion strength, which is the temperature gradient across

the whole inversion and determines its ability to trap pollution. We therefore combine both approaches. First, we identify near-surface inversions at the hourly level with a binary indicator marking the presence of any positive temperature gradient between the surface and 925 hPa (roughly equal to 750 m). We then adopt the approach by Wetzell and Brümmer (2011) to calculate the inversion strength as the temperature difference in degrees Celsius between the base and top layers of the inversion and multiply it by the binary indicator. We then aggregate this measure on the yearly level in order to match the frequency of our economic data. As robustness tests, we also use alternative instrument specifications, such as the binary, unweighted inversion measure at both 925 hPa and 850 hPa (around 1,500 m) or the presence of inversions interacted with pollution levels in the year prior to the start of our analysis, following the reasoning that inversions should have a stronger impact in more polluted areas.

The data is generated from satellite observations of temperature at different air pressure levels on a 0.25 x 0.25 degree (roughly equal to 30 x 30km) resolution from Hersbach et al. (2023). This resolution should be sufficiently disaggregated, as inversions mostly occur over areas that exceed this resolution (Largerion and Staquet, 2016).

To be a valid instrument, inversions (i) have to be meaningfully related to the concentration of air pollutants, and (ii) they must not be correlated with the error term. The first stages of our IV regressions are always highly significant (see Section 5), indicating that the first condition holds. The second condition is known as the exclusion restriction, which requires that the instrument affects the outcome of interest only through air pollution, but not directly or via any other channel. Since the inversions we study are relative temperature changes taking place at considerable height above the surface, there is no obvious way for inversions to impact economic outcomes directly. However, indirect channels through related meteorological factors are possible, as the meteorological literature points towards a set of factors that correlate with the formation of inversions and might also impact our outcomes of interest.

3.3 Estimation

We implement a two-stage least squares instrumental variable regression to account for the potential bidirectional causality between production and air pollution, employing temperature inversions as an instrument. Our outcome variables of interest are (i) the value of production, (ii) the number of hours worked, and (iii) the value of salaries paid – the latter is added to assess whether the hours-worked effect may be potentially offset by an increase in overtime. To make our results more comparable to the previous literature, we also add

an analysis considering (iv) production per hour worked. All regressions are implemented at both the plant- and firm-level, as different aggregation levels – notably for multiplant firms – might affect the results.

Since the data in raw form exhibit unit roots in both salaries paid and hours worked, which could lead to spurious regression results, we run the regressions in first differences.² Because we are interested in relative rather than absolute impacts, we take logarithms of the dependent variables before taking first differences. This implies that we study the effect of year-to-year changes of PM_{2.5} air pollution on the growth rate of our outcomes of interest. Tests according to Wooldridge (2010) and Wursten (2016) indicate the presence of autocorrelation for all our dependent variables. We mitigate this issue by using cluster-robust standard errors at the plant level, allowing for arbitrary within-cluster correlation. Alternative standard error specifications are explored as robustness tests.

For the first stage, we regress average PM_{2.5} air pollution at the municipality-year level m, t on the inversion instrument and a number of climate control variables. In the second stage, the outcome of firm/plant f in year t and municipality m is regressed on the instrumented average PM_{2.5} concentration in year t and municipality m and the same vector of climate controls as in the first stage. Year, η , as well as plant, θ , fixed effects and clustered standard errors at the unit (firm/plant) level are used in all regressions, unless specified otherwise. The structure of the first and second stages of the regressions we run is as follows:

$$\Delta \text{PM25}_{f,t,m} = \beta_1 \cdot \Delta \text{InversionStrength}_{f,t,m} + \sum_{k=0}^i \beta_k \cdot \Delta \text{climate}_{f,t,m}^k + \Delta \eta_t + \Delta \theta_f + \Delta \zeta_{f,t,m} \quad (4)$$

$$\Delta \ln(\text{Outcome})_{f,t,m} = \beta_1 \cdot \Delta \hat{\text{PM25}}_{f,t,m} + \sum_{k=0}^i \beta_k \cdot \Delta \text{climate}_{f,t,m}^k + \Delta \eta_t + \Delta \theta_f + \Delta \varepsilon_{f,t,m} \quad (5)$$

To measure the overall impact of air pollution, we use the total value of production as the outcome variable of interest. To learn more about the underlying mechanisms, we then focus on the impact of air pollution on the number of hours worked at the plant level. The effect on labor productivity, the extensive margin of the effect, can then be estimated using the formula provided before. We add an analysis of production per hour worked.

Our data include the actual number of hours worked. This excludes paid hours during which a worker was absent, e.g. due to illness, and includes overtime (FDZ, 2022b). This means that the effect of air pollution on this measure of labor understates absenteeism to the extent that it is replaced by overtime. We do have information on paid salaries, however,

²We implement a Harris-Tzavalis unit root test (Harris and Tzavalis, 1999), which assumes that T is fixed, a typical assumption for micro panel studies (Baltagi, 2008). We check that the first-differenced outcome data in logs are in fact stationary.

which includes payments for overtime. We can thus estimate the impact of air pollution on paid salaries, which provides us with an indication for firms’ compensation efforts. As we have no information about how much more a given company pays their employees for an hour of overtime, we cannot precisely identify the quantity of overtime. However, a non-positive effect on salaries paid would imply that firms only imperfectly compensate absences with overtime. Lastly, we cannot directly assess absences due to parents caring for sick children or other dependents, as they are not paid by the company but by the health insurance. We address this issue by interacting air pollution with the share of women in the labor force of firms, which is a proxy, albeit an imperfect one. We also carry out extensions that focus on pollution during weekdays vs. weekends and on mornings vs. evenings. Heterogeneity analyses consider interactions of the main explanatory variable with quantile dummies.

4 Data

The analysis relies on a combination of firm- and plant-level data with satellite-based meteorological data at the municipality level. The latter are obtained in a gridded format and are allocated based on the municipality code.

4.1 Plant- and Firm-level Data

Our analysis is based on the AFiD (“Amtliche Firmendaten für Deutschland”) panel, which provides administrative micro-data for all German plants over 20 workers (FDZ, 2022a). Our main data source are the sub-panels on manufacturing plants and firms. These panels include information about production, specifically the annual value of production, hours worked, and salaries paid by individual firms and plants, as well as other relevant variables. The value of production includes only production intended for sale at the sales value, regardless of whether the production was sold or not. Hours worked measure actual hours worked, which includes both overtime as well as absences. Salaries paid are in the same fashion actual salaries paid, including payments for overtime or bonuses. Since absenteeism due to short-term sickness (which air pollution likely contributes to) is covered by the employer in Germany, pollution-related absences would be reflected in hours worked, but not in salaries. In specific sectors with small firms, there is a lower reporting threshold of 10 employees.³ For small plants between 20 and 50 workers, only annual reporting is required, which does not cover hours worked. This results in a slightly smaller sample. To cover both the best available sample and obtain comparable results, we run the analysis for the full sample as well as

³Sectors 08.11, 08.12, 10.91, 10.92, 11.06, 16.10, 23.63.

for a balanced sample, which includes only the plants for which all outcomes are available. For the heterogeneity analysis, we supplement this with information from the cost structure survey, namely information about the female employee share, which is only mandatory for firms with over 500 employees, with additional data collected from a random sample of firms between 20 and 500 employees.

More detailed information on the AFiD data is provided in Koch and Migalk (2007) and Wagner (2010). The data are provided by the German Federal Statistical Office and the respective statistical offices of the federal states and firms are mandated to disclose information. A summary of the relevant plant- and firm-level variables is provided in Table 1.

Before the analysis, we engage in limited data cleaning. We first ensure that variables marked as missing are treated as such. Secondly, we impute missing industry classifiers at the firm level based on the most frequent plant-level value for the firm, and correct industry classifiers to the 2008 classification, as well as the municipality classification to the most recent version. Thirdly, we drop plants that are not active in manufacturing. Fourthly, we ensure that all variables are provided with the same units and on the same form of aggregation, for example, by converting non-annual variables into annual ones or by correcting for changes in variable definitions throughout the time frame of our analysis. Values are deflated to 2015 Euros using a GDP deflator for most variables, a producer price deflator for production value and a labor cost deflator for salaries. We then drop all values before 2003, as some variables are missing in the period before. As a last step, we drop observations with implausible values, for instance, if salaries, hours, employees, or production are below 1 or even negative. We also drop observations with hours per employee above 4,392, which would imply working more than 12 hours every day. Lastly, we standardize all explanatory variables to facilitate comparisons and log-transform the dependent variables. For the firm-level regressions, the variables that exist at the plant-level and cannot be summed up (e.g., climate variables) are averaged based on weighting by employee share.

4.2 Ambient Data

To measure ambient air quality, we use satellite-based observations of particulate matter obtained from NASA (GMAO, 2015). The data are provided on a $0.5^\circ \times 0.625^\circ$ resolution each hour, containing a range of aerosol measurements including the surface mass concentrations of dust, organic carbon, black carbon, sea salt, and SO_4 , which are summed up to obtain an overall $\text{PM}_{2.5}$ measure according to the weighted method described in Buchard et al. (2016).

Table 1: Summary Statistics Plant and Firm Data

Variable	Obs	Mean	SD	Median
<i>Plant Level</i>				
Value of Production in Mio. 2015 €	729,113	31	296	6
Hours Worked in Thousand Hours	478,031	294	1,040	136
Salaries Paid in Mio. 2015 €	762,866	6	41	2
Number of Employees	477,176	1562	310	1,563
Production per Hour in 2015 €	458,074	161	16,193	86
<i>Firm Level</i>				
Value of Production in Mio. 2015 €	458,074	46	373	12
Hours Worked in Thousand Hours	458,074	290	1,030	136
Salaries Paid in Mio. 2015 €	458,074	9	51	3
Number of Employees	457,651	1,566	303	1,564
Production per Hour in 2015 €	458,074	161	16,193	86

Values are based on (FDZ, 2022a) and are rounded to even numbers. We cannot disclose additional metrics, such as min/max values due to data disclosure rules.

We allocate this data to plants and firms by matching the four closest grid points to each municipality using inverse distance weighing, and finally aggregate them to the annual level. In addition, we consider the number of days with average air pollution above the pre-2021 24-hour WHO threshold of $25 \mu\text{g}/\text{m}^3$ and the current threshold of $15 \mu\text{g}/\text{m}^3$ (World Health Organization, 2021) in an extension. Using the number of days above this threshold accounts for the specific effect of high pollution levels caused by inversions.

Additional weather data used as controls are sourced from the German Weather Service (DWD, 2022; Kaspar et al., 2013), the European Copernicus Database (Hersbach et al., 2023), as well as ECAD (Cornes et al., 2018) and matched based on the municipality a firm/plant is located in. These measures include average temperature, precipitation, humidity, air pressure, cloud cover, and the number of summer and frost days. Since temperature is assumed to have non-linear impacts on productivity following Burke et al. (2015), it is additionally controlled for by a count of days in different temperature bins throughout the year. We include bins that account for the number of hours with wind from each direction weighted by the wind speed.

Summary statistics on the various ambient variables are provided in Table 2. Note that the standard deviation of mean $\text{PM}_{2.5}$ happens to be close to 1, which facilitates the interpretation of the main results. Figure 1 shows the distribution and development of air pollution in Germany, and Figure 2 presents averages over time for the country as a whole,

along with our inversion measure. Figure 3 furthermore shows the distribution changes of air pollution over time. We see that the concentration of PM_{2.5} remains roughly stable at a level between 8 and 14 $\mu\text{g}/\text{m}^3$ throughout the sample period, while there is a year-to-year and geographic variation correlated with inversions.

Table 2: Summary Statistics Air and Climate Data

Variable	Mean	Std. Dev.	Min	Max	Unit
Mean PM _{2.5}	10.424	0.904	6.253	14.354	$\mu\text{g}/\text{m}^3$
Mean PM _{2.5} Donkelaar et al.	13.072	1.871	7.047	22.946	$\mu\text{g}/\text{m}^3$
Mean PM _{2.5} Hammer et al.	13.069	1.863	7.000	22.800	$\mu\text{g}/\text{m}^3$
Threshold 25	2.502	1.442	0.25	9.188	Days with PM2.5 > 25 $\mu\text{g}/\text{m}^3$
Threshold 15	14.728	4.016	3.684	31.583	Days with PM2.5 > 15 $\mu\text{g}/\text{m}^3$
Humidity	0.006	0.000	0.005	0.007	%
Air Pressure	1,016.460	1.451	1,012.524	1,020.156	0.1 hPa
Cloud Cover	0.671	0.034	0.535	0.776	0–1
Summer Days	4.133	1.682	0.067	10.999	Days with Temp. $\geq 25^\circ\text{C}$
Frost Days	8.245	2.325	0.689	20.634	Days with Temp. $< 0^\circ\text{C}$
Mean Temperature	9.407	1.020	3.118	12.732	$^\circ\text{C}$
Mean Precipitation	76.952	20.930	28.157	283.544	mm
Inversion 925 hPa (C)	508.505	256.539	0.000	1460.000	Inv. Hours
Inv. 850 hPa (C)	373.963	159.959	0.000	1007.000	Inv. Hours
Inv. 850 hPa (S)	2,081.190	919.840	0.000	5,736.525	Inv. Hours * $\Delta^\circ\text{C}$
Inv. 925 hPa (S)	2,175.577	1,029.315	0.000	5,969.246	Inv. Hours * $\Delta^\circ\text{C}$

The table summarizes the PM 2.5 data sourced from GMAO (2015), the weighted and unweighted number of inversions at 925 hPa and 850 hPa (C for the count and S for strength, the weighted version) from Hersbach et al. (2023). Additional measures include alternative PM 2.5 data from Van Donkelaar et al. (2021) and Hammer et al. (2020). Furthermore, control variables from the German Weather Service (DWD, 2022; Kaspar et al., 2013), the European Copernicus Database (Hersbach et al., 2023) as well as ECAD (Cornes et al., 2018) are provided. The data has 175952 municipality-by-year observations for all variables.

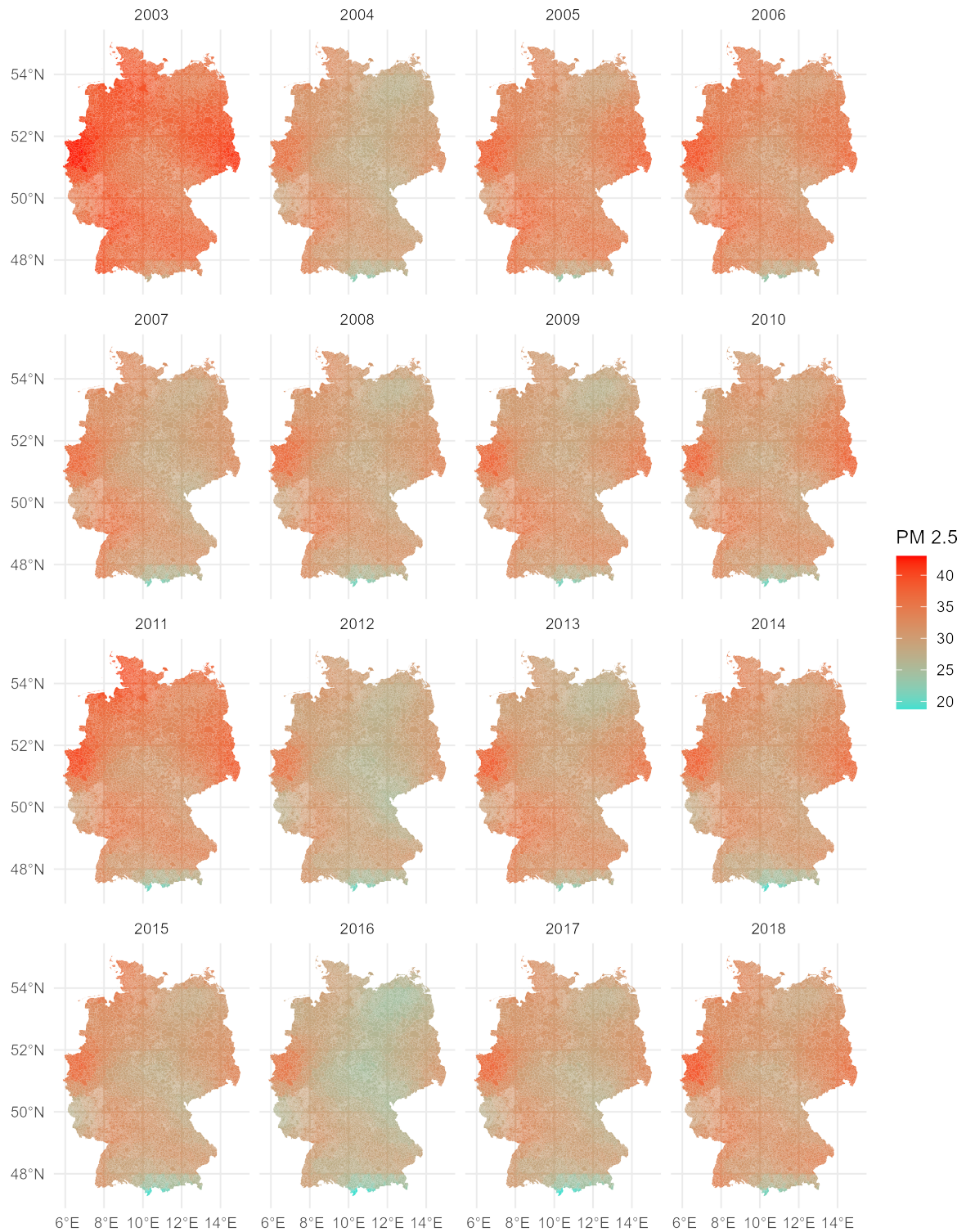
5 Results

5.1 Average effect of air pollution

The main regression results are reported in Table 3. All models include controls for plant and year-fixed effects and the full range of weather variables.⁴ Since OLS estimates are likely biased due to the two-way relationship between production and air pollution, our preferred specification instruments PM_{2.5} with inversion strength at 925 hPa. The main results are reported in column (3), which uses the largest sample available for each outcome variable.

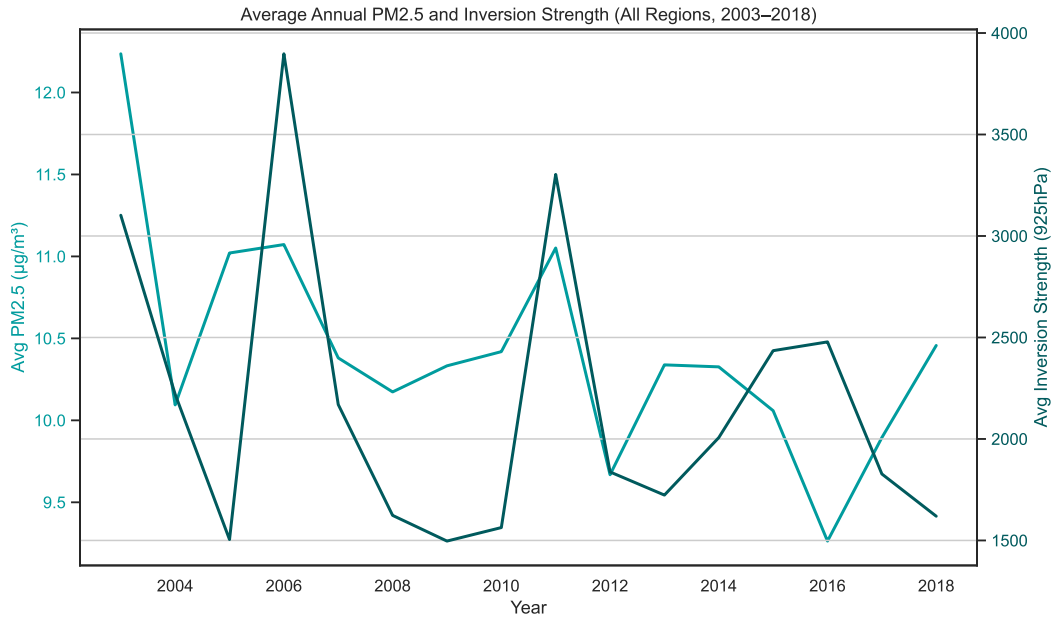
⁴For full details, please refer to table notes. Since we estimate our regressions in first differences, including plant FE is equivalent to allowing for plant-specific trends.

Figure 1: Annual Average PM_{2.5} Values in Germany, by Municipality and Year in $\mu g/m^3$.



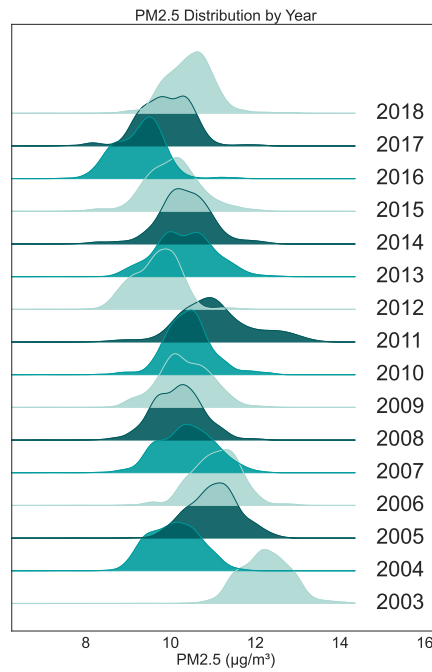
Source: Authors' illustration. PM_{2.5} is based on data by (GMAO, 2015), aggregated at the municipality level using inverse distance weighing. The data are then summed up at the annual level.

Figure 2: Annual Average PM_{2.5} ($\mu\text{g}/\text{m}^3$) and Inversions ($\text{hours} * \Delta^\circ\text{C}$) in Germany.



Source: Authors' illustration based on PM_{2.5} data by (GMAO, 2015).

Figure 3: Distribution of Annual Average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in Germany.



Source: Authors' illustration based on inversion data by Hersbach et al. (2023).

Our results show that an increase in $\text{PM}_{2.5}$ by one standard deviation (SD) decreases the **value of production** in German manufacturing plants by 1.6%. Removing outliers leads to a slightly higher estimate of 2%. Limiting the regression to a balanced sample and thereby to mostly larger firms results in a slightly lower negative and significant result of 1%. This hints at a potential heterogeneity of effects by firm size, which we study in more detail below. The reduced-form estimate is also negative and significant. These results confirm our first hypothesis and show that air pollution does in fact reduce plant-level production in the German manufacturing sector.

Hours worked are negatively affected by an increase in mean $\text{PM}_{2.5}$ air pollution, with one SD causing a decrease in overall hours worked by 1.1%. Additional specifications without outliers and a constant sample are both significant and negative, with a slightly smaller magnitude of 0.7% and 0.6%, respectively. The reduced form estimate is negative and significant. These results confirm our second hypothesis and show that air pollution causes an increase in absenteeism.

We find no effect on **salaries paid** in our preferred specification, and a negative effect for the regressions without outliers and for the constant sample. This implies that absences are not fully compensated through overtime, which is consistent with previous findings by Schmutte and Skira (2023). The fact that we find a negative effect in some specifications could be explained by children being particularly susceptible to acute respiratory symptoms (Odo et al., 2021). If parents stay at home because of their children and are not replaced by other workers, the salaries paid by firms will decrease due to workers' health insurance. Output-related payments, e.g. through bonuses, might also explain part of the decrease. While not as widespread as for managers, these are also common for many employees in non-leadership positions in Germany, with a recent survey indicating that they represent around 7% of total compensation (Grunau et al., 2025).

Some of the previous literature has focused on the effect of air pollution on output per worker and interpreted this as the effect on **labor productivity**. In our setting, the effect on labor productivity is captured by eq. 3. We use $\beta = 0.4$ as estimated by Hintermann et al. (2020) for the same firms as our central estimate. Here, we use the coefficients from the balanced sample model to ensure that the coefficients are directly comparable. Using the formula derived in Equation (3), this results in:

$$\frac{\partial \ln \omega_{ft}}{\partial P} = -1.0/0.4 - (-0.6) = -1.9 \quad (6)$$

In other words, a one-standard-deviation increase in $\text{PM}_{2.5}$ will lead to an expected productivity decrease of 1.9%. This exceeds the effect via absenteeism (0.6 %; see Table 3).

Table 3: Main Regression Results on Plant Level

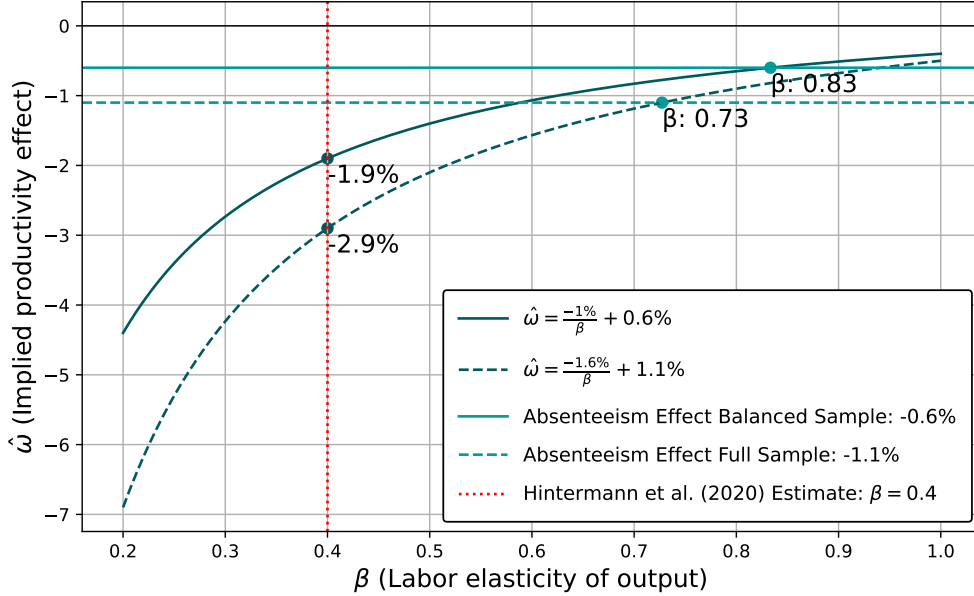
	(1)	(2)	(3)	(4)	(5)	(6)
Production	OLS	1st Stage	IV	IV No Outl.	IV Balanced	Red. Form
PM _{2.5}	-0.014*** (0.002)		-0.016*** (0.005)	-0.020*** (0.003)	-0.010* (0.006)	
Inv. Str. 925hPa		0.208*** (0.001)				-0.003*** (0.001)
N	638,011	642,768	638,011	613,216	381,614	638,011
R ²	0.163	0.901	0.000	0.001	0.000	0.163
F	9.08	13,844.7	8.77	24.61	4.94	5.99
rk Wald F			58,078	54,814	36,755	
Under-ID p			0.00	0.00	0.00	
Hours Worked	OLS	1st Stage	IV	IV No Outl.	IV Balanced	Red. Form
PM _{2.5}	-0.008*** (0.002)		-0.011** (0.005)	-0.007*** (0.002)	-0.006* (0.004)	
Inv. Str. 925hPa		0.198*** (0.002)				-0.002** (0.001)
N	397,667	402,044	397,667	385,539	381,614	397,667
R ²	0.255	0.925	0.001	0.001	0.001	0.255
F	9.02	8,512.16	9.00	19.43	9.88	8.14
rk Wald F			38,957	37,257	36,755	
Under-ID p			0.00	0.00	0.00	
Salaries	OLS	1st Stage	IV	IV No Outl.	IV Balanced	Red. Form
PM _{2.5}	-0.005*** (0.001)		-0.006 (0.004)	-0.007*** (0.002)	-0.008** (0.004)	
Inv. Str. 925hPa		0.208*** (0.001)				-0.001 (0.001)
N	666,933	672,014	666,933	649,842	381,614	666,933
R ²	0.172	0.902	0.000	0.001	0.000	0.172
F	6.30	14,338.73	6.20	17.96	7.00	5.93
rk Wald F			61,119	58,765	36,755	
Under-ID p			0.00	0.00	0.00	

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. IV regressions instrument PM_{2.5} with inversion strength at 925 hPa. Reported are: (1) OLS model, (2) first stage of the IV regression, (3) IV regression using the full sample, (4) IV regression that drops observations with a residual over two standard deviations, (5) IV regression using a balanced sample that considers only observations for which all dependent variables are non-missing, (6) a reduced-form regression. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value. Tests for overidentifying restrictions are not reported as only one instrument is used.

When using the estimates from the full sample, the effect on labor productivity becomes $\frac{\partial \ln \omega_{ft}}{\partial P} = -1.6/0.4 - (-1.1) = -2.9\%$, which again exceeds the absenteeism effect of 1.1%.

Naturally, this is subject to our assumption about the production elasticity with respect to labor. Estimates in this regard differ; Lochner and Schulz (2024) for instance estimate β to be 0.71, while Mertens and Mottironi (2023), who also consider intermediate inputs, estimate it to be around 0.3. To cover a range of potential elasticities, Figure 4 shows the labor productivity effect as a function of β . Given our balanced sample estimates, the productivity effect is stronger than the absenteeism effect as long as $\beta < 0.83$. For completeness, we also include the full sample estimate, which is stronger than the absenteeism effect as long as $\beta < 0.73$. Both thresholds are higher than plausible labor elasticities that have been published in the literature.

Figure 4: Calculated Productivity Effect vs. Labor Elasticity of Output ($\beta \in [0.2, 1]$)



The figure shows how the productivity effect $\frac{\partial \ln \omega_{ft}}{\partial P}$ calculated based on both the full and the balanced sample estimates changes with the labor elasticity of output. While our main estimates are based on the Hintermann et al. (2020) estimate of $\beta = 0.4$, this shows that the productivity effect is more pronounced than the estimated absenteeism effect for most plausible values of β .

5.2 Extensions

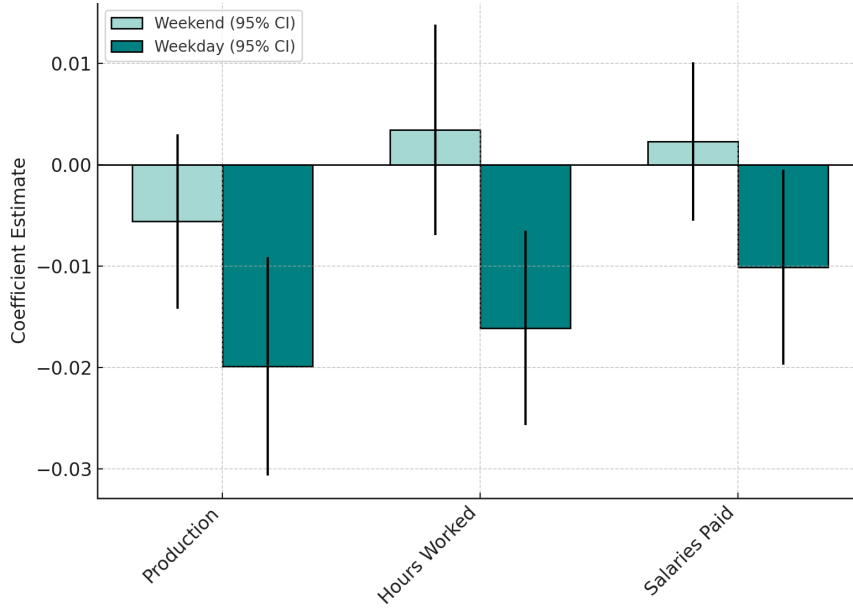
Time. Our data allow for an analysis of the effect of air pollution at certain times of the day or days of the week. If the effect is due to cumulative exposure, the timing of pollution would not matter. In contrast, meaningful differences in the effects according to the time pattern of

pollution would suggest that the detrimental effects of air pollution materialize in the short term. Figure 5 and the underlying regression results in Table A.1 in the appendix indicate that the effects on all three outcomes of interest are only significant during weekdays but not during weekends, and the differences between week and weekend estimates are statistically significant. The weekday effects are slightly stronger than the main results, with -2% for production, -1.6% for hours worked, and -1% for salaries. Not accounting for the lower relevance of pollution during the weekend may thus bias the aggregate results. Due to the fact that most people in Germany do not work on the weekend, one would expect – if the effects materialize in the short term – that only air pollution during the week affects the outcomes, which is why these results also serve as a falsification test. The finding that air pollution during the weekend has no effect therefore adds credibility to our main results. Focusing the analysis on individual days instead (see Tables A.2 to A.4) indicates that the effects are concentrated within the first three days of the week. Results for the time of day are shown in Figure 6 and Table A.5 in the appendix. Here, we split the inversion instrument into three parts: before 8 AM (morning), between 8 AM and 4 PM (day), and after 4 PM (evening). Differences between the estimated effects for different times of the day are small and not statistically significant. The point estimate for hours worked is largest in absolute value for the morning hours, which would align with people staying home because of acute respiratory symptoms. However, this estimate is very imprecise. These results suggest that the effects of air pollution do not materialize within the period of individual hours.

Thresholds. So far, we have focused on the effect of average air pollution levels. To investigate whether the effects are driven by periods of very high air pollution, we repeat our main regression with a $\text{PM}_{2.5}$ measure that is equal to the number of annual days with air pollution levels above the pre-2021 24-hour WHO threshold of $25 \mu\text{g}/\text{m}^3$ and the current lower threshold of $15 \mu\text{g}/\text{m}^3$ (World Health Organization, 2021). This approach follows Dechezleprêtre et al. (2019) and differences could indicate non-linear effects. The results of the regressions are shown in Tables A.6 and A.7.

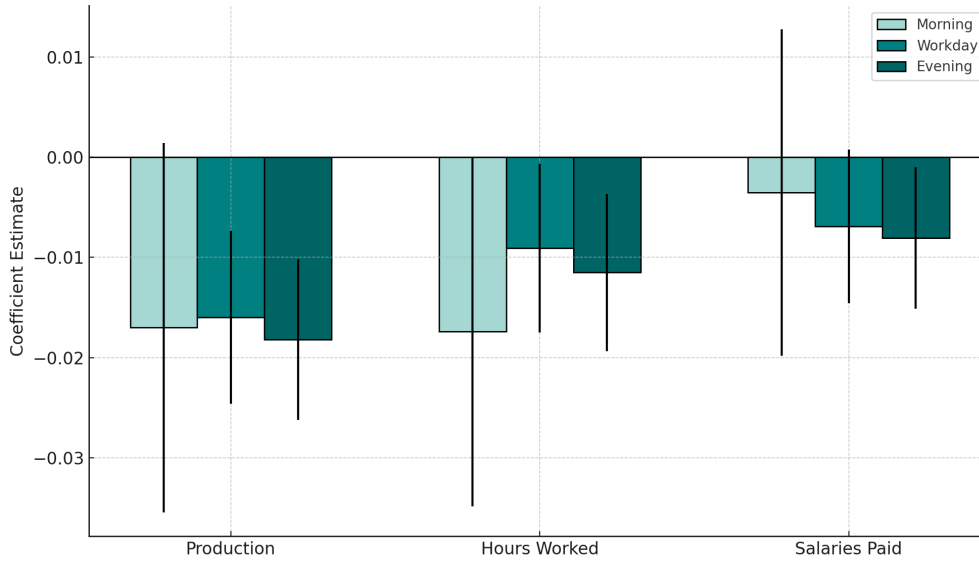
The results considering days above $15 \mu\text{g}/\text{m}^3$ show that an increase by one standard deviation leads to a significant decrease of production by 1.8% and of hours worked by 1.4%. There is no significant effect on salaries, mirroring the main results. An increase of days above the threshold of $25 \mu\text{g}/\text{m}^3$ follows the same pattern, but we find weaker effects, with 0.9% for production and 0.6% on hours, respectively. Considering the difference in standard deviation, these values imply an approximate 0.62% loss of production per day for the $25 \mu\text{g}/\text{m}^3$ threshold, compared to 0.45% per day for the lower threshold as well as 0.42% and 0.35% for hours worked, respectively. This could indicate a non-linearity in effect, similar to what Dechezleprêtre et al. (2019) find. These two results are, however, not statistically

Figure 5: Effect of $PM_{2.5}$ by Weekend and Weekday



The figure shows estimated regression coefficients for separate regressions considering the instrument and air pollution only for the respective time of day. Bars represent 95% confidence intervals. For the underlying regression results, see Table A.1.

Figure 6: Effect of $PM_{2.5}$ by Time of Day



The figure shows estimated regression coefficients for separate regressions considering the instrument and air pollution only for the respective time of day. Bars represent 95% confidence intervals. For the underlying regression results, see Table A.5.

different from each other based on a two-sample t-test for difference in coefficients and assuming independence.

Firm level. Exploring how our plant-level effects scale up to the firm level enables a comparison between our results and firm-level results from the literature, such as by Fu et al. (2021) and by Leroutier and Ollivier (2025), who scale up plant-level pollution to firm-level results. To obtain firm-level results, we aggregate our plant-level air pollution and inversion data based on worker share to the firm level, as we assume that the employees being exposed to air pollution are the driving factor, and use the same regression approach as for our main analysis. Table 4 shows the results.

The full IV regression shows that an increase in $PM_{2.5}$ by one SD decreases production by 1.6%, equal to the plant-level results. Furthermore, both the full and balanced sample results on salaries paid are significant, with -0.7 and -0.6%, respectively. However, the other results differ fundamentally from the plant-level estimates. Most striking are the insignificant zero results for hours worked in both the full and the balanced sample. Furthermore, balanced sample estimates for production are insignificant with a point estimate of -0.6%. These differences indicate that aggregating data at the firm level can lead to biases, which might explain potential differences between our results and those obtained by other authors.

Table 4: Main Regression Results on Firm-Level

	(1)	(2)	(3)	(4)	(5)	(6)
	Production		Hours Worked		Salaries Paid	
	Full	Balanced	Full	Balanced	Full	Balanced
$PM_{2.5}$	-0.016*** (0.004)	-0.006 (0.005)	-0.000 (0.003)	-0.000 (0.003)	-0.007** (0.003)	-0.006* (0.003)
N	546,486	329,491	329,491	329,491	546,476	329,491
R^2	0.001	0.001	0.001	0.001	0.000	0.001
F	12.170	5.770	10.930	10.930	9.320	9.230
rk Wald F	50,346	32,352	32,352	32,352	50,345	32,352
UnderID p	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting $PM_{2.5}$ with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Other air pollutants. While most of the literature focuses on $PM_{2.5}$, the effect observed in our analysis could be driven by other air pollutants potentially correlated with $PM_{2.5}$ and affected by the same instrument. In order to test for this potential issue, we run regressions that additionally control for NO_x , SO_2 and ozone, all of which are known to be harmful

pollutants. The estimates (see Table A.8 in the appendix) are similar to our main results and have the same significance pattern, with significant -1.6% for production, as in our main regression, a slightly lower significant result for hours worked with -1% and an insignificant result for salaries. This indicates that our results are not driven by other air pollutants, in line with other findings (see, e.g., Chang et al., 2016, for a similar result about ozone).

Production per hour. Our focus is on labor productivity in the sense of a labor augmenting factor. Other papers on air pollution impacts have instead considered productivity in the more straightforward sense of production per worker (e.g. Dechezleprêtre and Vienne, 2025) or production/earnings per hour (e.g. Chang et al., 2016). As an additional robustness check and to obtain comparable results, we also ran our regressions with production per hour as the dependent variable. Estimates are shown in Table A.9. While OLS results are significant, the main IV result is insignificant and relatively low, with an estimated -0.4% per SD in $PM_{2.5}$. This might be due to differing productivity effects depending on firm size, since the version with no outliers is highly significant and shows an effect of -0.9% per SD. The results nevertheless have the same sign and a similar magnitude as our main estimates.

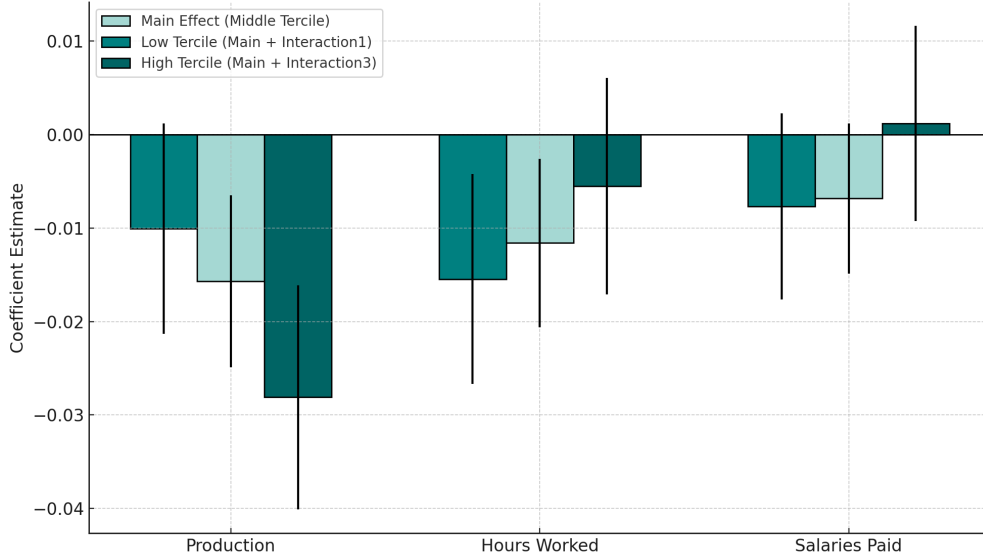
5.3 Effect Heterogeneity

In this subsection, we address potential treatment heterogeneity by focusing on specific dimensions of our data: The level of baseline air pollution, the share of women in a firm’s labor force, firm size, and time. We interact mean $PM_{2.5}$ with tercile dummies for the lowest and highest terciles of these heterogeneity dimensions, with the middle tercile being used as the reference category. Similarly, we also interact our inversion measure with these dummies and use these interactions, as well as the main inversion measure, as instruments. This follows the fully saturated approach with dummy-instrument interactions laid out in Abadie (2003). As we assume control slopes to not differ by treatment group, we do not employ the recently suggested adjustment by Abadie et al. (2024). We show graphs of tercile-specific effects, assuming independence.

Base level pollution. To explore a potential non-linearity in the relationship between air pollution and plant outcomes and differences by ex-ante pollution, we consider pollution level terciles in the year before our analysis as a dimension of heterogeneity. As the results in Figure 7 and Table A.10 show, the production effect for the reference category is in line with our main results, while the effect for the lowest tercile (below $11.5 \mu g/m^3$) is weaker, and the effect for the highest tercile (above $12 \mu g/m^3$) with -2.8% stronger. This indicates the presence of a non-linear overall effect, while the negative impact persists even for areas with the lowest levels of air pollution. For hours worked, the point estimates are

larger in absolute values for areas with lower base-level pollution but the differences are not statistically significant. For salaries, the effect for the high pollution tercile is statistically different from the main effect, effectively offsetting the significant negative effect of 0.7% found for the baseline.

Figure 7: Effect of $PM_{2.5}$ by Base Level Pollution Tercile

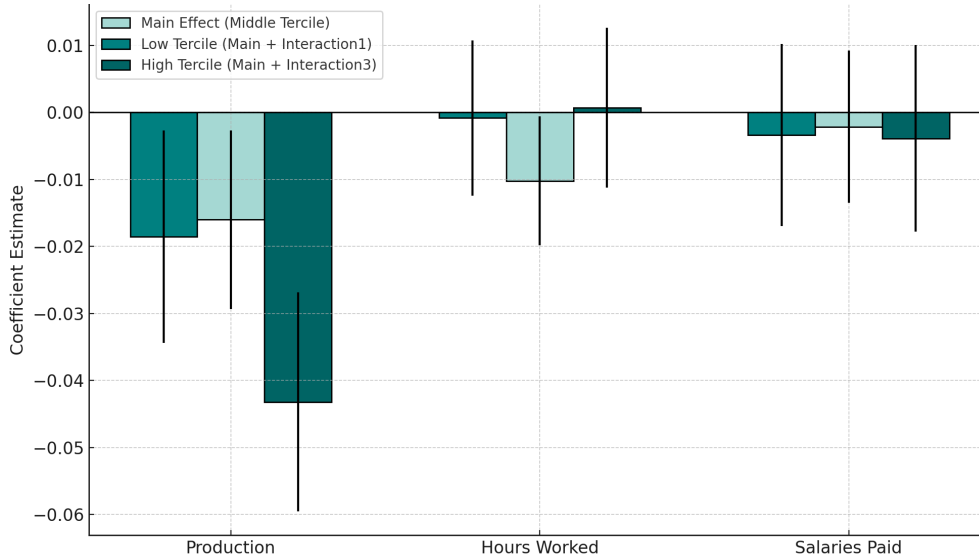


The figure shows estimated effects by tercile as reported in Table A.10. Assuming independence, the estimates are calculated by adding/subtracting the interactions for the highest/lowest tercile to and from the baseline effect for the left-out middle tercile. Bars represent 95% confidence intervals.

Share of female employees. Previous literature has demonstrated that air pollution effects tend to be stronger for women (Han et al., 2023; Montt, 2018; Gu et al., 2020). Figure 8 (and the regression results in Table A.11) confirm these findings for overall production, with a significantly stronger effect for plants with the highest share of female employees (over 29%), while the lowest tercile (below 15%) is not significantly different from the middle tercile with an effect of -1.6%. Note that the sample here is different from our main regression, since we have the female share only for a subsample of plants, which explains why the effects do not line up with the main results. The supposed underlying mechanism is absenteeism, based on the assumption that women are more likely than men to be the main responsible for taking care of children or the elderly, and may therefore miss work when these dependents are sick. However, we do not find that plants with a higher female labor share experience a larger effect on hours worked; in fact, the effect for the decile with the highest labor share shows no reduction in hours worked at all. The results for salaries are not statistically significant. So whereas our production results confirm the literature, the underlying mechanism is unclear. One potential explanation could be that the workers' health insurance covers the costs of

absenteeism due to sick children, which might make it easier for firms to replace absent workers at no extra cost. But we also need to be aware that plants with higher female labor shares might be fundamentally different from other plants, for instance in what and how they produce, potentially driving differences in the effect.

Figure 8: Effect of $PM_{2.5}$ by Female Employee Share Tercile

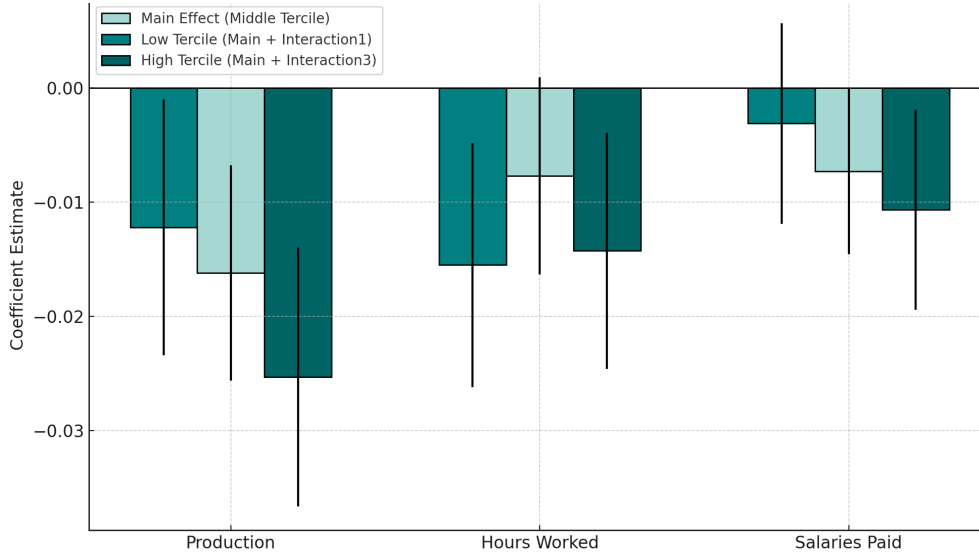


The figure shows estimated effects by tercile as reported in Table A.11. Assuming independence, the estimates are calculated by adding/subtracting the interactions for the highest/lowest tercile to and from the baseline effect for the left-out middle tercile. Bars represent 95% confidence intervals.

Plant size. While some previous studies have found that effects of air pollution can vary by firm size, there is a lack of consensus as well as a generally small empirical basis. We therefore study this question in our setting. The analysis is based on the full sample for each outcome, which limits comparability between the results but enables the largest possible coverage. Results are shown in Figure 9 and Table A.12.

Overall production results confirm Ye et al. (2024), indicating that air pollution effects increase with plant size. The effect for the largest tercile (more than 80 employees) is significantly stronger: it is 0.9 percentage points more negative than the baseline estimate of 1.6%. The results for hours worked show a more nuanced picture, with a significant baseline estimate of -0.8%. Results for the low and high tercile interactions both show an effect that is by -0.8 and -0.7 percentage points significantly stronger than the baseline. For salaries paid, there is a baseline estimate of -0.7%, with the smallest tercile interaction showing an effect that is by 0.4 percentage points significantly weaker than the baseline. This indicates that smaller firms see less of a reduction in salary costs, potentially because they have less flexible pay arrangements, while larger firms see the strongest production decrease.

Figure 9: Effect of PM_{2.5} by Number of Employee Terciles



The figure shows estimated effects by tercile as reported in Table A.12. Assuming independence, the estimates are calculated by adding/subtracting the interactions for the highest/lowest tercile to and from the baseline effect for the left-out middle tercile. Bars represent 95% confidence intervals.

Years. Effects of air pollution might change over time, either because of Germany's decreasing air pollution coupled with some non-linearity of the effect, because of improvements in air pollution protection technology, or for some other reason. To explore the impact across time, we group years into those before 2008, between 2008 and 2014, and those after 2014. As shown in Table A.13, effects for the middle period (which serves at the baseline in this regression) are comparable to the main effects. The earlier or later groups do not differ significantly from these results in any of our regressions, implying that there is no significant difference in the effects over time.

5.4 Robustness

We also implemented a variety of robustness tests, specifically considering alternative standard errors, instrument specifications, and other sources for air pollution data.

Alternative standard errors. Tables A.14 to A.16 show our main results with a range of different standard error configurations to check robustness, namely clustering by unit and year, by municipality, and by state, regular and robust Newey-West HAC SE (Newey and West, 1986), as well as Standard Errors following Thompson (2011).⁵ Our main results stay significant for production and hours worked, and insignificant for salaries.

⁵Two-way clustering by unit and year allows for arbitrary correlation of residuals within both dimensions, while clustering by municipality or state accounts for different aggregation levels. NeweyWest HAC standard errors correct both for serial correlation and heteroskedasticity, while robust NeweyWest SEs additionally

Alternative instruments. While our main instrument, Inversion Strength at 925 hPa, has the strongest first stage out of this group, we also report additional IV specifications in Tables A.17 to A.19. Some specifications include our main instrument, demonstrating that over-identifying restrictions hold. These regressions consider the following instruments: The number of hours with inversions at 925 hPa and the average strength of inversions at 925 hPa as a separate instrument; those and the share of winter inversions; the unweighted number of inversions both at 925 and 850 hPa; the number of inversions on both heights as well as the average strength of inversions across both; and the number and strength of inversions at 925 hPa interacted with base year pollution. The results for production are negative and significant for all specifications, with estimates centered around our main estimates. Results for hours worked are even closer to our main results across all specifications, with negative and significant estimates of about -1%. Findings for salaries range between -0.5% and -0.6% with around half of the models being significant.

Other data sources. Lastly, we present results using alternative satellite-based measures of PM_{2.5} from Van Donkelaar et al. (2021) and Hammer et al. (2020). For these sources, the standard deviations differ from our main source and are around 1.8 $\mu\text{g}/\text{m}^3$ (Hammer et al., 2020; Van Donkelaar et al., 2021). The regression coefficients are shown in Tables A.20-A.21. The analysis based on the Van Donkelaar et al. (2021) data shows a significant effect of -2.3% per 1 SD increase in mean PM_{2.5} air pollution on production, -1.4% on hours worked and an insignificant estimate of -0.8% for salaries. These findings are mirrored almost exactly by the results using data from Hammer et al. (2020), with significant -2.2% on production, -1.4% on hours worked and insignificant -0.8% on salaries. Adjusting for the difference in standard deviation, as main explanatory variables are standardized, both would equal around -1.1% for production, -0.7% for hours worked and insignificant -0.4% for salaries, which are slightly below, but comparable to our main results.

6 Conclusions

We find that an increase in PM_{2.5} air pollution in Germany by one standard deviation (equivalent to 0.9 $\mu\text{g}/\text{m}^3$) decreases production of manufacturing firms by 1% to 1.6%, depending on whether a reduced balanced sample or the full sample, which also includes smaller firms, is considered. The main channel is a reduction in labor productivity, which we calculate to be between 1.9% to 2.9%, but we also observe an increase in pollution-caused absenteeism of 0.6% to 1.1% per standard deviation in air pollution. We observe effects for pollution

adjust for small-sample bias. The standard errors proposed by Thompson (2011) extend corrections to settings with multiple potential clustering dimensions.

during workdays, but not during weekends. The production effect is stronger for plants with a higher share of female workers and for large firms, and it increases with baseline air pollution.

Our results imply that air pollution has considerable impacts on the economy, even in a country like Germany that has average $\text{PM}_{2.5}$ values that are quite low in a global comparison (around $10 \mu\text{g}/\text{m}^3$). We estimate higher impacts on economic production than most of the preceding literature (e.g., Dechezleprêtre et al., 2019; Behrer et al., 2023; Dechezleprêtre and Vienne, 2025; Leroutier and Ollivier, 2025). This could be due to the German setting, such as the fact that air conditioning/filtering systems are rare. We also find somewhat stronger results for absenteeism than previous studies. Yamada and Narita (2025), for instance, find a decrease of 0.5 hours per month per $1 \mu\text{g}/\text{m}^3$, roughly 0.34% considering their sample mean, while we find an effect of above 1.1% per $0.9 \mu\text{g}/\text{m}^3$ in our main specification. The production per hour estimates we provide for comparability and which range between insignificant -0.4% for the main specification and significant -0.9% our model without outliers, are broadly in line with other findings, such as Chang et al. (2016) finding that an increase in $\text{PM}_{2.5}$ by one $\mu\text{g}/\text{m}^3$ leads to a decrease of 0.8% in hourly labor productivity.

In 2018, the manufacturing sector added a value of 682 billion EUR to the German economy (World Bank, 2024). If we assume that overall production effects translate directly and linearly to value added, our results indicate that a reduction of air pollution in Germany by $1 \mu\text{g}/\text{m}^3$ would have led to an increase in value added of roughly 12.1 billion EUR in the manufacturing sector alone, which corresponds to 0.4% of Germany’s 2018 GDP. Considering that the population-weighted $\text{PM}_{2.5}$ levels in Germany decreased by $6.5 \mu\text{g}/\text{m}^3$ between 2010 and 2019 (Umweltbundesamt, 2023), our results imply that the subsequent increase in manufacturing production added roughly 79 billion EUR total to Germany’s GDP over the same period, corresponding to 2.3% of Germany’s 2018 GDP.

There are few estimates of the cost of reducing air pollution. Kunugi et al. (2018) estimate the lowest-cost policy of reducing air pollution in the Tokyo Metropolitan area by $18 \mu\text{g}/\text{m}^3$ to be 143 billion yen. Their estimates translate to a cost of 60 million EUR per $\mu\text{g}/\text{m}^3$ if we assume them to scale linearly. Considering population differences between Germany and Tokyo (approximately 80 million vs approximately 40 million), this translates to a cost of 120 million EUR for Germany. Since we assume that 12 billion EUR could have been gained by a $1 \mu\text{g}/\text{m}^3$ reduction of average air pollution in 2018, the benefits would thus outweigh the costs by around 100-to-1 – only considering gains in the manufacturing sector. A better comparison might be a German policy, the introduction of low emission zones (LEZ). Aydin et al. (2024) estimate a cost of approximately 84 million 2018 EUR and Bos et al. (2025) estimate that introducing LEZs led to a population-weighted reduction in

PM_{2.5} by 0.15 to 0.2 $\mu\text{g}/\text{m}^3$. If we assume that the costs of reducing emissions would be the same in every urban setting, this would result in costs of 2.92 billion EUR if we were trying to achieve a reduction of one $\mu\text{g}/\text{m}^3$ just via LEZ. This implies that the benefit to manufacturing sector’s production alone would outweigh the costs by around 3-to-1 when scaling both costs and manufacturing benefits to the urban population.⁶ Even though these are just rough approximations, both exercises show that reducing emissions, even in the relatively low-emission context of Germany, comes with significant benefits to the economy that are likely to outweigh policy costs.

Our work has some limitations linked to the data we use. Even though production data is available for the large majority of German manufacturing plants, only plants above 20 employees – and for hours worked only above 50 employees – are covered. Since we find that smaller firms may be less affected, it is possible that our results somewhat overstate the overall effect. Furthermore, our economic data is provided at the annual level only, such that we cannot investigate monthly effects. As our results indicate differences between plant- and firm-level results, it would be interesting for future work to expand plant-level analyses, for instance to study effects on other sectors of the economy. It might also be of interest to study countries where air pollution levels are even lower. Lastly, since we were unable to separate overtime from our measure of hours worked, it might be relevant to extend future research into the direction of firms’ coping strategies, looking into the question how firms are willing or able to compensate air pollution related absences.

Our findings imply that the reduction of air pollution should remain a priority, even in countries with relatively low air pollution levels, as there are considerable economic benefits to pollution reduction. Furthermore, since the effects are mainly driven by air pollution during the workweek, our results suggest that firms can benefit by protecting their workers from air pollution in the workplace.

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⁶Assuming that approximately 77% of Germans or approximately 60 million people live in cities, we can scale up the 11.5 million inhabitants of LEZ to the German urban population, resulting in hypothetical costs of 438 million EUR for an average reduction of 0.15 $\mu\text{g}/\text{m}^3$. We can then scale this up to a 1 $\mu\text{g}/\text{m}^3$ reduction, assuming it scales linearly. Assuming the share of manufacturing taking place within cities to be equal to the population share, this would imply a manufacturing sector production value of 525 billion EUR total and a benefit of 9.3 billion EUR.

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Online Appendix

A Additional tables

Table A.1: Regression Results for Week and Weekend

	(1)	(2)	(3)	(4)	(5)	(6)
	Production		Hours Worked		Salaries Paid	
	Weekend	Week	Weekend	Week	Weekend	Week
PM _{2.5}	-0.006 (0.004)	-0.020*** (0.006)	0.003 (0.005)	-0.016*** (0.005)	0.002 (0.004)	-0.010** (0.005)
N	638011	638011	397667	397667	666933	666933
R ²	0.000	0.000	0.000	0.000	0.000	0.000
F	8.300	8.850	8.740	9.240	6.110	6.300
rk Wald F	32039	39084	14192	29094	32804	41169
UnderID p	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.2: Regression Results for Production by Day on Plant-Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
PM _{2.5}	-0.0213*** (0.0050)	-0.0140** (0.0065)	-0.0193*** (0.0048)	-0.0158 (0.016)	0.0209 (0.048)	-0.0116** (0.0059)	-0.000657 (0.0036)
N	638011	638011	638011	638011	638011	638011	638011
R ²	0.000	0.000	0.000	0.000	-0.001	0.000	0.000
F	9.10	8.44	9.00	8.27	8.22	8.41	8.22
rk Wald F	21964	11056	27396	2677	192	13093	38086
UnderID p	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.3: Regression Results for Hours Worked by Day on Plant-Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
PM _{2.5}	-0.0206*** (0.0048)	-0.0137** (0.0058)	-0.0201*** (0.0045)	0.00256 (0.0098)	0.00854 (0.076)	0.00613 (0.0068)	0.000949 (0.0046)
N	397667	397667	397667	397667	397667	397667	397667
R ²	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000
F	9.58	8.98	9.66	8.73	8.72	8.76	8.72
rk Wald F	13577	8399	17322	4291	47	6143	15659
UnderID p	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.4: Regression Results for Salaries by Day on Plant-Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
PM _{2.5}	-0.0140*** (0.0044)	-0.00570 (0.0058)	-0.0102** (0.0043)	-0.000365 (0.014)	0.0148 (0.039)	0.000165 (0.0053)	0.00292 (0.0032)
N	666933	666933	666933	666933	666933	666933	666933
R ²	0.000	0.000	0.000	0.000	-0.001	0.000	0.000
F	6.57	6.14	6.37	6.09	6.10	6.09	6.13
rk Wald F	22798	11603	28366	2822	241	13372	38987
UnderID p	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.5: Regression Results for Time of Day

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Production			Hours Worked			Salaries Paid		
	Morning	Day	Evening	Morning	Day	Evening	Morning	Day	Evening
PM _{2.5}	-0.014 ** (0.006)	-0.019 ** (0.008)	-0.015 * (0.009)	-0.013 ** (0.006)	-0.017 ** (0.008)	-0.016 * (0.008)	-0.009 ** (0.003)	-0.011 *** (0.003)	-0.011 *** (0.003)
N	638011	638011	638011	397667	397667	397667	666933	666933	666933
R ²	0.000	0.000	0.000	0.001	0.001	0.001	0.000	0.000	0.000
F	8.390	8.390	8.390	8.910	8.910	8.910	5.720	5.720	5.720
rk Wald F	18325	18241	18190	13074	13011	12989	61113	61041	61000
UnderID p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.6: Regression Results using Days over the Threshold of 15 $\mu\text{g}/\text{m}^3$

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
Days >15 $\mu\text{g}/\text{m}^3$ PM _{2.5}	-0.018*** (0.005)	-0.014** (0.006)	-0.007 (0.005)
N	638011	397667	666933
R ²	0.000	0.000	0.000
F	8.760	9.000	6.200
rk Wald F	28151	16033	29462
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.7: Regression Results using Days over the Threshold of 25 $\mu g/m^3$

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
Days >25 $\mu g/m^3$ PM _{2.5}	-0.009*** (0.003)	-0.006** (0.003)	-0.004 (0.002)
N	638011	397667	666933
R ²	0.000	0.000	0.000
F	8.770	9.000	6.200
rk Wald F	65755	41654	68680
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.8: Regression Results controlling for Alternative Pollutants

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.016*** (0.005)	-0.010** (0.004)	-0.006 (0.004)
SO ₂	-0.002 (0.006)	-0.012** (0.005)	-0.005 (0.005)
O ₃	0.000 (0.005)	0.005 (0.004)	0.000 (0.004)
N	638011	397667	666933
R ²	0.000	0.001	0.000
F	8.630	8.950	6.210
rk Wald F	29884	23829	31914
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.9: Regressions Production per Hour

	1	2	3	4	5	6
	OLS FE	1st Stage	IV FE	IV No Outliers	IV Balanced	Reduced Form
PM _{2.5}	-0.007*** (0.002)		-0.004 (0.005)	-0.009*** (0.003)	-0.004 (0.005)	
Inv.Str. 925hPa		0.198*** (0.002)				-0.001 (0.001)
N	381614	385719	381614	364438	381614	381614
R ²	0.135	0.924	0.000	0.000	0.000	0.135
F	2.280	8197.070	1.450	3.350	1.450	1.140
rk Wald F			36754.630	34596.620	36754.630	
UnderID p			0.000	0.000	0.000	

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value.

Table A.10: Regression Results by Base Pollution Tercile

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.016*** (0.005)	-0.012** (0.005)	-0.007* (0.004)
PM _{2.5} * Low Tercile	0.006* (0.003)	-0.004 (0.003)	-0.001 (0.003)
PM _{2.5} * High Tercile	-0.012*** (0.004)	0.006 (0.004)	0.008** (0.003)
N	638011	397667	666933
R ²	0.000	0.000	0.000
F	8.710	8.380	5.960
rk Wald F	12994	7860	13865
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value. Tercile cutoffs are $11.5 \mu\text{g}/\text{m}^3$ and $12 \mu\text{g}/\text{m}^3$.

Table A.11: Regression Results by Female Share Tercile

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.016** (0.007)	-0.010** (0.005)	-0.002 (0.006)
PM _{2.5} * Low Tercile	-0.003 (0.004)	0.009*** (0.003)	-0.001 (0.004)
PM _{2.5} * High Tercile	-0.027*** (0.005)	0.011*** (0.004)	-0.002 (0.004)
N	282573	211504	300722
R ²	-0.001	0.000	0.000
F	6.930	6.500	3.370
rk Wald F	8395	6004	8943
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value. Tercile cutoffs are 15% and 29%.

Table A.12: Regression Results by Size Terciles

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.016*** (0.005)	-0.008 * (0.004)	-0.007* (0.004)
PM _{2.5} * Low Tercile	0.004 (0.003)	-0.008** (0.003)	0.004* (0.002)
PM _{2.5} * High Tercile	-0.009*** (0.003)	-0.007** (0.003)	-0.003 (0.003)
N	635471	397180	663446
R ²	0.000	0.000	0.000
F	10.04	8.47	5.56
rk Wald F	18961	9926	19997
UnderID p	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value. Tercile cutoffs are 60 and 80 for production and salaries, and 62 and 130 for hours worked due to the smaller sample.

Table A.13: Regression Results by Year Group

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.017*** (0.003)	-0.010*** (0.003)	-0.008*** (0.003)
PM _{2.5} * Early	0.007 (0.010)	-0.003 (0.009)	0.008 (0.009)
PM _{2.5} * Late	0.015 (0.012)	-0.000 (0.013)	0.008 (0.011)
N	638011	397667	666933
R ²	0.000	0.001	0.000
F	8.760	8.490	5.920
rk Wald F	11164	7157	11609
UnderID p	0.000	0.000	0.000

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value. Years are split in three equal groups, covering years before 2008, 2008-14 and after 2014.

Table A.14: Regression Results for Production on Plant-Level using different Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Cluster BNR-Year	Cluster AGS	Cluster Land	Newey-West	NW Robust	NW Cluster
PM _{2.5}	-0.0158*** (0.0047)	-0.0158*** (0.0049)	-0.0158*** (0.0049)	-0.0158*** (0.0052)	-0.0158*** (0.0052)	-0.0158* (0.0085)
N	638011	638011	638011	638011	638011	638011
R ²	0.000	0.000	0.000	0.000	0.000	0.000
F	8.77	7.96	7.96	7.19	5.58	133.19
rk Wald F	58080	52718	52718	41376	24066	18
UnderID p	0.00	0.00	0.00	0.00	0.00	0.22

Standard errors in parentheses are clustered at the plant level. * p < 0.10, ** p < 0.05, *** p < 0.01. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. (1) Two-way clustering by unit and year, (2) clustering by municipality, (3) clustering by state, (4) Newey-West HAC SE (Bartlett kernel, no clustering), (5) robust Newey-West HAC SE as well as Standard Errors following Thompson (2011). All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value.

Table A.15: Regression Results for Hours on Plant-Level using different Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Cluster BNR-Year	Cluster AGS	Cluster Land	Newey-West	NW Robust	NW Cluster
PM _{2.5}	-0.0109** (0.0046)	-0.0109** (0.0049)	-0.0109** (0.0049)	-0.0109** (0.0050)	-0.0109** (0.0052)	-0.0109* (0.0056)
N	397667	397667	397667	397667	397667	397667
R ²	0.001	0.001	0.001	0.001	0.001	0.001
Adj. R ²	0.000	-0.137	-0.137	-0.137	-0.137	0.000
F	9.00	7.91	7.91	7.37	7.43	57.96
rk Wald F	38959	34238	34238	27215	13732	25
UnderID p	0.00	0.00	0.00	0.00	0.00	0.20

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. (1) Two-way clustering by unit and year, (2) clustering by municipality, (3) clustering by state, (4) Newey-West HAC SE (Bartlett kernel, no clustering), (5) robust Newey-West HAC SE as well as Standard Errors following Thompson (2011). All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value.

Table A.16: Regression Results for Salaries on Plant-Level using different Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Cluster BNR-Year	Cluster AGS	Cluster Land	Newey-West	NW Robust	NW Cluster
PM _{2.5}	-0.00614 (0.0042)	-0.00614 (0.0044)	-0.00614 (0.0044)	-0.00614 (0.0046)	-0.00614 (0.0047)	-0.00614 (0.0044)
N	666933	666933	666933	666933	666933	666933
R ²	0.000	0.000	0.000	0.000	0.000	0.000
F	6.20	5.62	5.62	5.01	5.54	45.22
rk Wald F	61121	55460	55460	43538	25219	19
UnderID p	0.00	0.00	0.00	0.00	0.00	0.22

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. (1) Two-way clustering by unit and year, (2) clustering by municipality, (3) clustering by state, (4) Newey-West HAC SE (Bartlett kernel, no clustering), (5) robust Newey-West HAC SE as well as Standard Errors following Thompson (2011). All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the Kleibergen-Paap LM p-value.

Table A.17: Regression Results for Production on Plant-Level using different IV Specifications

	(1)	(2)	(3)	(4)	(5)
	Inv925 Both	Inv925 Both + Winter	InvCC	InvCC Both	Interact Base
PM _{2.5}	-0.011*** (0.004)	-0.010*** (0.004)	-0.010** (0.004)	-0.009** (0.004)	-0.019*** (0.005)
N	638011	638011	638011	638011	638011
r^2	0.000	0.000	0.000	0.000	0.000
F	8.570	8.560	8.540	8.540	8.960
rk Wald F	43807	29213	49600	33074	28388
UnderID p	0.000	0.000	0.000	0.000	0.000
OverID p	0.370	0.070	0.390	0.460	0.230

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. Specifications are: (1) Hours with inversions at 925hPa and average strength of inversions at 925hPa; (2) number of inversions at 925hPa, the average strength as well as the share of winter inversions at 925hPa; (3) number of inversions both at 925 and 850 hPa; (4) number of inversions on both heights as well as the average strength of inversions across both; (5) number and strength of inversions at 925 hPa interacted with base year pollution. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value, OverID p to the Hansen J p-value for overidentifying restrictions.

Table A.18: Regression Results for Hours on Plant-Level using different IV Specifications

	(1)	(2)	(3)	(4)	(5)
	Inv925 Both	Inv925 Both + Winter	InvCC	InvCC Both	Interact Base
PM _{2.5}	-0.010*** (0.004)	-0.010*** (0.004)	-0.010*** (0.004)	-0.010*** (0.004)	-0.010** (0.004)
N	397667	397667	397667	397667	397667
R^2	0.001	0.001	0.001	0.001	0.001
F	9.050	9.050	9.080	9.080	8.960
rk Wald F	27124	18091	29351	19572	20205
UnderID p	0.000	0.000	0.000	0.000	0.000
OverID p	0.770	0.950	0.900	0.920	0.050

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. Specifications are: (1) Hours with inversions at 925hPa and average strength of inversions at 925hPa; (2) number of inversions at 925hPa, the average strength as well as the share of winter inversions at 925hPa; (3) number of inversions both at 925 and 850 hPa; (4) number of inversions on both heights as well as the average strength of inversions across both; (5) number and strength of inversions at 925 hPa interacted with base year pollution. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value, OverID p to the Hansen J p-value for overidentifying restrictions.

Table A.19: Regression Results for Salaries on Plant-Level using different IV Specifications

	(1)	(2)	(3)	(4)	(5)
	Inv925 Both	Inv925 Both + Winter	InvCC	InvCC Both	Interact Base
PM _{2.5}	-0.006*	-0.006*	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
N	666933	666933	666933	666933	666933
R ²	0.000	0.000	0.000	0.000	0.000
F	6.240	6.240	6.200	6.200	6.160
rk Wald F	45994	30672	52006	34678	29969
UnderID p	0.000	0.000	0.000	0.000	0.000
OverID p	0.300	0.020	0.270	0.450	0.160

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. Specifications are: (1) Hours with inversions at 925hPa and average strength of inversions at 925hPa; (2) number of inversions at 925hPa, the average strength as well as the share of winter inversions at 925hPa; (3) number of inversions both at 925 and 850 hPa; (4) number of inversions on both heights as well as the average strength of inversions across both; (5) number and strength of inversions at 925 hPa interacted with base year pollution. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value, OverID p to the Hansen J p-value for overidentifying restrictions.

Table A.20: Regression Results using Hammer et al. (2020) Data

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.0216***	-0.0135**	-0.00833
	(0.0064)	(0.0057)	(0.0057)
N	638011	397667	666933
R ²	-0.000	0.000	0.000
F	8.76	8.99	6.20
rk Wald F	30549	24384	32561
UnderID p	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.

Table A.21: Regression Results using Van Donkelaar et al. (2021) Data

	(1)	(2)	(3)
	Production	Hours Worked	Salaries Paid
PM _{2.5}	-0.0226*** (0.0067)	-0.0141** (0.0059)	-0.00894 (0.0059)
N	637307	397217	666199
R ²	-0.000	0.000	0.000
Adj. R ²	-0.000	0.000	0.000
F	8.63	8.95	6.21
rk Wald F	29884	23829	31914
UnderID p	0.00	0.00	0.00

Standard errors in parentheses are clustered at the plant level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported are IV regressions instrumenting PM_{2.5} with inversion strength at 925 hPa. All regressions control for precipitation, humidity, air pressure, cloud cover, summer days, frost days as well as year and unit FE. rk Wald F refers to the Kleibergen-Paap rk Wald F statistic, UnderID p to the KleibergenPaap LM p-value.