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The economic cost of air pollution: Evidence from Europe

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Abstract/Résumé

The economic cost of air pollution: Evidence from Europe

This study provides the first evidence that air pollution causes economy-wide reductions in market economic activity based on data for Europe. The analysis combines satellite-based measures of air pollution with statistics on regional economic activity at the NUTS-3 level throughout the European Union over the period 2000-15. An instrumental variables approach based on thermal inversions is used to identify the causal impact of air pollution on economic activity. The estimates show that a 1µg/m^3 increase in $PM_{2.5}$ concentration (or a 10% increase at the sample mean) causes a 0.8% reduction in real GDP that same year. Ninety-five per cent of this impact is due to reductions in output per worker, which can occur through greater absenteeism at work or reduced labour productivity. Therefore, the results suggest that public policies to reduce air pollution may contribute positively to economic growth. Indeed, the large economic benefits from pollution reduction uncovered in the study compare with relatively small abatement costs. Thus, more stringent air quality regulations could be warranted based solely on economic grounds, even ignoring the large benefits in terms of avoided mortality.

JEL codes: J24, O13, Q53, Q51, R11

Keywords: air pollution, economic output, thermal inversions, instrumental variables

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Le coût économique de la pollution de l'air: une analyse empirique sur données européennes

Cette étude montre de manière empirique à partir de données européennes que la pollution de l'air a des effets négatifs directs sur la croissance économique. Elle combine des mesures de pollution atmosphérique obtenues par satellite avec des données sur le niveau de l'activité économique régionale au niveau NUTS-3 pour toute l'Union Européenne sur la période 2000-15. L'utilisation de variables instrumentales basées sur les inversions thermiques dans l'atmosphère permet d'établir l'effet causal de la pollution de l'air sur l'activité économique. Les résultats montrent qu'une augmentation de la concentration de particules fines (PM2,5) de 1µg/m^3 (correspondant à une augmentation d'environ 10% à la moyenne de l'échantillon) entraîne une réduction du Produit Intérieur Brut de 0.8% la même année. Quatre-vingt-quinze pour cent de cet impact provient d'une diminution de la production par travailleur, qui peut émaner d'une augmentation de l'absentéisme ou d'une baisse de la productivité au travail. Par conséquent, les résultats de cette étude suggèrent que les politiques publiques visant à réduire la pollution de l'air peuvent contribuer positivement à la croissance économique. En effet, les bénéfices économiques considérables liés à la réduction de la pollution atmosphérique établis par cette analyse dépassent largement les coûts d'abattement, de telle sorte que des règlementations plus sévères sur la qualité de l'air peuvent être justifiées pour des motifs purement économiques, même sans prendre en compte leurs bénéfices bien connus en termes de santé publique.

Classification JEL : J24, O13, Q53, Q51, R11

Mots clés : pollution atmosphérique, production, inversions thermiques, variables instrumentales

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The economic cost of air pollution: Evidence from Europe

By Antoine Dechezleprêtre, Nicholas Rivers and Balazs Stadler[1]

Executive summary

It is widely recognised that air pollution is a major threat to human health, causing 7 million deaths annually (one in eight deaths globally). In addition to these mortality effects, a series of recent empirical studies at the micro-level suggest that air pollution also has large negative impacts on labour productivity because it induces absenteeism at work and reduces individuals' cognitive and physical capabilities.

In this paper, we provide empirical evidence that these effects translate into significant reductions in economic output at the aggregate level. Our dataset combines satellite-based measures of PM2.5 concentration – the pollutant with the largest estimated impacts on mortality and health outcomes, used as an indicator of general exposure to air pollution by the World Health Organization – with statistics on gross domestic product for all 1 342 NUTS-3 regions across the European Union over the 2000-15 period. We identify the causal impact of air pollution on economic activity using an instrumental variables approach based on within-region random fluctuations in thermal inversions.

The study shows that air pollution substantially affects economic activity. A 1μg/m^3 increase in fine particulates concentration causes a 0.8% reduction in real GDP per capita that same year (put differently, reducing PM2.5 concentration by 1μg/m^3 boosts GDP by 0.8%). The impact stands between 0.5% and 1.5% depending on specifications, but is robust to multiple sensitivity checks. To put things in perspective, pollution decreased by 0.2μg/m^3 per year on average across Europe between 2000 and 2015, so the typical annual reduction in pollution boosts regional GDP by 0.16%. As a matter of comparison, regional GDP (at constant prices) grew by 1% per year on average over the period, so reductions in air pollution could explain up to 15% of recent GDP growth in Europe.

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Executive summary (*cont.*)

There are two major policy implications from these findings.

The first is that more stringent air quality regulations could be warranted based solely on economic grounds. This is because the large economic benefits from pollution reduction are greater than previously thought and compare with relatively small abatement costs: for example, reducing emissions of fine particulates by 25% across Europe would cost EUR 1.2 billion annually according to the European Commission, but the economic benefits from such emissions reductions would be at least two orders of magnitude greater. Consequently, such a reduction in pollution would easily pass a cost-benefit test, even ignoring the large benefits in terms of avoided mortality.

Secondly, air pollution control policies may contribute positively to economic growth, reinforcing the case for integrating green considerations into mainstream economic policy-making. Simulations suggest that reaching the air quality targets required by the European Commission Ambient Air Quality Directives for the period 2010-20 would increase European GDP by 1.25%, with the most polluted countries experiencing GDP growth of up to 3%. Since Eastern European countries face higher pollution levels on average, air pollution control policies could significantly contribute to economic convergence between Eastern and Western Europe, and could be seen as useful complements to structural policies aiming at fostering economic growth.

1. Introduction

1. Air pollution represents a major threat to human health in the 21st century. The World Health Organisation estimates that only 1 in 10 people globally live in areas where air pollution is below recommended levels and that air pollution is responsible for 7 million deaths a year – one in eight deaths globally. Air pollution dominates all other major avoidable causes of death including tobacco smoking, alcohol use, road accidents and transmissible diseases such as AIDS, malaria, and tuberculosis. Since air pollution continues to rise at an alarming rate worldwide, especially in low- and middle-income countries, these numbers may grow much larger in the years to come (OECD, 2016).

2. The consequences of air pollution on human health have led to the introduction of increasingly stringent environmental regulations around the world (Botta and Koźluk, 2014), but controversy remains over their appropriate stringency level. Imposing environmental regulations is typically seen as a trade-off between generating benefits to health and imposing costs on the economy, as resources are redirected away from productive activities towards pollution control activities. Therefore, this debate is often framed in terms of "jobs versus the environment" (Morgenstern, Pizer, and Shih, 2002). However, this ignores that health benefits can lead to improved productivity, which can itself translate into greater economic output.

3. The objective of this paper is to inform this debate by estimating the causal impact of air pollution on economic activity, using data from across Europe. The results show that higher levels of air pollution, as measured by $PM_{2.5}$ concentration (the pollutant with by far the largest estimated impacts on mortality and health outcomes), exert a substantial direct burden on the economy by reducing output per worker. This implies that reducing air pollution could yield large economic dividends in addition to the well-established health

benefits, and suggests that prior estimates of the benefits of pollution reduction are substantially too low.

4. In cost-benefit analyses of air pollution control policies, the benefits are typically vastly dominated by non-market impacts such as avoided deaths. In contrast, market benefits – such as absenteeism at work – appear of second order importance in these evaluations. For example, the US Environmental Protection Agency estimates that the benefits of the Clean Air Act Amendments over the period 1990-2020 amount to USD 12 trillion (in 2006 USD), with 85% of these benefits attributable to reductions in premature mortality (US EPA, 2011). Similarly, recent analysis by the OECD estimates that the total annual market costs of outdoor air pollution (including reduced agricultural yields, absenteeism at work and health expenditures) amount to 0.3% of global GDP in 2015 while the welfare costs from non-market impacts represent 6% of total income (OECD, 2016).

5. However, poor air quality may cause direct reductions in economic activity because it negatively impacts cognitive or physical ability (for a summary, see Graff Zivin and Neidell, 2018). This literature – which is reviewed in detail in the following section and further in Annex A – mostly focuses on observing the changes in individual productivity caused by concurrent exposure to poor air quality. For example, air pollution has been shown to decrease workers' productivity at a large farm in California (Graff-Zivin and Neidell, 2012), at a garment manufacturing facility in India (Adhvaryu et al., 2014) or at a Chinese call centre (Chang et al., 2016). There is also evidence that pollution affects productivity in high-skill tasks, such as student performance in standardized high-school examinations (Ebenstein et al., 2016) or investors' performance at the New York Stock Exchange (Heyes et al., 2016). Most recently, a large-scale study using data on the near-universe of manufacturing plants in China found evidence that a 1$\mu g/m^3$ increase in average annual $PM_{2.5}$ concentration (up from a mean of 53 $\mu g/m^3$) reduces workers' productivity (value added per worker) by 1.1% (Fu et al., 2017).

6. Taken together, these studies suggest that air pollution negatively impacts productivity, but they focus on idiosyncratic groups (e.g. box packers, stock traders) or on non-OECD countries with high pollution levels (China, India). In this paper, we advance on this literature by providing the first estimate of the causal impact of air pollution (measured by $PM_{2.5}$ concentration) on aggregate economic activity in a developed country context, using regional data from Europe for the period 2000-15. We focus on the relationship between annual pollution and economic output, for the population at large, and thus get around both the concern about idiosyncratic populations as well as potential productivity displacement effects within a year and factor reallocation across firms. Our study is based on data from highly disaggregated European administrative regions (NUTS3 regions, similar to US counties) between 2000 and 2015, and thus reflects the impact of pollution on developed countries in a contemporaneous period.

7. Estimating the causal effect of air pollution on economic outcomes at an aggregate level is challenging because of the potential for reverse causality. Not only might air pollution impact economic output and productivity (the effects we seek to measure), but economic activity clearly also affects pollution emissions through a number of potential channels. To circumvent this problem, we adopt an instrumental variables strategy, in which we use thermal inversions as an instrument, which generates quasi-random variation in pollution. Thermal inversions strongly predict pollution, are not themselves caused by economic activity or pollution, and do not affect economic outcomes (conditional on weather) except through their effect on pollution.

8. The results show that air pollution adversely affects economic activity substantially: a 1µg/m^3 increase in the average annual concentration of $PM_{2.5}$ – the mean concentration in the sample period being 15µg/m^3 – causes a short-run reduction in economic activity, as measured by real gross domestic product per capita, of between 0.5% and 1.5% depending on the specification, with 0.8% the central estimate. This implies that a 10% reduction in $PM_{2.5}$ average concentration across Europe would increase European GDP by around EUR 100-200 billion. On a per capita basis, this works out to EUR 200-400 per person per year. The impact of high pollution levels is heterogeneous across sectors, with the agriculture and the construction sectors being the most severely affected, but affects both rural and urban areas.

9. The magnitude of these findings is large but are in line with other recent empirical analyses, in particular Fu et al. (2017). To put things in perspective, consider that pollution decreased by 0.2µg/m^3 per year on average across NUTS-3 regions between 2000 and 2015, so the typical annual reduction in pollution boosts regional GDP by 0.16%. As a matter of comparison, regional GDP (at constant prices) grew by 1% per year on average over the period, so reductions in air pollution may explain a significant proportion of recent GDP growth in Europe.

10. These findings can inform ex-ante cost-benefit evaluations of air pollution reduction policies. On the benefits side, a back-of-the-envelope calculation suggests that the market benefits of reducing air pollution uncovered in this study are of similar magnitude to the widely recognized non-market benefits from reduced mortality. This compares with relatively small abatement costs: a recent assessment by the European Commission of the cost of reducing $PM_{2.5}$ emissions by 25% in the European Union would be EUR 1.2 billion annually. Our estimates suggest that the economic benefits from such emissions reductions would be unquestionably greater than these costs and – if they translate linearly into reductions in concentration of similar magnitude –around 200 times greater. Therefore, stronger air quality regulations could be warranted based on their previously underestimated economic benefits.

11. Simulations based on our model show that the improvement in air quality between 2010 and 2020 required by the European Commission Ambient Air Quality Directives would increase European GDP by 1.25%, with some countries experiencing GDP growth of up to 3%. For countries which, in 2018, have not yet met their target, the further potential GDP gain amounts to 1% on average, and up to 3% for the more polluted countries. Therefore, environmental policies may have contributed positively to economic growth in Europe in the recent period, and could further contribute to growth in the near future, as well as to the economic convergence between Western and Eastern European regions.

12. The rest of the paper is organized as follows. Section 2 provides the background on the potential effects of pollution on economic outcomes based on a review of the epidemiological and economic literature. Section 3 describes our approach to estimating the causal effect of pollution on economic activity, including a discussion of our instrumental variable approach. Section 4 introduces the data. Section 5 provides the main results of our empirical analysis. Section 6 discusses the implications of our results, including by comparing our results to other studies, comparing the economic benefits of pollution reduction estimated in this study with estimates of mortality and morbidity benefits used in regulatory impact assessments, and by comparing our estimates of the benefits of pollution reduction to estimates of the cost of pollution reduction. Finally, Section 7 concludes.

2. Background

2.1. From air pollution to economic activity: The channels

13. Theoretically, air pollution can affect economic output through four channels:

- By affecting the size of the working population (through deaths and migration).
- By reducing the amount of hours worked per worker, if they are sick and cannot work (or have to attend for a sick relative).
- By reducing workers' productivity, conditional on being at work.
- By affecting the quality of natural capital, which is an input into production in particular in the agriculture sector.[2]

14. This simple conceptual framework illustrates the mechanisms through which pollution can impact economic output. It is used to show how we would measure the impacts of pollution on total economic output and to motivate the empirical analysis that follows. A more formal presentation of this framework is presented in **Error! Reference source not found.**.

15. The literature suggests that pollution could reduce economic output through all of the channels identified in this simple framework.

Box 1. Theoretical framework

A representative firm in a closed economy has output given by $Y = Y(K, L, P)$, where Y is economic output, K is capital input, L is effective labor input, and P is pollution. We define y as per capita economic output, such that $Y = Ny$, where N is the population. Each of the N representative households has an endowment of time, and uses its income to finance consumption of the produced good. The total time endowment (t) of each household is specified as $t = h + s(P)$, where h is labor and where we use $s(P)$ to capture time periods in which the household is sick, and cannot work. Because the focus of this paper is not on optimal regulation of pollution, in this simple framework, we maintain pollution as an exogenous variable (see Graff Zivin and Neidell, 2013, for a similar model in which pollution is treated as exogenous). The effective labour force available for work is $L = N(P)\varphi(P)h$, where $\varphi(P)$ reflects the impact of pollution on worker productivity, conditional on not being sick, and where we model the total population as a function of the level of pollution, to capture the idea that pollution can affect births, deaths, and migration. Given these assumptions, total economic output is given by:

$$Y = Y\left(K, N(P)\varphi(P)\left[t - s(P)\right], P\right)$$

[2] For simplicity, we do not consider here the dynamics of capital accumulation, and thus ignore impacts of pollution on the capital stock.

Box 1. Theoretical framework *(cont.)*

The impact of pollution on economic output is then given by:

$$\frac{d\log Y}{dP} = \psi\left[\frac{\partial \log N}{\partial P} - \theta\frac{\partial \log s}{\partial P} + \frac{\partial \log \phi}{\partial P}\right] + \frac{\partial \log Y}{\partial P} \quad (1)$$

where ψ is the elasticity of output with respect to effective labor and $\theta = \frac{s}{t-s}$ is the benchmark ratio of sickness to labor supply.

In square brackets, the first term is the impact of pollution on total economic output as a result of changes in population. The second term is the impact of pollution on output as a result of changes in the number of hours worked, conditional on population. The third term is the effect of pollution on the productivity of the labour force. Finally, the last term on the right-hand side (outside of the square brackets) captures the potential that air pollution directly affects economic output.

In the empirical analysis that follows, we estimate the sign and magnitude of $\frac{d\log Y}{d\,P}$, $\frac{\mathrm{d}\ln(Y/\text{Population})}{\mathrm{d}P}$ and $\frac{\mathrm{d}\ln(Y/\text{Working Population})}{\mathrm{d}P}$, thus focusing on the changes in total economic output, per capita economic output and economic output per worker (through absenteeism and productivity, which we lack direct data on) as a result of changes in pollution.

2.2. What do we know from micro studies?

16. A synthetic review of the literature on the four channels identified above is provided below, but a more systematic review of the literature is available in Annex A.

(1) *Pollution and population.* The burden that air pollution imposes on human health is well recognized (Graff Zivin and Neidell, 2013). Large cohort-based studies conducted by epidemiologists have provided evidence since at least 25 years ago that pollution by small airborne particles ($PM_{2.5}$, particulate matter less than 2.5 microns in diameter) increases the rate of death, especially through increases in respiratory and heart diseases (Dockery et al., 1993; Pope et al., 2002). A substantial literature also finds evidence that pollution impacts infant mortality and birth outcomes (Chay and Greenstone, 2003; Currie and Neidell, 2005). Recent research also suggests that air pollution impacts migration: for example, Chen et al. (2017) find great movement between provinces in China to avoid air pollution. Taken together, these studies suggest that air pollution likely reduces population in a region, by increasing deaths, reducing live births, and increasing net out-migration.

(2) *Pollution and absenteeism.* In addition to its effect on overall population, pollution has been found to affect sickness, and as a result, absenteeism. Earlier studies focused on school absenteeism (Ransom and Pope III, 1992; Currie et al., 2009), but more recent studies address absenteeism from work (e.g. Holub et al., 2016; Hanna and Oliva, 2015; Aragon et al., 2017). Interestingly, Aragon et al. (2017) finds that a key factor in explaining absenteeism from work, especially at moderate pollution levels, is the presence of dependents in the household (since, if a child is sick, a parent may have to stay home). Thus there may be a link between the school and work absenteeism outcomes.

(3) *Pollution and productivity.* In addition to causing substantial ill-health and mortality, air pollution also impairs cognitive and physical function. Again $PM_{2.5}$ is of particular concern. When this pollutant is inhaled, the particles can enter deep into the lung and pass into the bloodstream, where they can affect the heart and brain function (Calderon-Garciduenas et al., 2014; Du et al., 2016; Ranft et al., 2009). Because pollution affects physical and cognitive function, there is a clear pathway through which it can impact workplace productivity. A number of studies have shown that elevated pollution causes decreases in productivity, focusing on groups of individuals for which productivity is directly observable and for whom tasks cannot easily be delayed or shifted in location. For example, air pollution has been shown to decrease the daily number of pieces harvested by workers at a large farm in California (Graff-Zivin and Neidell, 2012), the number of garments sewn per hour at a garment manufacturing facility in India (Adhvaryu et al., 2014), the number of boxes packed at an indoor facility (Chang et al., 2016b). Chang et al. (2016a) show that the effect is not limited to physical workers: air pollution also affects the number of calls handled by workers at a Chinese call centre. There is also evidence that pollution affects productivity in high-skill tasks, such as student performance in standardized high-school examinations (Ebenstein et al., 2016) or investors performance at the New York Stock Exchange (Heyes et al., 2016). Most recently, a large-scale study using data on the near-universe of manufacturing plants in China found evidence that a $1\mu g/m^3$ increase in average annual $PM_{2.5}$ concentration reduces a plant's productivity by 1.1%.

(4) *Pollution and natural resources productivity.* In addition to impacts of pollution that are mediated through the labour market, air pollution may also have a direct impact on output, in particular in the agricultural or forestry sectors, where air pollution has the potential to damage crops or trees and thus cause reductions in yield. A number of papers find that agricultural output is impacted by ambient pollution (e.g. Chameides et al., 1999; Van Dingenen et al., 2009; Avnery et al., 2011). Outside of the agricultural sectors, Li et al (2017) find that $PM_{2.5}$ pollution in China causes large losses in solar photovoltaic output (by 20% on an annual average basis in Eastern China) as it reduces direct radiation reaching solar panels.

17. These recent results, based on study populations around the world, suggest that air pollution affects population health and size, absenteeism, on-the-job productivity (of both low-skill and high-skill workers), and has direct impacts on output in the agricultural sector through reductions in crop yields. Our aim in this paper is to tie these results together by examining overall impacts on economic performance due to high levels of air pollution. It is important to acknowledge that the analysis is not able to separately assess each of the channels highlighted in the framework due to data restrictions.

3. Estimating the macroeconomic effects of air pollution

3.1. Econometric model

18. Consider a basic equation characterising the relationship between economic output and pollution concentration in region *i* in year *t*:

$$\ln Y_{it} = \beta_1 P_{it} + \beta_2 f(W_{it}) + \eta_i + \gamma_{ct} + \varepsilon_{it} \quad (2)$$

where Y_{it} is a variable measuring economic output (GDP per capita, GDP, or gross value-added by sector), P_{it} is the average (population-weighted) $PM_{2.5}$ pollution concentration in region i in year t, $f(W_{it})$ is a flexible function that captures how economic output may be affected by weather (temperature, precipitation, humidity, atmospheric pressure, wind speed etc.), η_i are region fixed effects which capture any time-invariant differences between regions, such as differences in geography, γ_{ct} are country-year fixed effects which account for unobserved time-varying shocks which might be correlated with both economic activity and pollution across regions within each country, and ε_{it} is a random disturbance term.

19. To sweep out the region fixed effects and ensure that any persistent differences between regions, such as due to differences in geography, do not contribute to identification of the effect, and to address non-stationarity in the left hand-side variable, we estimate Equation (2) in first differences:[3]

$$\Delta \ln Y_{it} = \beta_1 \Delta P_{it} + \beta_2 \Delta f(W_{it}) + \Delta \gamma_{ct} + \Delta \varepsilon_{it} \tag{3}$$

20. The first-differences specification models the *levels* of GDP (or GDP per capita), not the impact on growth rates, just like the fixed effects estimator. Therefore, the coefficient β_1 can be interpreted as the contemporaneous growth rate of GDP stemming from a one unit increase in the pollution concentration.[4] To estimate the impact on growth rates, one would need to difference *only* the left hand side variable. The interpretation of the coefficient would be different, though, and focused on the long-run impact on growth rather than the contemporaneous impact on GDP.

21. Our objective is to capture the causal effect of pollution on economic activity. This is not straightforward, because reverse causality is likely a major feature in this relationship. On the one hand, high levels of air pollution might increase absenteeism, mortality, and morbidity, and reduce workplace productivity, all of which contribute to reductions in overall economic activity, as in Equation (1). This is the effect we seek to investigate. However, on the other hand, changes in economic activity affect air pollution, through changes in emissions due to technology, scale, preferences, trade, or other determinants. As a consequence, a simple regression of economic outcomes on pollution, even controlling for other variables, will confound these two effects, and yield uninformative estimates of the effect of pollution on economic activity. In order to overcome the challenge associated with reverse causality, we require one or more variables that affect pollution exogenously, and whose only effect on economic activity occurs via their effect on

[3] Note that we run a first-differenced regression, which means that we subtract year $t-1$ variables from year t variables and run the regression using these differenced variables. This approach absorbs region fixed effects (they are not different from one period to another, by definition, so they disappear upon differencing), so they are implicitly in the regression. This method is very similar to the fixed effects model (Equation (2)), which is implemented by demeaning each variable (i.e. subtracting average values of variables from across all time periods from the current realization) and also absorbs region fixed effects which are constant across time. As noted by Wooldridge (2009), when $T = 2$, the two approaches are exactly identical. For $T > 2$, the two approaches are both unbiased and consistent provided the error term is i.i.d. It is unlikely that this is the case with our data as GDP is non-stationary. By taking first differences, we obtain a stationary left-hand side variable, which ensures that the estimator is unbiased. For this reason, the literature using GDP as a left-hand side variable almost always uses a differencing approach – as we do here.

[4] $\Delta \ln Y_t = \ln Y_{t+1} - \ln Y_t = \ln \frac{Y_{t+1}}{Y_t} \approx \frac{Y_{t+1}-Y_t}{Y_t}$ for small ΔY_t. Thus, if $\Delta P_t = 1$, then $\frac{Y_{t+1}-Y_t}{Y_t} = \beta_1$.

pollution. We adopt thermal inversions as an instrumental variable and carry out a two-stage estimation, in which we predict pollution in the first stage, based on observed prevalence of thermal inversions, and in the second stage, estimate the effect of our predicted pollution measure on economic output. We explain the relevance of the instrument in the next sub-section.

22. The first stage of the model can be written as:

$$\Delta \ln P_{it} = \alpha_1 \Delta TI_{it} + \alpha_2 \Delta f\,(W_{it}) + \Delta\lambda_{ct} + \pi_{it} \quad \textbf{(4)}$$

where TI_{it} is a measure of the frequency and strength of thermal inversions in region i in year t, W_{it} is a set of weather controls, λ_{ct} are country-year fixed effects and π_{it} is a disturbance term.

23. We then estimate the effect of our predicted pollution measure on economic output:[5]

$$\Delta \ln Y_{it} = \beta_1 \Delta \widehat{\ln \mathrm{P}}_{it} + \beta_2\, \Delta f\,(W_{it}) + \Delta\gamma_{ct} + \nu_{it} \quad \textbf{(5)}$$

where ν_{it} is a random disturbance.

24. Both regressions are estimated in first differences, which implies that identification of the impact of pollution on economic activity is based on *within-region* differences in pollution. The regression equations also include country-year fixed effects (λ_{ct} and γ_{ct} respectively), to account for changes in economic activity and pollution that are common across regions within each country, such as the 2008-09 economic downturn which differently affected European countries.

25. It is important to note that the instrumental variable approach to estimating the effect of air pollution on economic activity also addresses the other two main sources of endogeneity, namely measurement error in air pollution – a feature of all studies on this topic (Graff Zivin and Neidell, 2013) – and omitted variables. In an Ordinary Least Square framework, any omitted variables that are correlated with both air pollution and economic activity would lead to biased estimates, and it is easy to think of such omitted variables, such as technological change, which is likely to affect both polluting emissions and economic growth. However, for us to be concerned about omitted variables in our instrumental variable setting, these would need to be correlated both with within-region yearly changes in economic activity and with within-region year-to-year variation in thermal inversions. It is therefore difficult to think what the omitted variables in this dimension might be, in particular since we include a full range of country-year fixed effects.

3.2. Instrumental variables

26. Our 2-stage approach to estimating the effect of air pollution on economic activity requires instrumental variables that (1) affect pollution (i.e. are relevant instruments); (2) are not caused by pollution or economic activity (i.e. are exogenous and thus as good as randomly assigned); and (3) only affect the dependent variable through their effect on air

[5] Note that we can directly estimate the reduced form equation:

$$\Delta \ln Y_{it} = \beta_1\, \Delta TI_{it} + \beta_2\, f\,(\Delta W_{it}) + \kappa_t + \varphi_{it}$$

which recovers the impact of our instrumental variables directly on economic activity.

pollution, the endogenous variable (i.e. satisfy the exclusion restriction). Thermal inversions satisfy these requirements and are used in the analysis (see Box 2 for details).

3.3. Weather controls

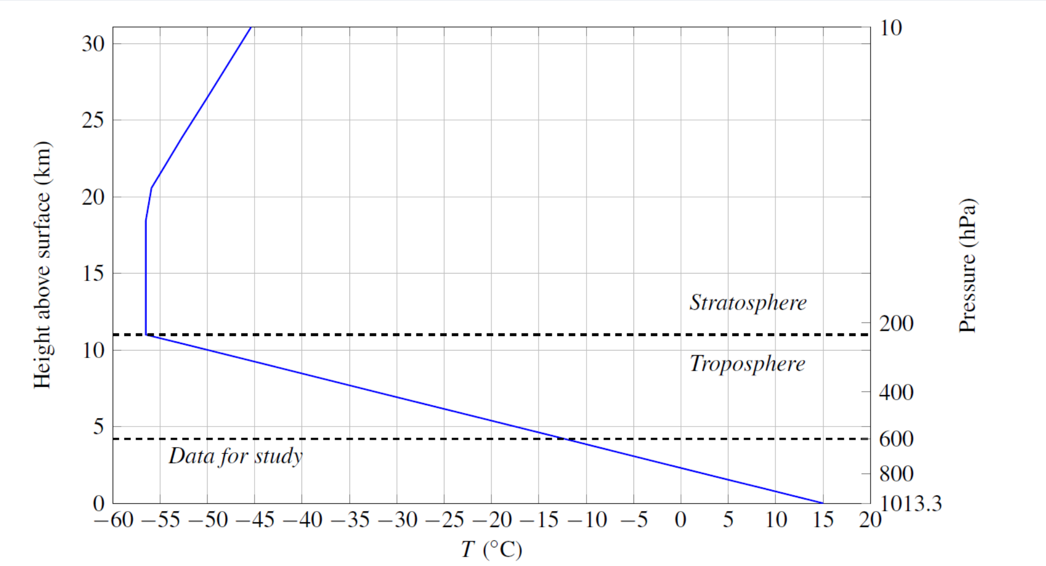
27. Our proposed instruments satisfy the exclusion restriction *provided that we control for weather on the ground*. That is, conditioning on weather covariates, the only pathway through which thermal inversions affect economic activity is via their effect on pollution. Therefore, we control very flexibly for a large variety of weather variables. Specifically, the function $f(W_{it})$ in equations (4) and (5) above includes a count of the number of days each year in which the average daily temperature falls into 20 temperature bins (that span the range of observed temperatures), 20 bins for daily precipitation levels, a count of the number of days each year in which the daily average wind speed falls into one of 12 wind speed bins (defined using the Beaufort wind scale), second-degree polynomials in relative humidity and sea-level pressure, and interaction terms between all 20 temperature bins and both humidity and squared humidity. We check the robustness of our results to changes in the definitions of weather variables in regressions that we report later in the paper.

Box 2. Thermal inversions instrument

Relevance

The relationship between air temperature and pressure/altitude under normal atmospheric conditions is illustrated in Figure 1. Under normal conditions, air temperature decreases with altitude above the surface through the troposphere. At an altitude of roughly 11 km above sea level, temperature reaches -56.5°C, and remains constant throughout the stratosphere before increasing towards the top of the atmosphere.

Figure 1. Typical relationship between altitude, pressure and temperature.



Note: Under normal atmospheric conditions, temperature falls linearly with height above surface until about 11km in elevation, where it reaches a temperature of about -56.5◦C. Above that point, temperature is stable and then increasing until the top of the atmosphere. In this study, we retain temperatures below 600 hPa (4.2km above sea level) – given by the lower dashed black line.

Box 2. Thermal inversions instrument *(cont.)*

Thermal inversions are a deviation from the normal monotonic relationship between air temperature and altitude/pressure which occur in the lower troposphere (below an altitude of around 4 km). They form when a mass of cooler air becomes trapped below a warm mass of air. For example, the large-scale movement of air masses throughout the atmosphere typically forms thermal inversions at its leading edge, as warm air masses pass over cooler air masses. Thermal inversions also form in winter at higher latitudes, as the low-angle sun heats the air higher in the atmosphere faster than the air at ground-level. Thermal inversions can also form as the surface cools overnight. It is important to note that thermal inversions work with different mechanisms in winter and in summer. Summer inversions typically happen during the morning, whereas winter inversions usually take place in the afternoon, which also implies that they will have a different effect on the pollution levels (Hicks et al, 2016).

Under normal atmospheric conditions, warm air at the surface is drawn upwards as a result of its lower density. This atmospheric ventilation can help to reduce pollution levels at the surface. During a thermal inversion, however, the inversion layer prevents the normal atmospheric ventilation from taking place, trapping polluted air at the surface. This effect is widely known, and has been documented in the scientific literature (Wallace and Kanaroglou, 2009; Gramsch et al., 2014). A clear example of the impacts of a thermal inversion on surface-level pollution is given in Figure B.1. A strong relationship between thermal inversions and pollution has been observed in many papers, such as Hicks et al. (2016), Chen et al. (2017), and Fu et al. (2017). In the results section, we formally demonstrate that air pollution, as measured by $PM_{2.5}$ concentration, increases significantly with thermal inversions.

Exogeneity

To demonstrate that thermal inversions are not caused by pollution or economic activity, we appeal to three branches of literature. First, in the climate economics literature, deviations in surface-level temperature from one year to the next within a region are typically assumed to be exogenous (e.g. Deryugina and Hsiang, 2017; Dell et al., 2012; Burke et al., 2015). Once we accept the exogeneity of the surface-level temperatures, the exogeneity of higher-level temperatures is easy to accept. Second, in the atmospheric dispersion literature, we have found no studies that point to feedbacks from pollutants to thermal inversions (i.e. pollution is not taken to cause inversions). With the risk of oversimplifying, pollution is usually assumed to be the function of (vertical and horizontal) winds, settling and the source of emissions (Sharan and Gopalakrishnan, 2003). In these models, thermal inversions appear as a phenomenon which reduces atmospheric ventilation via vertical winds and thus causes pollution to accumulate at ground level. Third, the thermodynamic models of inversions show that inversion is a function of chemical potential and other natural parameters (Ferrini, 1979; Whiteman and McKee, 1982). In addition, thermal inversions tend to be associated with continental-scale movement of air masses, and as a result, unlikely to be affected by shifts in small-scale regional activity that we examine.

Box 2. Thermal inversions instrument *(cont.)*

Exclusive channel

To show that thermal inversions affect the economy only via pollution, it is important to remember that inversions are an atmospheric phenomenon that takes place above ground level (where economic activity takes place). This fact should guarantee that thermal inversions satisfy the exclusion restriction. However, thermal inversions are linked with weather, which can potentially influence economic activity on the ground (Dell et al., 2012; Burke et al., 2015). For example, thermal inversions often occur in winter, when surface temperatures are cooler. In order to rule out the potential correlation between inversions and economic conditions that occurs through weather, we carefully and flexibly control for on-the-ground weather conditions in all our regressions, as described below. These flexible controls for ground-level weather are given by the functions $f(W_{it})$ in Equations (4) and (5), and should ensure that our instrument satisfies the exclusion restriction.

It remains that, as discussed below, $PM_{2.5}$ is correlated with other pollutants that are also likely affected by thermal inversions. Consequently, we test the sensitivity of the results to controlling for the concentration of other pollutants in section 5.1.2.

3.4. Economic outcomes and population data

28. We obtain region-level data on economic outcomes and population (including total population and working-age population) from Eurostat.[6] Our main indicator variable is gross domestic product at current prices by NUTS3 regions. We deflate this to real prices using the country-specific Harmonized Index of Consumer Prices, and we refer to this measure of real economic output as Y_{it}, where i indexes NUTS3 regions and t indexes year. We measure GDP per capita by dividing GDP by total population and GDP per worker by dividing GDP by the size of the working-age population. We also use data on gross value added by sector to measure economic outcomes at the sector level (we deflate in the same way). The source and construction of these variables are described in Table B.1 in Annex B.

3.5. Air pollution data

29. The key explanatory variable in our model is air pollution. There are a large number of potential air pollutants, and specific concern focuses on particulate matter, ground-level ozone, nitrogen oxides, and sulphur oxides.[7] Our analysis focuses on fine particulate matter, $PM_{2.5}$. There are two key reasons for this choice. First, $PM_{2.5}$ stands out as the pollutant with by far the largest estimated impacts on mortality and health outcomes. For this reason, the World Health Organization uses $PM_{2.5}$ concentration as an indicator of general population exposure to air pollution (World Health Organization, 2016) and most of the studies reviewed in this paper use $PM_{2.5}$ as a proxy for air pollution. Second, we are able

[6] The data is available at: http://ec.europa.eu/eurostat/web/rural-development/data.

[7] Measures of these pollutants are used to construct the European Air Quality Index, produced by the European Environment Agency: https://www.eea.europa.eu/themes/air/air-quality-index. The US EPA constructs its Air Quality Index using a similar range of pollutants (also including CO): https://www3.epa.gov/airnow/aqi_brochure_02_14.pdf.

to gather a comprehensive estimate of $PM_{2.5}$ concentrations covering the temporal and geographic scope required for our study, whereas data on concentration of other pollutants is typically not readily available.

30. Although we focus on this pollutant in our empirical application, it is important to emphasize that our empirical estimates of the impact of pollution on economic output may confound the effect of $PM_{2.5}$ with that of other air pollutants, since various air pollutants are typically correlated with one another. Indeed, ambient air pollutants share many sources in common – in particular they are all released as a by-product of combustion and industrial activity. Table 1 shows the correlation between some of the major air pollutants based on European monitoring station data from AirBase, the European air quality public database. $PM_{2.5}$ concentration is positively correlated with SO_2 and NO_2, but negatively correlated with ozone (note that these are unconditional correlations).

31. We lack the data to control for all these other major air pollutants and as a result, our estimates could include the effect of other air pollutants correlated with $PM_{2.5}$, rather than just the effect of $PM_{2.5}$.[8] However, we show in the sensitivity checks that the results are robust to controlling for SO_2 concentration, the pollutant most highly correlated with $PM_{2.5}$ and for which we could assemble data across our sample. This provides reassurance that we are able to reasonably recover the marginal effect of $PM_{2.5}$ on economic output.

Table 1. Correlation between various pollutants

	$PM_{2.5}$	SO_2	O_3	NO_2
$PM_{2.5}$	1	0.49	-0.42	0.43
SO_2		1	-0.23	0.31
O_3			1	-0.65
NO_2				1

Source: Authors' calculations based on data from AirBase.

32. Like a number of other papers, we make use of gridded air pollution data derived from a combination of satellite observations and emissions inventories. This has the advantage of providing complete geographic and temporal coverage for the period and units covered by our analysis. In contrast, the air pollution monitoring station record is extremely patchy over the period and region covered by our analysis for $PM_{2.5}$.

33. For our baseline specifications, air pollution data are drawn from Van Donkelaar et al. (2016). This product merges satellite air quality measurements of aerosol optical depth[9] with a particulate transport model, and combines it with data from surface air monitoring stations in order to obtain an improved match with surface air quality measures compared to raw satellite measures. Data are available globally at an annual basis on a very fine resolution grid (0.1 degree). These data are widely-used. For example, the Lancet and World Health Organization use the data to produce the Global Burden of Disease report, and the OECD uses it to measure exposure to poor levels of air quality. Data are available at an annual frequency, and we obtain data from 2000 to 2015 for the entire region covered

[8] Most other research in this area is likewise unable to disentangle the individual effect of multiple pollutants. For examples, see Schlenker and Walker (2015) and Chang et al. (2017).

[9] Satellite measurements of aerosols, called aerosol optical depth (AOD), are based on the fact that the particles change the way the atmosphere reflects and absorbs visible and infrared light. An optical thickness of less than 0.1 (palest yellow) indicates a crystal clear sky with maximum visibility, whereas a value of 1 (reddish brown) indicates very hazy conditions.

by our study. Based on the Van Donkelaar et al. (2016) database, we obtain the annual mean $PM_{2.5}$ concentration for each grid cell in Europe from 2000 to 2015.

34. We combine this data with gridded population data from the European Commission's Global Human Settlement in order to obtain population-weighted $PM_{2.5}$ concentration at the NUTS3 level. This account for the fact that population may be unevenly distributed within each region and exposed to different levels of concentration depending on their location. As a consequence, our measure of pollution concentration at the NUTS3 level measures the exposure of the average inhabitant of each region, rather than the average concentration in the region. We aggregate all gridded data to political boundaries as described in Annex B. In a nutshell, for each NUTS3 region, we take the average of all gridded data points within that region or use the observations from the closest gridded data point for NUTS3 regions that are not overlain by any gridded data points.

35. As a sensitivity test, we conduct our analysis with three alternative air pollution measures which all have limitations in terms of precision, time and geographical coverage.[10] Therefore our preferred air pollution measure is the Van Donkelaar et al. (2016) database, because it combines high geographical precision with complete time and regional coverage.

3.6. Thermal inversions, wind and weather data

36. Thermal inversions data come from NASA's MERRA database.[11] We obtain measures of daily mean air temperature from 2000 to 2015 at each grid cell for all altitude levels between the surface and about 1 km above sea level.[12] As discussed in section 3.2.1,

[10] The first alternative is based on NASA's MERRA-2 database (for a thorough description, see Buchard et al., 2017). MERRA is a gridded database that produces a continuous estimate of suspended particulates (aerosols) since 1980 with complete global coverage. Grid cells are 2/3 degree longitude and 1/2 degree latitude, or about 60 km by 60 km. MERRA produces an estimate of five different species of fine particulate matter, and we aggregate these into a consolidated estimate of $PM_{2.5}$ concentrations using the method of Buchard et al. (2016): $PM_{2.5} = [DUST2.5] + [SS2.5] + [BC] + 1.4 \times [OC] + 1.375 \times [SO4]$, where SS is sea salt, BC is black carbon, and OC is organic carbon. MERRA estimates these particulate emissions by combining satellite measurements with estimates of particulate sources from an emissions inventory. The inputs are then assimilated using a global three-dimensional circulation model, including climate variables as well as aerosol transport and chemistry. By combining satellite measures of aerosol optical depth (AOD) using an assimilation model based on well-understood physical and chemical dynamics, MERRA achieves substantial improvements in fit compared to raw satellite AOD measures (Buchard et al., 2016). The second alternative data source is CAMS (the Copernicus Atmospheric Modeling Service), which combines meteorological data, satellite data, and ground-level air quality monitoring data. The CAMS grid is finer than the MERRA grid, with grid cells approximately 10km by 10km, but data are available only for the period 2008-15. The third alternative is based the European Environmental Agency's monitoring station data (AirBase and AirQuality e-reporting), which compiles the observations from air pollution monitoring stations across Europe. Unlike the Van Donkelaar and CAMS, this is a sparse dataset as most NUTS3 regions still don't have stations which monitor $PM_{2.5}$ concentrations.

[11] We used the M2I3NPASM files.

[12] We first retain only observations in which the pressure is above 600 hPa (as illustrated in Figure 1), which under normal atmospheric conditions corresponds to an altitude of about 4.2km above sea level. There are 22 pressure levels defined in the MERRA product that are at or above

the mechanisms and hence the effect of thermal inversions are likely to be different in summer and in winter. Therefore, we distinguish between summer and winter inversions, splitting the years into a period between April 15th to October 14th and between October 15th to April 14th.[13]

37. An inversion is a deviation from the normal monotonic declining relationship between air temperature and altitude. We operationalize this definition in two different ways, in order to ensure that our results are not sensitive to the choice of thermal inversion definition. A schematic overview of the manner in which we account for thermal inversions is given in Figure B.1 in Annex B. We define the presence of thermal inversions in the following ways:

(1) If temperature is higher at the second lowest level of the atmosphere than at the lowest level above the surface.[14] This measure of thermal inversions is closest to that adopted by Chen et al. (2017).

(2) If temperature is higher at any level below 1,000m than at the surface.[15]

38. In addition to measuring the presence of thermal inversions, it is possible to measure the strength of thermal inversions, as the magnitude of the positive temperature anomaly. We conduct our regressions using the presence of inversions rather than the strength, because the results are more straightforward to interpret. However, the results are robust to using the strength of thermal inversions rather than their presence as an instrumental variable.

39. We obtain data on daily surface temperature, precipitation, and sea level pressure from the European Climate Assessment and Dataset.[16] This gridded database is produced by amalgamation of all weather station data across Europe and interpolation (Haylock et al.,

600 hPa. This is to ensure that we focus on the region in which there is a monotonic relationship between temperature and pressure under normal atmospheric conditions. We further restrict the air temperature data to the first 1 000m above sea level to focus on inversions that are most germane to ground-level pollution. We undertake these restrictions in two steps because ground-level pressure varies both by geography (some places are at higher altitude than others) and by time (sea level pressure changes as weather systems move through). We thus calculate the pressure at the lowest atmospheric level dynamically.

[13] The results are however robust to various definitions of seasonality, and to considering winter and summer inversions together rather than separately.

[14] Indexing atmospheric levels from $v = \{1, 2, \ldots 22\}$ with $v = 1$ representing the lowest atmospheric level above surface, we formally generate an indicator variable $TI_{LL} = 1(Tv{=}2 - Tv{=}1 > 0)$. It is important to note that in many cases, we do not observe temperature at the lowest pressure (1 000 hPa) reported by MERRA because surface pressure is below 1 000 hPa either because the land surface is elevated or due to a low pressure system. As a result, the set v is defined dynamically – in each grid cell in each day – with the index v = 1 always corresponding to the lowest pressure level above surface.

[15] Formally, we generate an indicator variable that is equal to one if there is any layer of the atmosphere (above 600hPa and below 1 000m above surface) in which the temperature is above the surface temperature: $T\ I_S = 1(\exists v\ (Tv - Tv{=}1) > 0)$.

[16] See http://www.ecad.eu.

2008). The grid resolution is one quarter of a degree. We obtain daily wind speed and relative humidity from the MERRA dataset.[17]

40. We aggregate weather data (including data used to construct the instruments) up to the annual NUTS3 level in the same way as pollution data, as described above.

3.7. Key data patterns

41. Figure 2 shows the average concentration of $PM_{2.5}$ over the entire period covered by our data, for each NUTS3 region. $PM_{2.5}$ concentrations are typically higher in Eastern Europe and the Mediterranean coast compared to the Atlantic coast and Scandinavia. There is a substantial range in $PM_{2.5}$ concentrations, even averaging over 16 years, with average population-weighted concentrations as low as 3.1 $\mu g/m^3$ and as high as 33.1$\mu g/m^3$ in others. At the annual level, the distribution is even more spread, with a minimum of 2.7$\mu g/m^3$ (Scotland, 2000) and a maximum of 61.7 $\mu g/m^3$ recorded in Northern Italy in 2014.

42. Figure 3 shows the trends in the instrumental variables (proportion of days with a thermal inversion, split between summer and winter) as well as $PM_{2.5}$ concentrations, averaged over all of the regions and weighted by each region's population. We observe a downward trend in $PM_{2.5}$ concentrations but not in the share of days with inversions. Average $PM_{2.5}$ concentration across Europe decreased from 16.5 $\mu g/m^3$ to 13 $\mu g/m^3$ between 2000 and 2015, but with some significant year-on-year variation. In addition, some correlation between thermal inversion strength and $PM_{2.5}$ concentrations is visually apparent from the figure even at the aggregate level – for example, the years 2003, 2011 and 2014 show peaks in both thermal inversions and $PM_{2.5}$ concentrations.

43. Figure B.4 in Annex B shows that even after removing NUTS3 and country-year fixed effects, there remains a substantial amount of variation in winter and summer inversions, the two instrumental variables used to identify the impact of air pollution on economic activity in our baseline specification. In addition, Figure B.5 and Figure B.6 show that the variation in the instrumental variables differs across regions. This highlights the benefits of using two instruments in the analysis: by distinguishing between summer and winter thermal inversions, we use variation from across Europe and thus ensure that our results are representative of the impact of air pollution across the continent and not only in some part of it.

[17] These variables are also derived from the M2I3NPASM files, and we use the same bounding box and temporal restrictions as for the thermal inversions data, above.

Figure 2. Average 2000-2015 $PM_{2.5}$ concentrations in economic regions used in the study

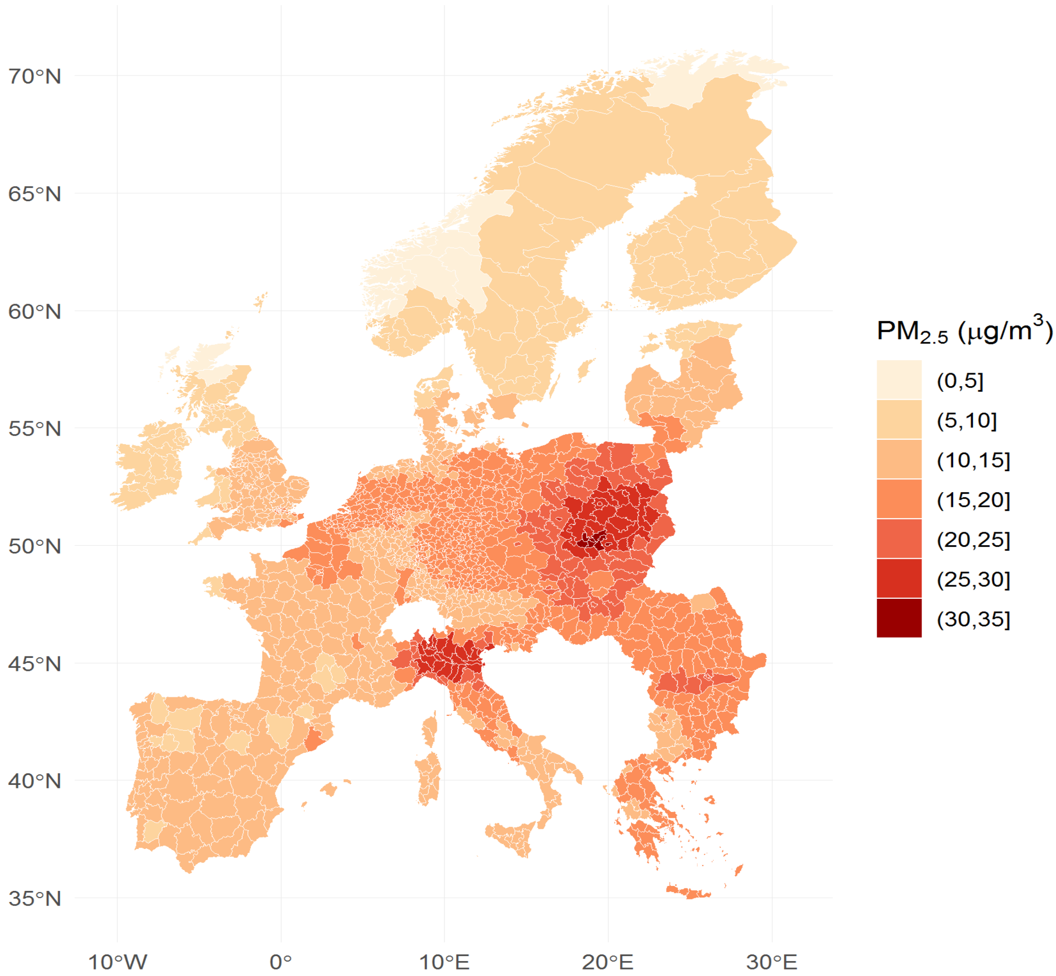
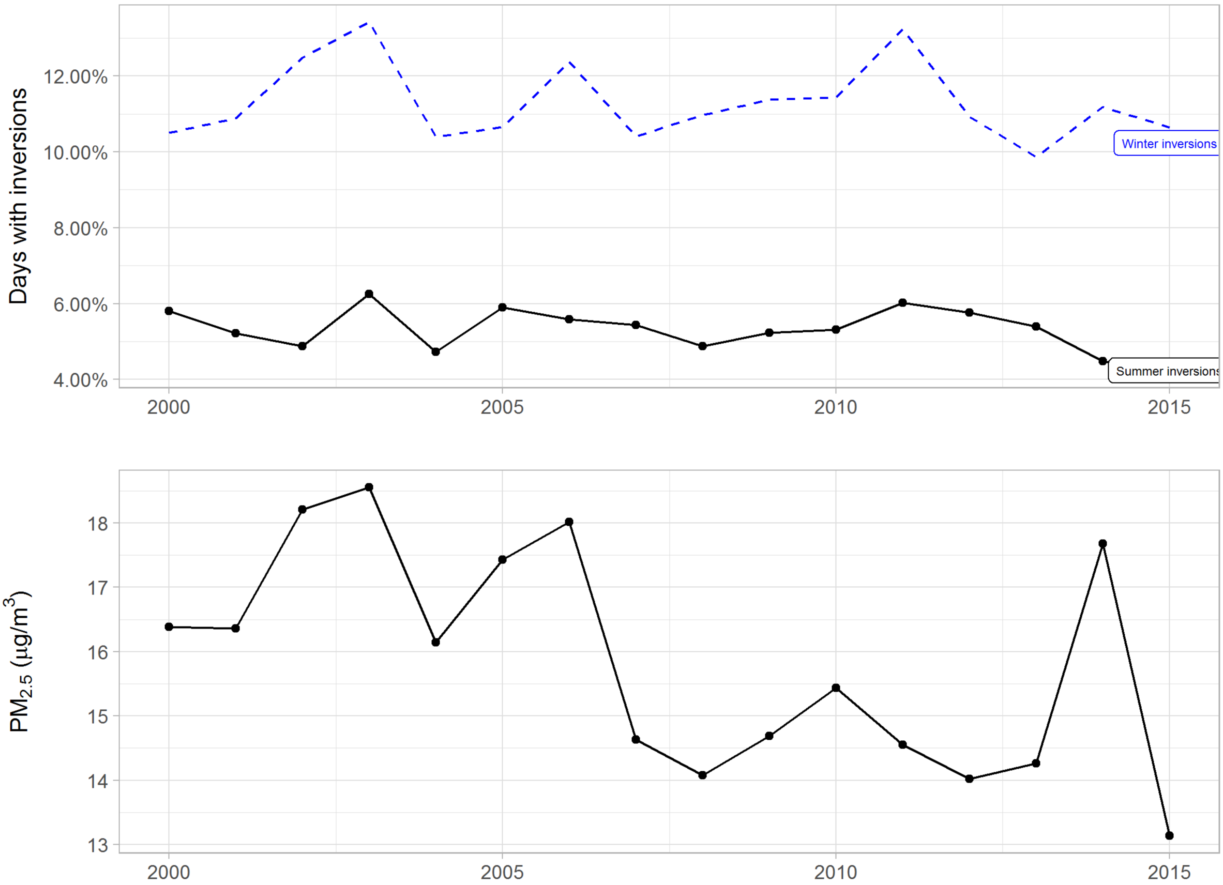


Figure 3. Annual trends in key independent variables.



Note: The top panel shows the variation in inversions over time (distinguishing between summer and winter inversion), averaged across all of the regions in the data. Inversions are measured at the lowest atmospheric level (see text). The bottom panel shows annual particulate matter concentrations averaged over all the regions in the data. In both panels, the data are weighted by the population of each region.

44. A look at the distribution of NUTS3-level year-on-year changes in $PM_{2.5}$ concentration across the sample period (Figure B.7) reveals a highly skewed pattern, with a small number of observations that lie far outside the typical changes over a year. Since $PM_{2.5}$ concentrations are drawn from a satellite-based reanalysis dataset and are hence extrapolated, measurement error is a usual concern and we suspect that those implausibly large changes in concentration over one year (e.g. from 22 $\mu g/m^3$ to 54 $\mu g/m^3$ *annual concentration*) are due to measurement issues. Therefore, in all the baseline regressions we exclude outliers at the top and bottom 1% in terms of the year-on-year changes in $PM_{2.5}$ concentrations. This ensures that the results are valid for 98% of the distribution of annual changes in $PM_{2.5}$ concentrations and not driven by extreme values.

4. Results

4.1. Main results

4.1.1. First-stage results: The effect of thermal inversions on pollution

45. Table 2 reports the results of the first stage in our two-stage approach where we estimate the impact of the instrumental variables on $PM_{2.5}$ concentrations, after conditioning on weather covariates (Equation (4)).[18] In these baseline regressions, we define inversion as a positive change in temperature between the lowest and second lowest atmospheric layers above ground level. The inversion instrument is the share of days in a year in which thermal inversions are observed, distinguishing between winter and summer. We test the robustness of the results to alternative definitions later in the paper.

Table 2. First stage results: Instruments' effect on $PM_{2.5}$

	(1)	(2)	(3)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
ΔSummer inversions	4.519 ***	4.488 ***	
	(1.094)	(1.089)	
ΔWinter inversions	2.046 **		2.002 **
	(0.859)		(0.854)
Observations	16462	16462	16462
R^2	0.592	0.596	0.611

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

46. Column (1) of Table 2 shows the results of the first stage when both summer and winter thermal inversions are used as an instrument. Column (2) uses only summer inversions as an instrument, and column (3) uses only winter inversions. The results suggest that both instruments have a strong impact in the predicted direction on pollution concentrations, even when used simultaneously. Specifically, increasing the share of days with thermal inversions from 0 to 1 (i.e. all days in the year) is predicted to cause a 4.5 $\mu g/m^3$ (summer) and 2.0 $\mu g/m^3$ (winter) increase in annual average $PM_{2.5}$concentrations. Column (2) and column (3) show that the coefficients are not sensitive to excluding one or the other instrument, suggesting they provide two independent sources of variation.

47. Both of these effects are highly statistically significant and large relative to baseline $PM_{2.5}$concentrations of 16 $\mu g/m^3$, suggesting that they are valid instruments.

[18] Summary statistics for all variables used in the econometric analysis are provided in Table B.2 in Annex B.

4.1.2. Second-stage results: The effect of pollution on economic output

48. Table 3 reports estimates of equation (5) in which we regress economic activity on instrumented pollution and controls.[19] Coefficients are weighted by the population of each region so as to be representative of the average inhabitant in Europe rather than the average region. Column (1) uses (log) GDP divided by working-age population as the dependent variable, column (2) uses (log) GDP per capita, and column (3) uses (log) GDP, thus recovering the effect of pollution on total economic output. An F-test on the excluded instruments produces a value of 9.4, confirming the relevance of our selected instruments. Across the three specifications, the coefficient on instrumented pollution shows that a 1 $\mu g/m^3$ increase in $PM_{2.5}$concentration causes a 0.8% reduction in economic activity. The effect is statistically significant at the 5% level and substantial in magnitude (when recovering the elasticity at the sample mean, a 10% increase in $PM_{2.5}$ concentration decreases GDP per capita or GDP by 0.8%). Note moreover that 63% of the distribution of year-on-year changes in $PM_{2.5}$ concentration lie outside the range of [-1;1], so a 1 $\mu g/m^3$ increase or decrease in pollution concentration from one year to the next is quite typical.

Table 3. Instrumental variable estimation of the economic effect of $PM_{2.5}$.

	(1)	(2)	(3)
	Δln(GDP per working pop)	Δln(GDP per capita)	Δln(GDP)
$\Delta PM_{2.5}$	-0.0080 **	-0.0081 **	-0.0083 **
	(0.0038)	(0.0038)	(0.0038)
Observations	16789	16789	16789
Weak id. stat.	9.391	9.391	9.391
Hansen J stat. p-value	0.115	0.121	0.103

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

49. In Section 2, we argued that pollution can affect economic activity through its impact on population, presence at work, productivity at work, as well as a direct impact through natural resource productivity. Unfortunately, we do not observe presence at work and cannot measure the direct impact ofpollution on output conditional on presence at work and productivity, so we are only able to decompose our results into two components – the effect of pollution on output per capita and the effect of pollution on total economic output. It is important to note that the impact of pollution on output per capita is the joint effect of changes in work attendance, changes in work productivity conditional on attendance, as well as any direct impact of pollution on output, such as in the agricultural sector. Column (1) of Table 3 shows that an increase in $PM_{2.5}$ concentration by 1 $\mu g/m^3$ decreases output per worker by 0.80% while column (3) shows that the same increase reduces total GDP by 0.83%. This implies that about 95% of the total effect of $PM_{2.5}$ concentration on economic output is due to reduced output per worker, which is consistent with the findings from the medical literature that $PM_{2.5}$ pollution can only affect mortality of old people and young

[19] The OLS results without instrumental variables and the reduced-form results where we directly estimate the effect of thermal inversions on economic output are presented respectively in Table C.1 and Table C.2 in Annex C.

children (who do not contribute to economic activity), and very rarely of working-age individuals.

50. These baseline results are robust to multiple sensitivity tests. Key results and motivation for robustness checks are highlighted in Box 3 (the dependent variable in all of these tests is GDP over working-age population). Table 4 reports the coefficient and associated statistical significance level for our key variable of interest $\Delta PM_{2.5}$ for the various robustness checks. Further details can be found in Annex D. The marginal impact of a 1 μg/m^3 increase in $PM_{2.5}$ concentration on GDP varies between -0.56% and -1.47% depending on the specification, suggesting that our baseline estimate of -0.8% is lies on the conservative side of the point estimate distribution.

Box 3. Robustness checks

(1) *Weather controls.* Our results are invariant to adopting an even more flexible approach to including the effect of temperature (including 70 temperature bins instead of 20) and to further adding interaction terms between these 70 temperature bins with humidity and squared humidity.

(2) *Alternative instruments*. In our main specification, we adopt a particular definition for the thermal inversion variables (inversions calculated between the lowest and second lowest atmospheric level, and splitting the year between summer and winter). We re-run the analysis with a different definition for the inversions (measuring inversions at the surface) and using annual inversions or 4 seasons instead of 2). Overall, our results are robust to using different instrumental variables. The main coefficient varies between -0.056 and -0.105 depending on the instrument, but none of these alternative coefficients are statistically significantly different from the baseline.

(3) *Time trends and fixed effects.* We test the sensitivity of our results to the inclusion of alternative fixed effects and control variables. We add NUTS3 time trends to our baseline regression, replace country-year fixed effects with NUTS1-year fixed effects (thus controlling for any NUTS1-year shocks that might be correlated with both GDP and pollution, such as region-specific technological change), and in the most demanding specification we combine NUTS3 time trends with NUTS1-year fixed effects. The coefficient remains unchanged when adding NUTS3 time trends and remains statistically significant when including NUTS1-year fixed effects (with or without NUTS3 time trends). Interestingly, the coefficient increases when controlling flexibly for unobserved time-varying heterogeneity at the NUTS1-year level.

(4) *Additional controls.* One of the main potential issues with using $PM_{2.5}$ concentration as the measure of air pollution is that, as discussed in Section 4.2, $PM_{2.5}$ is correlated with other pollutants so that the main coefficient might capture the effect of other air pollutants correlated with $PM_{2.5}$, rather than just the effect of $PM_{2.5}$. We lack the data to control for all other major air pollutants, but the results are robust to controlling for SO_2 concentration, the pollutant most highly correlated with $PM_{2.5}$ and for which we could assemble data across our sample. In addition, controlling for lagged GDP (if pollution affects investment) has no impact on the key coefficient.

Box 3. Robustness checks *(cont.)*

(5) *Alternative air pollution data.* We re-estimate the model with different air pollution data (see section 4), based on the CAMS, MERRA, and Airbase (monitoring stations) databases. Both CAMS and MERRA return a coefficient that is statistically significant and greater in magnitude (but not statistically significantly so) than our baseline estimate. The monitoring station data is too patchy to allow precise estimates with so many control variables and fixed effects included, but we take reassurance from the fact that the coefficient is basically exactly the same as in the baseline specification.

(6) *Autocorrelation*. Allowing for spatial autocorrelation by clustering standard errors on country-year in addition to NUTS3 or on NUTS2 level leaves the results statistically significant but now at the 10% level.

(7) *Outliers*. Results are not statistically different from the baseline if one removes outliers respectively at the top and bottom 0.5%, 2.5% or 5%, and remain statistically significant. Including extreme values by not removing any outliers increases the standard error by 30% (p-value = 0.15) but the coefficient is not statistically different from the baseline.

Table 4. Summary of robustness checks.

Robustness check		Coefficient
Weather controls	70 temp. bins	-0.0071 **
	70 temp. bins interacted with humidity	-0.0084 **
Instrument choice	Low inversions (annual)	-0.0105 **
	Low inversions (4 seasons)	-0.0067 *
	Surface inversions (annual)	-0.0062 **
	Surface inversions (4 seasons)	-0.0056 **
Time trends and fixed effects	NUTS3-trends	-0.0083 **
	NUTS1-year fixed effects	-0.0145 *
	NUTS3-trends & NUTS1-year fixed effects	-0.0148 *
Additional controls	SO2 concentration	-0.0080 **
	Lagged GDP	-0.0096 **
Database choice	CAMS	-0.0147 **
	MERRA	-0.0135 *
	EEA monitoring data	-0.0078
Clustering	Clustered on NUTS3 + country-year	-0.0080 *
	Clustered on NUTS2	-0.0080 *
Outliers	Removing top and bottom 0.5%	-0.0078 **
	Removing top and bottom 2.5%	-0.0064 **
	Removing top and bottom 5%	-0.0059 *
	No outliers dropped	-0.0066

Note: This table summarises the effect of the robustness checks on the main coefficient. : * $p<0.1$,** $p<0.05$,*** $p<0.01$. Detailed results are available in Annex C.

4.2. Extensions

4.2.1. Heterogeneity

51. Going beyond the average effect across European regions, the possibility of heterogeneous effects across sectors, income levels and population density is explored. To this end we either create categorical variables that divide the sample of regions into corresponding groups or simply split the sample by groups. It is important to recognize at the outset that regions in our sample differ in many ways, so that – while we are estimating a causal relationship of pollution on output – we cannot estimate causally how this relationship changes with heterogeneity, since there may be multiple dimensions of heterogeneity that co-vary.

52. Dividing the sample according to population concentration into urban, rural, and "intermediate" regions,[20] we find an impact of $PM_{2.5}$ concentration across all types of regions (Table 5). These results are consistent with the non-linearity results presented below: we observe that $PM_{2.5}$ concentrations are typically not much higher in urban than rural regions, and highest in intermediate regions, perhaps because manufacturing activities are more likely to be located in those intermediate regions.

Table 5. Economic effects of $PM_{2.5}$ for urban vs rural regions

	(1)
	Δ ln(GDP)
Δ $PM_{2.5}$ (Urban)	-0.0070 **
	(0.0031)
Δ $PM_{2.5}$ (Intermediate)	-0.0063 **
	(0.0030)
Δ $PM_{2.5}$ (Rural)	-0.0089 **
	(0.0041)
Observations	16789
Weak id. stat.	-
Hansen J stat. p-value	-

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

53. Results differentiating regions by level of income show an "inverted-U" relationship, with the largest marginal effects of pollution evident in the lowest- and highest-income regions, and smaller marginal impacts of $PM_{2.5}$ concentration in medium-income regions (Table 6). In all cases, we estimate a negative and statistically significant impact of pollution on output. The "inverted-U" pattern is hardly causal, since there are many factors that are correlated with income and vary between regions, such as economic structure.

[20] The region classifications are from the OECD's Regional Database, which is based on the urban population and population density as a classification measure.

Table 6. Effect of pollution by income quantiles (GDP per capita)

	(1)
	Δ ln(GDP)
Δ $PM_{2.5}$ (1st quantile)	-0.0069 *
	(0.0042)
Δ $PM_{2.5}$ (2nd quantile)	-0.0034 *
	(0.0019)
Δ $PM_{2.5)}$ (3rd quantile)	-0.0032
	(0.0027)
Δ $PM_{2.5}$ (4th quantile)	-0.0020
	(0.0023)
Δ $PM_{2.5}$ (5th quantile)	-0.0064 **
	(0.0031)
Observations	16789
Weak id. stat.	4.759
Hansen J stat. p-value	0.00784

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

54. As for sectoral outcomes, Table 7 reports the results from a series of separate regressions, in which we use the gross value added of economic sectors (as reported in Eurostat data) as a left-hand side variable in our second-stage equation. We focus on the sectors for which Eurostat has complete geographical coverage across Europe: agriculture, construction, and manufacturing. We find a much larger impact of increases in air pollution on the agricultural sector, where a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration leads to a 4.6% reduction in sector gross value added. This is in line with a number of studies that have shown the sensitivity of the agriculture sector to high levels of pollution concentration (e.g. Wahid et al., 1995; Agrawal et al., 2003) due to both direct output effects and reductions in agricultural worker productivity (Graff Zivin and Neidell, 2012). The impact is also larger than the baseline in the construction sector (consistent with the fact that workers in this sector typically work outdoors) while the impact in the manufacturing sector is not different from the baseline. The coefficient is not precisely estimated in these last two cases. This is likely due to greater measurement error in the air pollution measure (since economic activities can be unevenly distributed across NUTS3 regions), which is amplified by the presence of a large set of country-year and regions fixed effects (Schlenker et al., 2013), and also suggests large heterogeneity *within* sectors in the impact of pollution.

Table 7. Effects of $PM_{2.5}$ by sector

	(1)	(2)	(3)
	Agriculture	Construction	Manufacturing
Δ $PM_{2.5}$	-0.0462 **	-0.0135	-0.0093
	(0.0233)	(0.0119)	(0.0118)
Observations	16668	16789	16789
Weak id. stat.	10.69	4.957	6.409
Hansen J stat. p-value	0.119	0.971	0.691

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

4.2.2. Nonlinearity with respect to background concentration

55. We next explore the possibility that the effects of air pollution on GDP vary with the level of pollution. We model such potential non-linearity in various ways. We first include the interaction of $\Delta PM_{2.5}$ with $PM_{2.5}$ levels as an endogenous variable. We instrument these with both the baseline (first-differenced) inversions instruments and interaction terms between first-differenced inversions (ΔTI) and inversions in level (TI). Results are shown in Table 8, column (1). The effect of the interaction term is close to statistical significance (p = 0.11) and negative, suggesting that the effect of increased $PM_{2.5}$ concentrations on economic activity becomes negative only above background concentrations around 8 $\mu g/m^3$ (56/7).

56. To further explore this potential non-linearity, the sample is split in two subsamples of equal size according to each NUTS3 region's median $PM_{2.5}$ concentration (columns 2 and 3), comparing, within each region, the impact of a pollution increase when pollution is above or below the median concentration over our sample period. We find that the marginal impact of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration on GDP when pollution is low (below median) is equal to -0.58% and not statistically significant while the impact of the same 1 $\mu g/m^3$ increase when pollution is above median causes a 1.0% reduction in economic activity – 25% larger than the mean impact. Therefore, *within each region*, the impact of higher $PM_{2.5}$ concentration increases as the baseline pollution concentration grows. Note that the standard error increases slightly (p = 0.06), as expected since the number of observations is twice as low as in the baseline.

57. Finally, we use the number of days above a certain $PM_{2.5}$ concentration within the year instead of the average concentration (which implicitly assumes the daily effects to be linear), choosing 10µg/m^3 and 25µg/m^3 as thresholds as they correspond to the maximum concentration limits recommended by the World Health Organisation.[21] We find that an

[21] The World Health Organisation (2006) recommends 10µg/m^3 as the maximum value for annual average concentration and 25µg/m^3 as the maximum value for average concentration in any single day. Note that Van Donkelaar only has annual data so the daily concentration measures are taken from MERRA.

additional day with pollution concentration above 10µg/m³ reduces real GDP by 0.005% while an additional day with pollution concentration above 25µg/m³ reduces real GDP by 0.015%, again suggesting a non-linear response of economic activity to pollution increases depending on the baseline concentration.

Table 8. Nonlinearities in $PM_{2.5}$'s effect on GDP

	(1) Interaction with pollution levels	(2) Below region median	(3) Above region median	(4) Threshold model	(5) Threshold model
$\Delta PM_{2.5}$	0.0056	-0.0058	-0.0100 *		
	(0.0096)	(0.0065)	(0.0054)		
$\Delta PM_{2.5} \times PM_{2.5}$	-0.0007				
	(0.0004)				
$\Delta Days(PM_{2.5} > 10g/m^3)$				-0.0004	
				(0.0004)	
$\Delta Days(PM_{2.5} > 25g/m^3)$					-0.0015 **
					(0.0007)
Observations	16789	8847	7911	16789	16789
Weak id. stat.	7.855	5.957	7.381	7.451	9.390
Hansen J stat. p-value	0.791	0.169	0.437	0.0128	0.148

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

5. Discussion and policy implications

5.1. *Magnitude and comparison with existing studies*

58. The most striking feature of our results is the magnitude of the effects we uncover. Our baseline (GDP-weighted) estimates show that a 1 $\mu g/m^3$ decrease in $PM_{2.5}$ concentration would increase Europe's GDP by 0.8%. Given that the European Union's GDP is about EUR 15 trillion in 2017, this translates into a short-run increase of EUR 120 billion. This a large number – roughly the size of a small EU Member Country such as Slovakia or Hungary. On a per capita basis, this represents around EUR 200 per inhabitant per year. To put things in perspective, consider that pollution decreased by 0.2 $\mu g/m^3$ per year on average across NUTS-3 regions between 2000 and 2015, so the typical annual reduction in $PM_{2.5}$ concentration boosts regional GDP by 0.16%. As a matter of comparison, regional GDP (at constant prices) grew by 1% per year on average over the period, so reductions in air pollution explain around 15% of GDP growth.

59. However, our result are comparable to those reported in this emerging literature. Only three studies to date have looked at long-term exposure in a general population, but their findings are remarkably consistent with ours. Fu et al. (2017) estimate that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration causes labour productivity to decrease by 1.1% in Chinese manufacturing plants. Our results are *smaller* in magnitude, suggesting that air pollution matters even at much lower concentration levels than those observed in China but that the effect is non-linear. Borgschulte et al. (2016) focus on pollution peaks in the US caused by forest fires. They estimate that spending one day in a smoke plume causes a reduction in

income of 10% across all workers. They estimate that smoke increases $PM_{2.5}$ concentration by 4µg/m^3. Thus, a 1µg/m^3 increase in pollution causes a 2.5% reduction in income, which is much *higher* than our baseline estimates.

5.2. Implications for cost-benefit analyses of pollution control policies

60. These findings can inform ex-ante and ex-post cost-benefit evaluations of air pollution reduction policies. They suggest that the direct economic benefits from air pollution control policies might be much greater than previously thought, and are also much larger than abatement costs.

5.2.1. Comparison with market and non-market benefits

61. It is useful to compare the market benefits from air pollution reductions uncovered in this study with existing cost-benefit analyses of air pollution control policies. A first example is a recent assessment carried out by the European Commission when it proposed a new Directive to further reduce emission of certain atmospheric pollutants in Europe by the year 2025 (European Commission, 2013).[22] The scenarios analysed focus on reductions in $PM_{2.5}$ emissions by 17% to 45%. The market benefits from reduced $PM_{2.5}$ emissions analysed were lost working days, damage to the built environment, crop value losses and healthcare costs. The direct market benefits from reducing $PM_{2.5}$ emissions by 17% would be EUR 1 billion annually, and around EUR 2 billion for a 25% reduction (see details in in Annex E). Therefore, the direct market benefits from a 10% reduction in emissions as calculated by the European Commission are less than EUR 1 billion – two orders of magnitude smaller than what our estimates suggest. Note that modelling exercises of this type do take into account some of the countervailing effects of air pollution, for example an increase in healthcare spending is considered as a cost because people are forced into sub-optimal expenditures on health (when they would have preferred to consume other goods or services) but it also boosts the health sector. Such effects are not captured in an empirical study, so it is not surprising that the modelling results lead to lower costs, but we only observe that the modelling results are *much lower* than our empirical estimates, suggesting they so far do not capture all of the market costs associated with air pollution.

62. The scenarios examined by the European Commission focus on emission reductions rather than decrease in concentration, and it is not easy to translate emission reductions into concentration. There is not necessarily a linear relationship between the reductions in emissions of primary $PM_{2.5}$ and the reductions in ambient air concentrations, because in addition to primary emissions of particles, $PM_{2.5}$ can also be formed from the chemical reactions of gases such as SO_2 and NOx, and because wind can transport particles over long distances. However, between 2006 and 2014, primary $PM_{2.5}$ emissions decreased by 17% in the EU28 while in the same period, $PM_{2.5}$ concentrations as measured by government-owned monitoring stations declined by 20% on average (indicating a small reduction in secondary PM also). Therefore, as a first approximation, it is not unreasonable to assume a linear relationship between emissions and concentration, especially for a large region such as Europe. [23]

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[22] See http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52013SC0532&from=EN

[23] The relationship is likely very different for a small region where most pollution might be imported. For example, a study of the Paris region showed that between 2009 and 2020 $PM_{2.5}$ emissions in the

63. Another example is the assessment of the costs and benefits of the US Clean Air Act Amendments (CAAA) conducted by the US Environment Protection Agency (EPA). Here, the market benefits included minor restricted activity days, work loss days, reduced outdoor worker productivity and agricultural and forest productivity, and the US EPA estimates that the combined benefits amount to USD 20.5 billion annually (see details in Table A.2 in Annex E). Since the US CAAA led to a reduction in $PM_{2.5}$ emissions by 11% in 2010 compared to a scenario without CAAA (and -17% in 2020), the results in this paper suggest that the market benefits would in fact be in the order of USD 105 billion annually.[24]

64. Therefore, the results in this study make a significant difference to the predicted benefits from policy action, even accounting for non-market benefits associated with reduced mortality. In the European Commission assessment mentioned above, the non-market benefits of a 25% reduction in $PM_{2.5}$ emissions amount to USD 30 to USD 100 billion annually, a figure which is smaller than the estimated market benefits. We conclude from this analysis that including the direct economic benefits of air pollution control into cost-benefit analyses of policies would substantially increase the expected benefits from policy action.

5.2.2. Comparison with abatement costs

65. How do these numbers compare to the marginal abatement costs of decreasing $PM_{2.5}$ concentration? The European Commission cost-benefit study presented above suggests the marginal cost of mitigating $PM_{2.5}$ emissions by about 17% would be EUR 221 million annually. Similarly, the marginal cost of a 25% reduction would be about EUR 1.2 billion (see details in Table E.4 in Annex E). Thus the cost of a 10% reduction in emissions would be less than EUR 1 billion annually. An earlier impact assessment by the European Commission conducted in 2005 (see details in Table E.3 in Annex E) concluded that the cost of reducing average urban background *concentration* of $PM_{2.5}$ by an average of 20% (Scenario A) or 25% (Scenario B) in the EU-25 between 2010 and 2020 would be around EUR 5 billion (resp. EUR 8 billion) per annum.[25] In contrast, our estimates suggest that the direct economic benefit of a 10% reduction in emissions would be at least one order of magnitude larger. The US EPA estimates are larger with the annual abatement costs associated with the CAAA amounting to USD 65 billion annually (Table E.5 Annex E), but these numbers include abatement of many pollutants other than $PM_{2.5}$ (e.g. NO_X, CO, SO_2, PM_{10}) and even then these numbers are around twice as small as the estimated direct market benefits.

66. We conclude from this analysis that significant reductions in air pollution would easily pass a cost-benefit test, even ignoring their large benefits in terms of avoided mortality. Therefore, more stringent air quality regulations could be warranted based solely on economic grounds.

baseline scenario are projected to decrease by 35%, while $PM_{2.5}$ concentrations are projected to only go down by 6% (Airparif, 2015).

[24] Taking the US 2010 GDP of USD 15 000 billion and assuming our results are valid in the US with the same magnitudes.

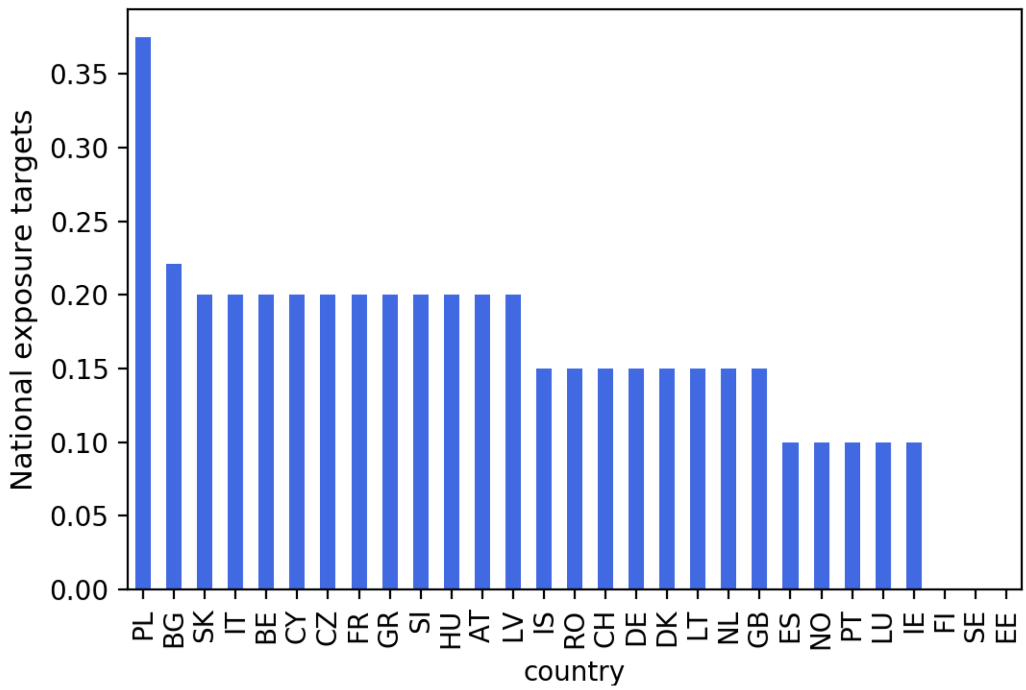
[25] Although these numbers look much larger than the ones from the 2008 Directive assessment (possibly because of the focus on emissions rather than on concentrations and the cost decreases of abatement technologies made possible by technological progress since 2008), they are still way smaller than the direct economic benefits estimated in this study.

5.3. Contribution of environmental policy to economic growth

67. The second major policy implication of our findings is that environmental policies may have contributed positively to economic growth in the recent period.

68. In May 2008, the European Commission adopted Directive 2008/50/EC on "ambient air quality and cleaner air for Europe", which laid out new air quality objectives for $PM_{2.5}$. Under the Directive, Member States are required to reduce exposure to $PM_{2.5}$ in urban areas by 2020 by a target which depends on average concentration in the reference years 2008-10. For example, countries with initial concentration between 18µg/m^3 and 22µg/m^3 must reduce concentrations by 20% by 2020, but countries with initial concentration between 8.5µg/m^3 and 13µg/m^3 must reduce concentrations by 10% (countries with initial concentration below 8.5µg/m^3 have no reduction target). Figure 4 shows the required pollution targets by country. The measures necessary to ensure that these targets are met are left at the discretion of the Member States.

Figure 4. Required reduction of air pollution based on EC Directive 2008/50.

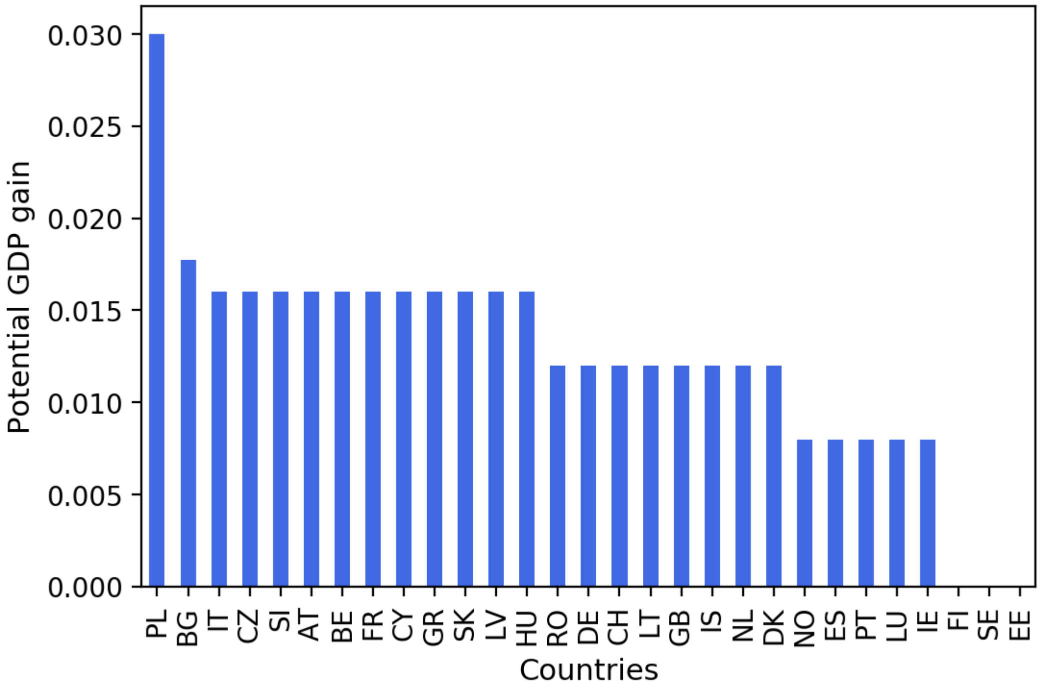


Source: European Environment Agency (2017).

69. As an illustration, we calculate the predicted impact on GDP for all European Union Member States from meeting their pollution reduction targets laid out in the Directive 2008/50/EC on ambient air quality shown in Figure 4. Results are presented in Figure 5. On average, our model predicts that European GDP would grow by 1.28% between 2010 and 2020 if all countries met their targets, accounting for the costs of abatement of around 0.01% of GDP reported in Table E.4 in Annex E. This average number hides significant heterogeneity between countries, with the most polluted countries with more ambitious targets increasing their GDP by up to 2.9% for Poland and 1.7% for Bulgaria. The impact is around 1.5% for Austria, Belgium, Italy, Czech Republic and France. The GDP increases

for Germany and the UK stand at 1.2%, and even for low-pollution countries such as Norway, the GDP increases are still substantial at around 0.8%.

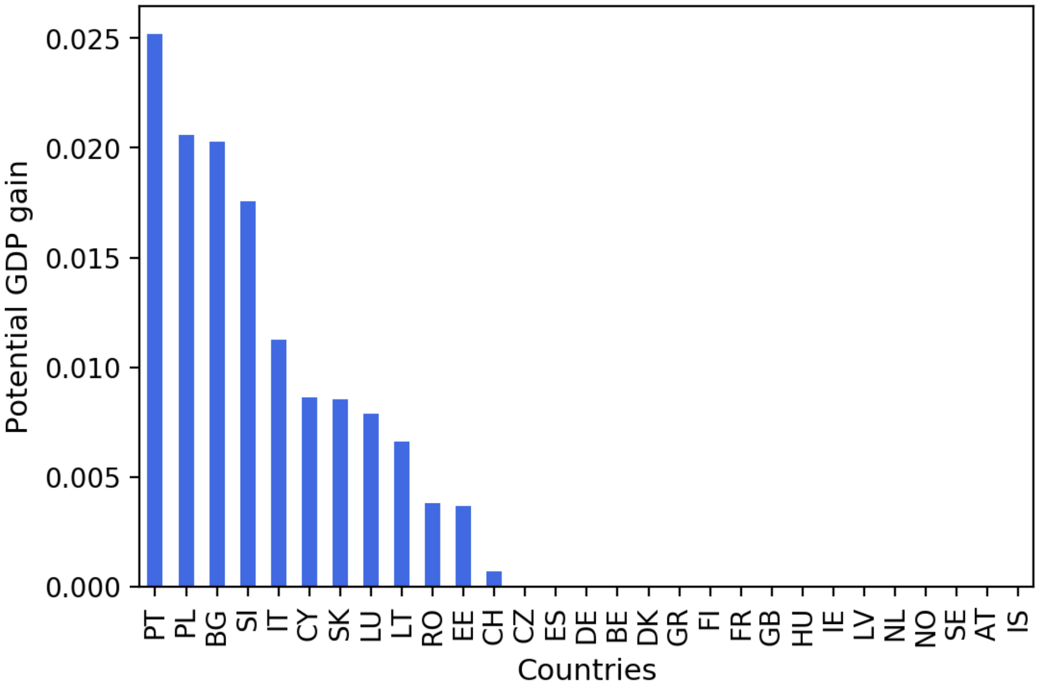
Figure 5. Predicted impact of EC Directive 2008/50 on country-level GDP.



Source: Authors' own calculations.

70. Since 8 years have passed since the legislation came into power, it is interesting to look at how far countries went in meeting their targets and what would be the further potential GDP gain if countries fulfil the remaining obligations (Figure 6). 17 countries have already met their targets and for them there is no further GDP gain in this calculation (even if there would still be potential GDP gains from reducing $PM_{2.5}$ concentration further). In total, meeting their target would induce a further 1.07% GDP increase for the 12 countries which still have not met their targets (representing a 0.24% increase in GDP for the EU as a whole). This again hides important heterogeneity, with countries that are still furthest from their European Commission targets, such as Portugal where pollution actually increased recently, increasing their GDP by up to 2.5%. Thus, our results suggest that air pollution control policies could have significantly contributed to recent economic growth in Europe, and in particular to economic convergence between Eastern and Western Europe, and could further contribute to economic development in the future.

Figure 6. Potential GDP gain for countries that have not yet met the EC 2010/50 targets.



Source: Authors' own calculations.

6. Conclusions and possible future work

71. This paper provides causal evidence on the impact of air pollution on economic activity in Europe. Results suggest that increases in air pollution cause substantial reductions in economic activity that are mostly driven by reductions in output per capita. Thus, the study contributes to broader efforts to understand the drivers of productivity growth. The findings are of substantial importance to cost-benefit evaluations of air pollution reduction policies and suggest that much stronger air quality regulations could be warranted even ignoring their positive impacts on reduced mortality. They also suggest that air pollution control policies can significantly contribute to economic growth and can usefully complement other mainstream structural policies.

72. The analysis could be extended in several directions.

- First, the analysis shows that air pollution affects economic output mostly through reductions in output per capita, which points to potential effects on labour productivity (and absenteeism at work), but a better understanding of the drivers of the impact and of their heterogeneity across workers is needed. Carrying out such an analysis would require microdata at the level of firms and individuals. This would allow for much richer analyses of the heterogeneity of the impact of pollution across types of firms, workers' skills and level of education, etc. Microdata studies would make it possible to investigate the distributional consequences of pollution, in a static way but also in a dynamic perspective, where pollution affect workers' migration, contributing to the polarization of the economy between high-productivity, low-pollution and low-productivity, high-pollution regions.

- Second, the data focuses on Europe, and it would be interesting to investigate if the results are valid beyond this region. The analysis could be extended to other countries or regions for which sub-national data on economic output is available (pollution and weather data are available at the global level).
- Finally, the econometric analysis focuses on contemporaneous air quality and economic output, and so the estimates do not include any longer-run effects of pollution. These can be large, however, especially considering impacts on health for children, which can have repercussions on their school results, and thus long term career prospects and productivity. Therefore the results may at present underestimate the overall costs of air pollution. It might be possible to look at longer-run effects but this would require longer time series.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham, "Management and shocks to worker productivity: evidence from air pollution exposure in an Indian garment factory," *Un- published Working Paper, University of Michigan*, 2014.

Agrawal, M., B. Singh, M. Rajput, F. Marshall, and J.N.B Bell, "Effect of air pollution on peri-urban agriculture: a case study," *Environmental Pollution*, 2003, *126* (3), 323 – 329.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2008.

Aragon, Fernando M, Juan Jose Miranda, and Paulina Oliva, "Particulate matter and labor supply: the role of caregiving and non-linearities," *Journal of Environmental Economics and Management*, 2017.

Archsmith, James, Anthony Heyes, and Soodeh Saberian, "Air Quality and Error Quantity: Pollution and Performance in a High-skilled, Quality-focused Occupation," 2016.

Avnery, Shiri, Denise L Mauzerall, Junfeng Liu, and Larry W Horowitz, "Global crop yield reductions due to surface ozone exposure: 1. Year 2000 crop production losses and economic damage," *Atmospheric Environment*, 2011, *45* (13), 2284–2296.

Borgschulte, Mark, David Molitor, and Eric Zou, "Smoked out: The effect of wildfire smoke on labor market outcomes," Technical Report, *Technical report. Working Paper* 2016.

Botta, E. and T. Koźluk (2014), "Measuring Environmental Policy Stringency in OECD Countries: A Composite Index Approach", *OECD Economics Department Working Papers*, No. 1177, OECD Publishing, Paris, https://doi.org/10.1787/5jxrjnc45gvg-en.

Buchard, V, AM da Silva, CA Randles, P Colarco, R Ferrare, J Hair, C Hostetler, J Tackett, and D Winker, "Evaluation of the surface PM 2.5 in Version 1 of the NASA MERRA Aerosol Reanalysis over the United States," *Atmospheric Environment*, 2016, *125*, 100–111.

Buchard, V, CA Randles, AM da Silva, A Darmenov, PR Colarco, R Govindaraju, R Ferrare, J Hair, AJ Beyersdorf, LD Ziemba et al., "The MERRA-2 aerosol reanalysis, 1980 onward. Part II: Evaluation and case studies," *Journal of Climate*, 2017, *30* (17), 6851–6872.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Global non-linear effect of tem- perature on economic production," *Nature*, 2015, *527* (7577), 235–239.

Calderón-Garcidueñas, Lilian, Ricardo Torres-Jardón, Randy J Kulesza, Su-Bin Park, and Amedeo DAngiulli, "Air pollution and detrimental effects on childrens brain. The need for a multidisciplinary approach to the issue complexity and challenges," *Frontiers in human neuro- science*, 2014, *8*, 613.

Chameides, William L, H Yu, SC Liu, M Bergin, X Zhou, L Mearns, G Wang, CS Kiang, RD Saylor, C Luo et al., "Case study of the effects of atmospheric aerosols and regional haze on agriculture: an opportunity to enhance crop yields in China through emission controls?," *Proceedings of the National Academy of Sciences*, 1999, *96* (24), 13626–13633.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell, "The effect of pollution on worker productivity: evidence from call-center workers in China," Technical Report, National Bureau of Economic Research 2016.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell, "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy*, 2016, *8* (3), 141–69.

Chang, Tom Y, Wei Huang, and Yongxiang Wang, "Something in the Air: Pollution and the Demand for Health Insurance," *Review of Economic Studies,* 2017.

Chay, Kenneth Y and Michael Greenstone, "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession," *The quarterly journal of economics*, 2003, *118* (3), 1121–1167.

Chen, Shuai, Paulina Oliva, and Peng Zhang, "The Effect of Air Pollution on Migration: Evi- dence from China," Technical Report 24036, National Bureau of Economic Research 2017.

Cohen, Aaron J, Michael Brauer, Richard Burnett, H Ross Anderson, Joseph Frostad, Kara Estep, Kalpana Balakrishnan, Bert Brunekreef, Lalit Dandona, Rakhi Dandona et al., "Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015," The Lancet, 2017, 389 (10082), 1907–1918.

Currie, Janet and Matthew Neidell, "Air pollution and infant health: what can we learn from California's recent experience?," *The Quarterly Journal of Economics*, 2005, *120* (3), 1003–1030.

Currie, Janet, Eric A Hanushek, E Megan Kahn, Matthew Neidell, and Steven G Rivkin, "Does pollution increase school absences?," *The Review of Economics and Statistics*, 2009, *91* (4), 682–694.

Dasgupta, Susmita, Benoit Laplante, Hua Wang, and David Wheeler, "Confronting the envi- ronmental Kuznets curve," *Journal of economic perspectives*, 2002, *16* (1), 147–168.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature and income: reconcil- ing new cross-sectional and panel estimates," *American Economic Review*, 2009, *99* (2), 198–204.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "Temperature shocks and economic growth: Evidence from the last half century," *American Economic Journal: Macroeconomics*, 2012, *4* (3), 66–95.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 2014, *52* (3), 740–98.

Deryugina, Tatyana and Solomon Hsiang, "The Marginal Product of Climate," Technical Report 24072, National Bureau of Economic Research 2017.

Deryugina, Tatyana and Solomon M Hsiang, "Does the environment still matter? Daily temperature and income in the United States," Technical Report, National Bureau of Economic Research 2014.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif, "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction*," Working Paper 22796*, National Bureau of Economic Research November 2016.

Dingenen, Rita Van, Frank J Dentener, Frank Raes, Maarten C Krol, Lisa Emberson, and Janusz Cofala, "The global impact of ozone on agricultural crop yields under current and future air quality legislation," *Atmospheric Environment*, 2009, *43* (3), 604–618.

Dockery, Douglas W, C Arden Pope, Xiping Xu, John D Spengler, James H Ware, Martha E Fay, Benjamin G Ferris Jr, and Frank E Speizer, "An association between air pollution and mortality in six US cities," *New England journal of medicine*, 1993, *329* (24), 1753–1759.

Donkelaar, Aaron Van, Randall V Martin, Michael Brauer, N Christina Hsu, Ralph A Kahn, Robert C Levy, Alexei Lyapustin, Andrew M Sayer, and David M Winker, "Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors," *Environmental science & technology*, 2016, *50* (7), 3762–3772.

Du, Yixing, Xiaohan Xu, Ming Chu, Yan Guo, and Junhong Wang, “Air particulate matter and cardiovascular disease: the epidemiological, biomedical and clinical evidence,” *Journal of thoracic disease*, 2016, *8* (1), E8.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth, “The long-run economic consequences of high-stakes examinations: evidence from transitory variation in pollution,” *American Economic Journal: Applied Economics*, 2016, *8* (4), 36–65.

European Commission, 2005. Commission Staff Working Paper SEC (2005) 1133, Annex to The Communication on Thematic Strategy on Air Pollution and The Directive on “Ambient Air Quality and Cleaner Air for Europe”, Impact Assessment

Ferrini, F, “Thermodynamic theory of temperature inversion in the earth atmosphere,” *Astro- physics and Space Science*, 1979, *61* (2), 267–275.

Fu, Shihe and Mengmeng Guo, “Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance,” 2017.

Fu, Shihe, V Brian Viard, and Peng Zhang, “Air quality and manufacturing firm productivity: compre- hensive evidence from China,” 2017.

Graff-Zivin, Joshua and Matthew Neidell, “The impact of pollution on worker productivity,” *The American Economic Review,* 2012, 102 (7), 3652–3673.

Graff-Zivin, Joshua and Matthew Neidell, “Environment, health, and human capital,” *Journal of Economic Literature*, 2013, 51(3), 689–730.

Graff-Zivin, Joshua and Matthew Neidell, “Air pollution's hidden impacts,” Science, 2018, 359 (6371), 39–40.

Gramsch, E., D. Cceres, P. Oyola, F. Reyes, Y. Vsquez, M.A. Rubio, and G. Snchez, “Influ- ence of surface and subsidence thermal inversion on $PM_{2.5}$ and black carbon concentration,” *Atmospheric Environment*, 2014, *98*, 290 – 298.

Grossman, Gene M and Alan B Krueger, “Economic growth and the environment,” *The Quar- terly Journal of Economics*, 1995, *110* (2), 353–377.

Hanna, Rema and Paulina Oliva, “The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City,” *Journal of Public Economics*, 2015, *122*, 68–79.

Hansen, Anett C and Harald K Selte, “Air pollution and sick-leaves,” *Environmental and Re- source Economics*, 2000, *16* (1), 31–50.

Haylock, MR, N Hofstra, AMG Klein Tank, EJ Klok, PD Jones, and M New, “A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006,” *Journal of Geophysical Research: Atmospheres*, 2008, *113* (D20).

He, Jiaxiu, Haoming Liu, and Alberto Salvo, “Severe air pollution and labor productivity: evi- dence from industrial towns in China,” *American Economic Journal: Applied Economics*, 2018.

Herrnstadt, Evan and Erich Muehlegger, “Air pollution and criminal activity: Evidence from Chicago microdata,” Technical Report 21787, *National Bureau of Economic Research* 2015.

Heyes, Anthony, Matthew Neidell, and Soodeh Saberian, “The Effect of Air Pollution on In- vestor Behavior: Evidence from the S&P 500,” *Technical Report 22753*, National Bureau of Economic Research 2016.

Hicks, Daniel, Patrick Marsh, and Paulina Oliva, “Air pollution and procyclical mortality: Causal evidence from thermal inversions,” *Technical Report, working* paper, Jacobson, M. (2002). Atmospheric Pollution. History, Science, and Regulation, 1st ed. Cambridge, UK: Cambridge University Press 2016.

Holub, Felix, Laura Hospido, and Ulrich J Wagner, “Air pollution and labor supply: Evidence from social security data,” 2016.

Isen, Adam, Maya Rossin-Slater, and W. Reed Walker, “Every Breath You TakeEvery Dollar Youll Make: The Long-Term Consequences of the Clean Air Act of 1970,” *Journal of Political Economy*, 2017, *125* (3), 848–902.

Islam, Nazrul, “Growth empirics: a panel data approach,” *The Quarterly Journal of Economics*, 1995, *110* (4), 1127–1170.

Jayachandran, Seema, “Air quality and early-life mortality evidence from Indonesias wildfires,” *Journal of Human resources*, 2009, *44* (4), 916–954.

Krupnick, Alan, Daniel Sullivan “The Benefits of Uniform Compliance with National Air Quality Standards”, *Paper presented at WCERE 2018*

Nickell, Stephen, “Biases in dynamic models with fixed effects,” *Econometrica: Journal of the Econometric Society*, 1981, pp. 1417–1426.

OECD (2016), *The Economic Consequences of Outdoor Air Pollution*, OECD Publishing, Paris. http://dx.doi.org/10.1787/9789264257474-en

Pope, C Arden III, Richard T Burnett, Michael J Thun, Eugenia E Calle, Daniel Krewski, Kazuhiko Ito, and George D Thurston, “Lung cancer, cardiopulmonary mortality, and long- term exposure to fine particulate air pollution,” *Jama*, 2002, *287* (9), 1132–1141.

Ranft, Ulrich, Tamara Schikowski, Dorothee Sugiri, Jean Krutmann, and Ursula Krämer, “Long-term exposure to traffic-related particulate matter impairs cognitive function in the el- derly,” *Environmental research*, 2009, *109* (8), 1004–1011.

Ransom, Michael R and C Arden Pope III, “Elementary school absences and PM10 pollution in Utah Valley,” *Environmental research*, 1992, *58* (1-2), 204–219.

Roman, Henry A., Katherine D. Walker, Tyra L. Walsh, Lisa Conner, Harvey M. Richmond, Bryan J. Hubbell, and Patrick L. Kinney, “Expert Judgment Assessment of the Mortality Impact of Changes in Ambient Fine Particulate Matter in the US,” *Environmental Science and Technololgy*, 2008, *42*, 2268–2274.

Roy, R. and N. Braathen (2017), “The Rising Cost of Ambient Air Pollution thus far in the 21st Century: Results from the BRIICS and the OECD Countries”, *OECD Environment Working Papers*, No. 124, OECD Publishing, Paris. http://dx.doi.org/10.1787/d1b2b844-en

Schlenker, Wolfram and W Reed Walker, “Airports, air pollution, and contemporaneous health,” *The Review of Economic Studies*, 2015, *83* (2), 768–809.

Schlenker, Wolfram, Maximilian Auffhammer, Solomon Hsiang, and Adam Sobel (2013), "Using Weather Data and Climate Model Output in Economic Analyses of Climate Change." 2013. Review of Environmental Economics and Policy, 7(2): 181-198.

Schulze, E-D, “Air pollution and forest decline in a spruce (Picea abies) forest,” *Science*, 1989, *244* (4906), 776–783.

Sharan, M. and S.G. Gopalakrishnan, “Mathematical Modeling of Diffusion and Transport of Pollutants in the Atmospheric Boundary Layer,” *Pure and Applied Geophysics*, Jan 2003, *160* (1), 357–394.

Stern, David I, "The rise and fall of the environmental Kuznets curve," *World development*, 2004,*32* (8), 1419–1439.

Wahid, A., R. Maggs, S.R.A. Shamsi, J.N.B. Bell, and M.R. Ashmore, "Air pollution and its impacts on wheat yield in the Pakistan Punjab," *Environmental Pollution*, 1995, *88* (2), 147 – 154.

Wallace, Julie and Pavlos Kanaroglou, "The effect of temperature inversions on ground-level nitrogen dioxide (NO2) and fine particulate matter ($PM_{2.5}$) using temperature profiles from the Atmospheric Infrared Sounder (AIRS)," *Science of The Total Environment*, 2009, *407* (18), 5085– 5095.

Ward, Courtney J, "It's an ill wind: The effect of fine particulate air pollution on respiratory hospitalizations," *Canadian Journal of Economics/Revue canadienne d'économique*, 2015, *48* (5), 1694–1732.

Whiteman, C David and Thomas B McKee, "Breakup of temperature inversions in deep mountain valleys: Part II. Thermodynamic model," *Journal of applied Meteorology*, 1982, *21* (3), 290–302.

Wooldridge, Jeffrey (2009). Introductory Econometrics. A Modern Approach. South-Western.

World Health Organization, "Burden of disease from ambient air pollution for 2012," *Technical Report* 2012.

World Health Organization, Air Quality Guidelines: Global Update 2005: Particulate Matter, Ozone, Nitrogen dioxide, and Sulfur dioxide, Copenhagen, Denmark: World Health Organization, 2006.

World Health Organization, "Ambient air pollution: A global assessment of exposure and burden of disease," *Technical Report* 2016.

Wood, S. N. (2006), *Generalized additive models: an introduction with R. Chapman and Hall/CRC.*

Annex A. Prior literature

73. This annex provides a more systematic summary of the literature reviewed in section 2.

Pollution and population

74. It is widely recognized that air pollution imposes a substantial burden on human health (Graff Zivin and Neidell, 2013). Large cohort-based studies conducted by epidemiologists have provided evidence since at least 25 years ago that pollution by small airborne particles ($PM_{2.5}$, particulate matter less than 2.5 microns in diameter) increases the rate of death (Dockery et al., 1993; Pope et al., 2002), especially through increases in respiratory and heart diseases. Calculations based on these and other studies suggest that ambient (outdoor) air pollution (especially $PM_{2.5}$) caused about 3.7 million deaths worldwide in 2012 (5.4% of all deaths) (World Health Organization, 2012). More recent estimates using a similar approach show that ambient $PM_{2.5}$ alone caused 4.2 million deaths worldwide in 2015 (7.6% of all deaths), and was one of the leading causes of premature loss of life and loss of health (Cohen et al., 2017).

75. A substantial literature also finds evidence that pollution impacts birth outcomes. For example, Chay and Greenstone (2003) find that reductions in total suspended particulates (TSP, including both $PM_{2.5}$ as well as coarser particulates) caused reductions in infant mortality. They estimate that a 1% reduction in TSP reduced infant mortality by 0.35% in the early 1980s. Currie and Neidell (2005) find that reductions in PM_{10} and carbon monoxide (CO) in California both cause reductions in infant mortality. Jayachandran (2009) uses variation in exposure to smoke from the 1997 Indonesia forest fires to estimate “missing children” in downwind communities. She finds a large effect of exposure to forest fire smoke on infant mortality.

76. Recent research also suggests that air pollution may impact migration. Chen et al. (2017) find great movement between provinces in China to avoid air pollution. Taken together, these studies suggest that air pollution likely reduces population in a region, by increasing deaths, reducing live births, and increasing net outmigration.

Pollution and absenteeism

77. In addition to its effect on overall population, pollution has been found to affect sickness, and as a result, absenteeism. Ransom and Pope III (1992) provided an early evidence on the relationship between outdoor pollution and absenteeism, by focusing on school attendance in Utah. They found that an increase in monthly PM_{10} of $100\mu g/m^3$ was associated with a 40% increase in absenteeism. Currie et al. (2009) report similar findings in Texas schools for carbon monoxide (CO).

78. Similar studies have been conducted addressing absenteeism from work. For example, Holub et al. (2016) find that a $10\mu g/m^3$ increase in PM_{10} concentration results in a 1.6% increase in job absenteeism in Spain. Similarly, Hanna and Oliva (2015), Hansen and Selte (2000), and Aragon et al. (2017) show that increases in pollution reduce hours of work by a substantial magnitude. Interestingly, Aragon et al. (2017) finds that a key factor in explaining absenteeism from work, especially at moderate pollution levels, is the

presence of dependents in the household (since, if a child is sick, a parent may have to stay home). Thus there may be a link between the school and work absenteeism outcomes.

Pollution and productivity

79. In addition to causing substantial ill-health and mortality, air pollution is also believed to impair cognitive and physical functions. Again $PM_{2.5}$ is of particular concern. When this pollutant is inhaled, the particles can enter deep into the lung and damage lung function. Additionally, they pass through the lung into the bloodstream, where they can affect the heart and brain function (Calderon-Garciduenas et al., 2014; Du et al., 2016; Ranft et al., 2009). Because pollution affects physical and cognitive function, there is a clear pathway through which it could impact workplace productivity. Starting with Graff Zivin and Neidell (2012), a number of studies have investigated the link between productivity and other economic outcomes and elevated pollution. These studies have typically focused on groups of individuals for which productivity, or some similar measure is directly observable and for whom tasks cannot easily be delayed or shifted in location.

80. Chang et al. (2016b) examine the daily productivity of pear-packers at an indoor facility. They find that the number of boxes packed is reduced on days when air quality is poor. Adhvaryu et al. (2014) use data on hourly worker output at a garment manufacturing facility in India to show that that increases in $PM_{2.5}$ concentrations cause reductions in worker productivity (measured by the number of garments sewn per hour). He et al. (2018) obtain data on worker-level output from two textile manufacturing facilities in China. They find that a sustained increase in $PM_{2.5}$ causes a reduction in worker output. Chang et al. (2016a) show that the effect isn't limited to physical workers. They obtain a worker-level dataset from a Chinese call centre, and find that the number of calls handle by worker falls with increases in the air quality index, due to longer breaks at work taken by workers on polluted days.

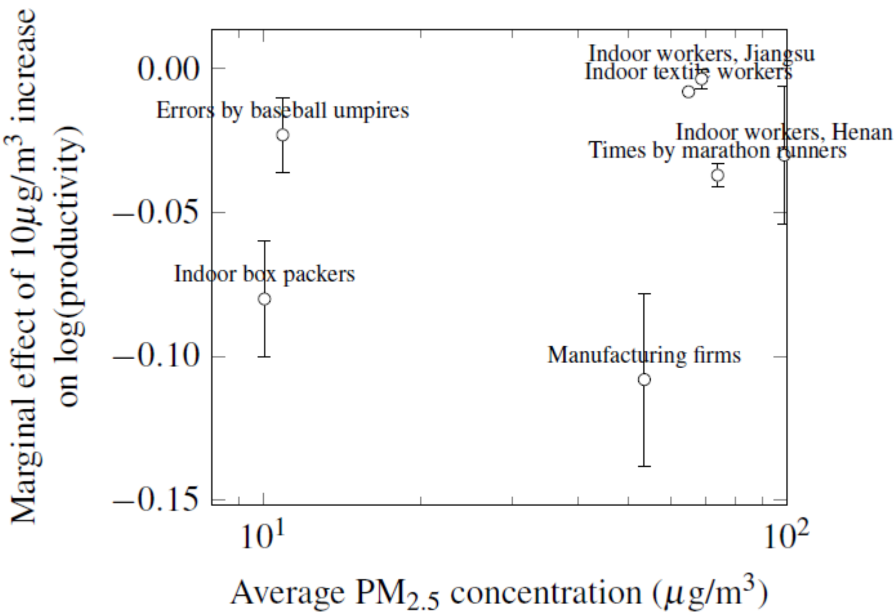
81. Estimating the potential effect of pollution on high-skill workers is more challenging, because tasks are typically less routinized and can often be shifted in time and space. Nevertheless, there is some evidence that pollution also affects productivity in high-skill tasks. For example, Ebenstein et al. (2016) estimate the causal effect of poor air quality on student performance in standardized high-school examinations, and find that a 10μg/m^3 increase in $PM_{2.5}$ concentration causes a 0.023% decline in exam scores. Archsmith et al. (2016) finds that the number of incorrect calls made by major-league baseball umpires increases by 2.6% when $PM_{2.5}$ increases by 10μg/m^3, and Heyes et al. (2016) finds that a 7μg/m^3 increase in $PM_{2.5}$ in New York causes a same-day fall of 12% in NYSE returns.

82. Some of the key conclusions from these studies are reproduced in Figure A.1. The values reported in this figure were extracted as follows:

- Fu and Guo (2017) estimate the impact of air pollution on marathon runnings times. We use the coefficient on log($PM_{2.5}$) in Table 9, column 2, which shows that a 1% increase in $PM_{2.5}$ increases marathon completion time by 0.270%. From Table 1, mean $PM_{2.5}$ concentration in the sample is 73.89μg/m^3. Thus the increase in marathon completion time caused by a 1μg/m^3 increase in $PM_{2.5}$ is $0.270/73.89 \times 0.01 = 0.37\%$.

- Holub et al. (2016) estimate that a 13.38µg/m^3 increase in PM_{10} concentration increases propensity to take sick leave by 0.005 percentage points from the mean of 0.228%, so 2.2%. Alternatively a 10µg/m^3 increase causes a 1.64% in absenteeism.
- Archsmith et al. (2016) show that a 10µg/m^3 increase in $PM_{2.5}$ concentration causes umpires to make 0.4 extra incorrect calls per 100 pitches (Table 2, column 8), which is a 2.3% increase in error quantity.
- Adhvaryu et al. (2014) show that a 10µg/m^3 increase in $PM_{2.5}$ concentration reduces efficiency of textile workers by 0.8% (Table 2, column 6). In the figure this is *Indoor textile workers, A*.
- Chang et al. (2016b) show that a 10µg/m^3 increase in $PM_{2.5}$ concentration reduces productivity of indoor box packers by 8% (Table 3, column 5).
- He et al. (2018) estimate that a 10µg/m^3 increase in $PM_{2.5}$ concentration sustained over 25 days reduces labour productivity in two Chinese textile plants by 0.38% to 3% (see Table 4, 2SLS estimates, 25 day lag). In the figure, the figure (for two sites) are labelled with the site names.
- Fu et al. (2017) estimates that a 1µg/m^3 increase in $PM_{2.5}$ concentration leads to a 1.08% reduction in value added per worker (Table 2).

Figure A.1. Estimates of ambient $PM_{2.5}$ on productivity from prior studies.



83. While it is difficult to generalize from these highly-specific tasks to the broader population, and while the magnitude of the measured impacts on these populations due to air pollution are quite varied, the emerging evidence points towards an increasingly consistent finding that air pollution impacts on-the-job outcomes, conditional on being at work. It is important to note that most of these studies focus on contemporaneous air quality and productivity, and so the estimates do not include any longer-run effects of pollution on

productivity. An exception is Fu et al. (2017), who examines annual productivity, and He et al (2018), who estimate productivity based on cumulative exposure over 25 days.

Impacts of pollution on the productivity of natural resources

84. In addition to impacts of pollution that are mediated through the labor market, air pollution may also have a direct impact on output. This is most likely in the agricultural or forestry sectors, where air pollution has the potential to damage crops or trees and thus cause reductions in yield.

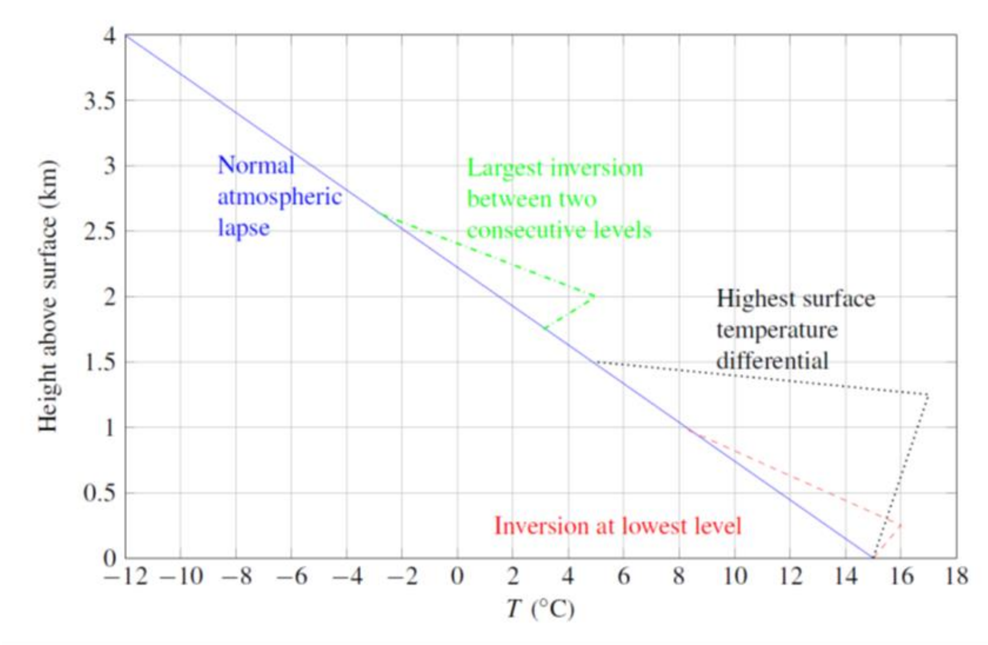
85. A number of papers find that agricultural output is impacted by ambient pollution. Van Dingenen et al. (2009) use empirical dose-response relationships to estimate that current levels of pollution (primarily ozone) reduce global yields by 7-12% for wheat, 6-16% for soybean, and 3- 4% for rice and maize. Avnery et al. (2011) report very similar results. Chameides et al. (1999) estimates that most crop yields in China are depressed by 5-30% as a result of suspended particulate matter, as this pollutant causes reductions in direct sunlight reaching plants, which is well known to depress yields. Schulze (1989) shows that deposition of air pollutant in soils affects soil acidity, and thus tree root development, long term growth rates, and tree health. Outside of the agricultural sectors, Li et al (2017) find that $PM_{2.5}$ pollution in China causes large losses in solar photovoltaic output (by 20% on an annual average basis in Eastern China) as it reduces direct radiation reaching solar panels.

Annex B. Data details

Figure B.1. Pollution during a thermal inversion

Source: Wikimedia.

Figure B.2. Schematic to define inversion variables used in the paper.



Note: The solid blue line shows the normal atmospheric lapse rate. Over the altitudes considered, temperature is monotonically declining with altitude under normal atmospheric conditions. The dashed red line shows our measure of inversions at the lowest level of the atmosphere. The dotted black line shows our second measure of inversions, which is the highest positive deviation between the surface and atmospheric temperatures. The dash-dotted green line shows our third measure of inversions, which is the largest positive deviation between any two adjacent atmospheric levels.

Source of data

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

Table B.1. Additional details on variables construction

Variable	Construction details
Dependent variables	
GDP	Regional gross domestic product in current prices is obtained from the Eurostat data catalogue. We obtain annual data for each NUTS3 region from 2000-15 (Eurostat table: nama 10r 3gdp). We calculate the real 2015 values using the Harmonised Index of Consumer Prices (HICP) available from Eurostat (Eurostat table: prc hicp aind).
GVA	Gross value added by sector is obtained from Eurostat (table: nama 10r 3gva).
Population	Population data is from Eurostat (table: demo r pjanaggr3).
Independent variables	
$PM_{2.5}$	We obtain daily mean $PM_{2.5}$ concentration for each grid cell covering Europe from the Van Donkelaar (2016) database between 2000 and 2015. We obtain an annual measure of $PM_{2.5}$ in each NUTS3 region as the mean of all grid cells overlapping the region.
Temperature	We obtain daily mean temperature from the European Climate Assessment for grid cells spanning the bounding box defined by the (longitude,latitude) coordinates (-15,35) to (35,70). We obtain a daily measure of temperature in each NUTS3 region as the mean of all grid cells overlapping the region. We cut the continuous temperature into a number of temperature bins that span the range of observed tem- peratures. We count the number of days that mean daily temperature falls into each of these bins in each year and regions in the sample.
Precipitation	Precipitation data is derived from the same source as temperature data, and variable construction generally follows an identical procedure. We construct mean precipitation across all days of the year.
Relative humidity	We obtain relative humidity from the MERRA2 M2I3NPASM reanalysis files and follow the same procedure as described above to arrive at an annual mean relative humidity.
Surface pressure	We obtain surface pressure from the European Climate Assessment files and follow the same procedure as described above to arrive at an annual mean pressure.
Wind speed	We obtain daily mean easterly and northerly wind speeds at surface from the MERRA2 M2I3NPASM reanalysis files. We obtain a daily measure of wind speed in each NUTS3 region as the mean of all grid cells overlapping the region. We count the number of days that wind speed falls into bins defined by the Beaufort scale in each year and NUTS3 region.

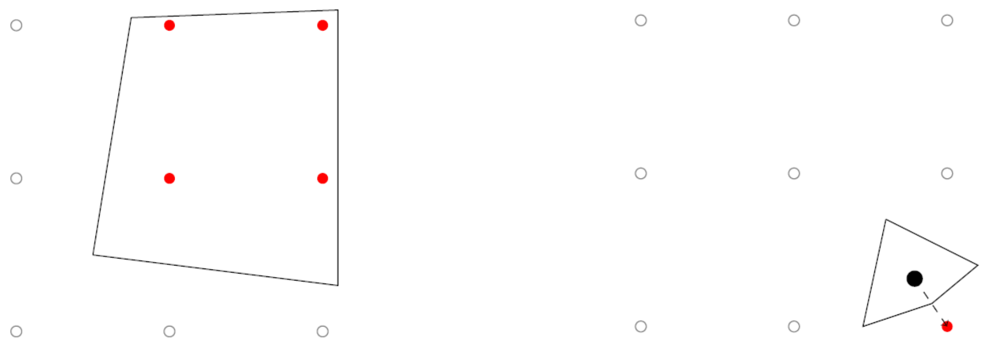
Merging data

87. Our dependent variables are measured annually in each NUTS3 region. In contrast, our main independent variables are measured at daily frequency on a gridded geographic scale. We first aggregate all gridded data to political boundaries, as illustrated in Figure B.3. Specifically, for each NUTS3 region that is overlain by at least one gridded data point, we take the average of all gridded data points that overlie the region as representative of atmospheric conditions in the region. For NUTS3 regions that are not overlain by any gridded data points, we calculate the distance between the centroid of the NUTS3 region and gridded data points, and use the observations from the closest gridded data point as representative of atmospheric conditions in the region.

88. Once data are aggregated to the geographic scale corresponding to the dependent variables, we proceed to aggregate from daily to annual data. For several variables (identified in the text, and table B.1 above), we simply take the annual average of daily observations. For other variables (identified in the text, and table B.1 above) we instead count the number of days where the variable falls within a given range. For example, the main specification counts the number of days in which temperature within the region falls

within a number of exhaustive temperature bins. This allows the possibility of capturing the potentially non-linear relationship between the independent and dependent variables.

Figure B.3. Merging data.



Note: Gridded data points are given by small circles and political boundaries are given by black polygons. In the left panel, several gridded data points overlie the political boundary (and are coloured red). The atmospheric conditions in the political boundary are taken as the average across all points that overlie the region. On the right, no gridded data points overlie the political boundary. In this case, we take observations from the closest gridded data point (shaded red) to the centroid of the polygon (shaded black) as representative of atmospheric conditions in the political boundary.

Residual variation

89. Figure B.4 shows the identifying variation in the thermal inversions instrumental variables. The figure shows a histogram of these variables after removing time and region fixed effects. The figures indicate that even after removing these fixed effects, there remains a substantial amount of variation in these variables. For example, it is normal to observe 5% or 365×0.05=18 days more or less of thermal inversions than the average (i.e. the standard deviation in the share of days with inversions is approximately 5%). It is evident there exists considerable variation in these instruments, which we leverage for identification in our regressions. Figures B.5 and B.6 also report the distribution of geographic variance in the instrumental variables. The figures show that Northern Europe and the Baltic region experience the most variation in winter inversions from year to year, and the coastal areas experience the most variation in summer inversions. These regions will contribute most to identification of the impact of pollution on GDP.

Figure B.4. Residual variation in the inversion instruments after NUTS3 and country-year fixed effects

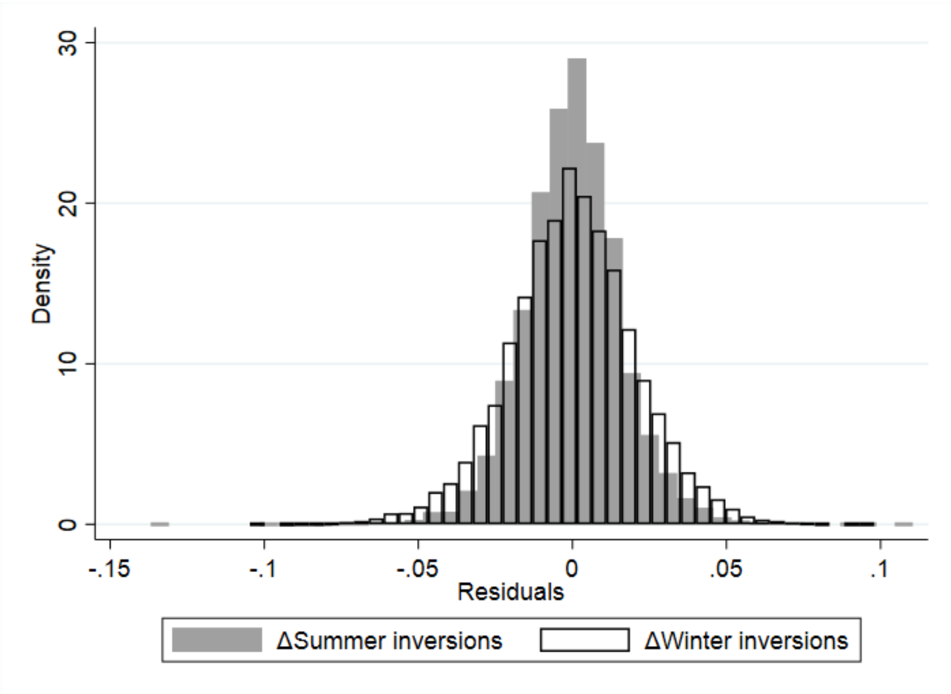
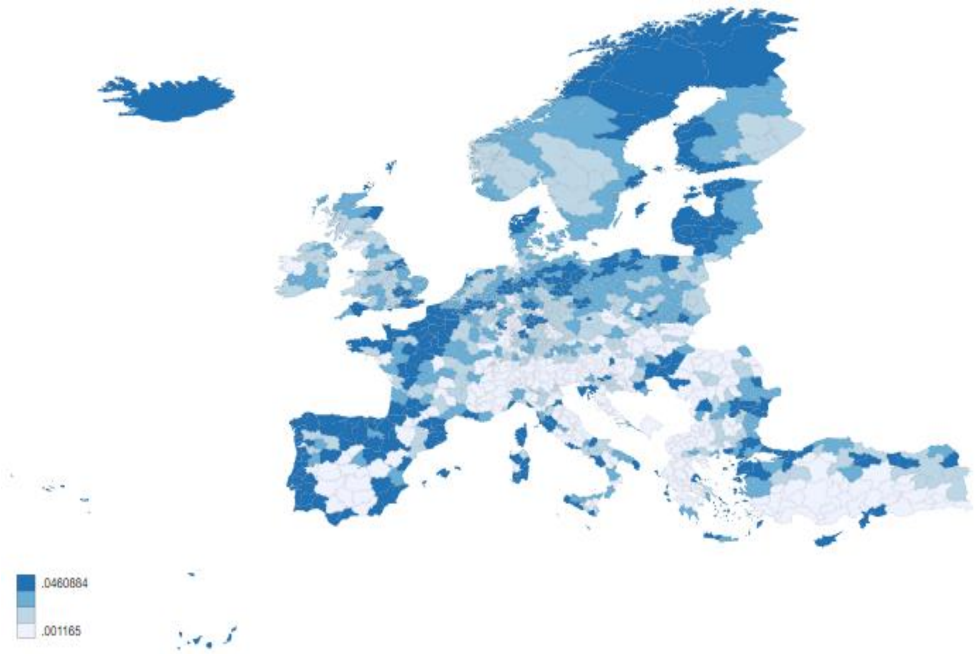
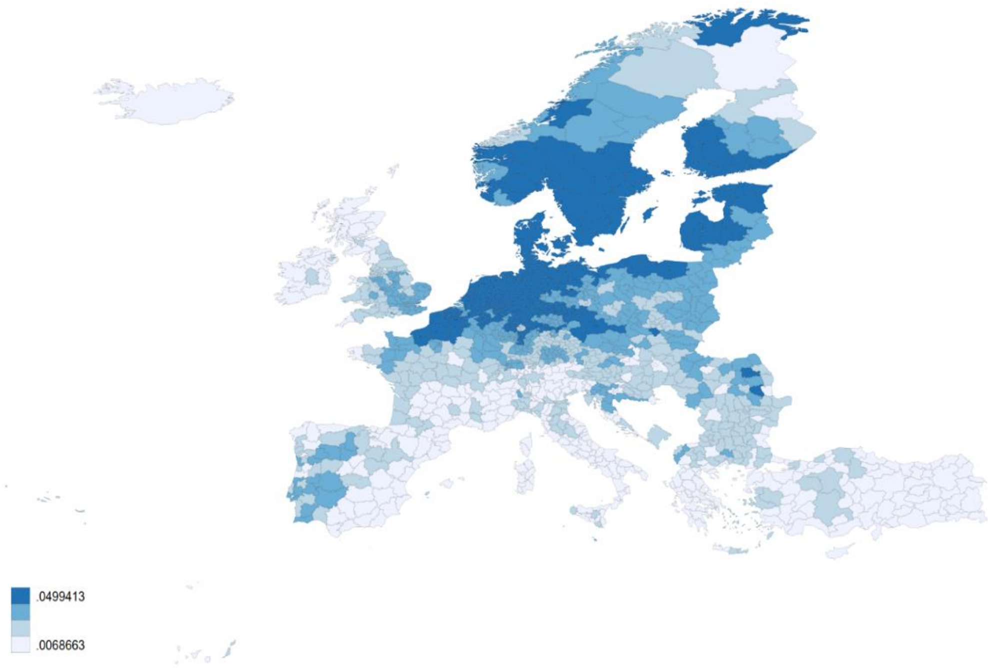


Figure B.5. Geographic variation of the summer inversion instrument



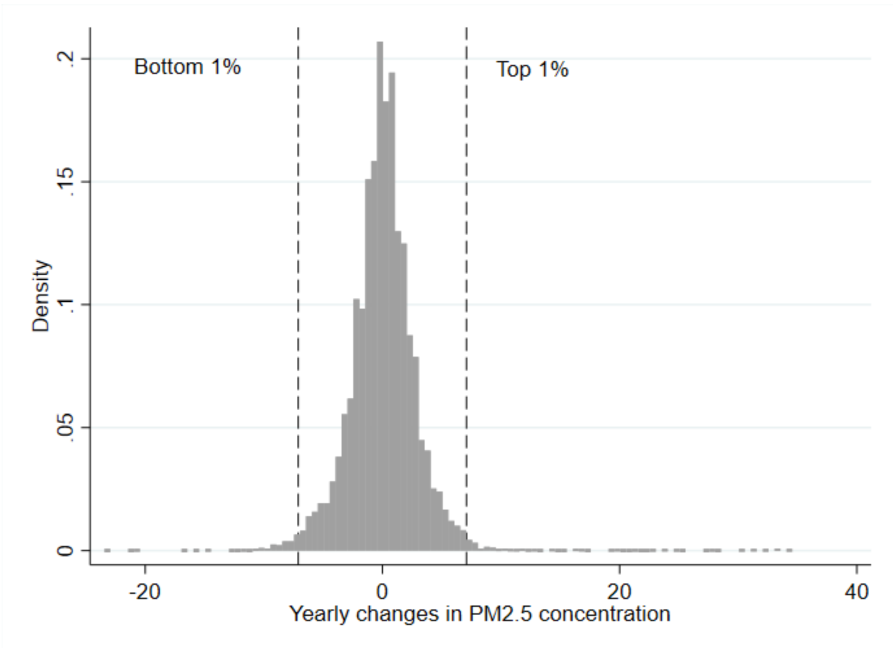
Note: The figure is produced by calculating the standard deviation of annual inversion frequency separately in each NUTS3 region.

Figure B.6. Geographic variation of the winter inversion instrument



Note: The figure is produced by calculating the standard deviation of annual inversion frequency separately in each NUTS3 region.

Figure B.7. Distribution of NUTS3-level year-on-year changes in PM2.5 concentration



Note: This graph shows the distribution of NUTS3-level year-on-year changes in PM2.5 concentration across the sample period. The dashed lines indicate the top and bottom 1% of that distribution.

Summary statistics

Table B.2. Summary statistics

Variable	Mean	SD	Min.	Max.	Obs.
Year	2007.195	4.38	2000	2015	19760
$PM_{2.5}$	15.96	5.63	2.72	61.68	19760
Surface relative humidity	0.732	0.07	0.464	0.881	19760
Precipitation	2.11	0.775	0.251	7.485	18634
Pressure	1015.957	2.107	1002.326	1030.665	18946
Temperature	10.302	2.635	-1.895	19.016	19760
Summer inversions	.0509575	.0377478	0	.3479452	19760
Winter inversions	.1168648	.0662488	0	.4191781	19760
Real GDP (M EUR)	10446.87	16316.73	191.8702	219192.1	19760
Real GDP per capita	27197.21	19324.23	1864.688	465409.6	19760
Real GDP per working-age population	41209.46	27206.6	1745.84	640873.6	19760
Total population	374854.16	421452.39	19243	6425522	18782

Annex C. Additional regression results

OLS results

90. Table C.1 shows results from an ordinary least squares specification without instrumental variables, (i.e. Equation (3)). In all regressions, we condition flexibly on ground-level weather and include country-year fixed effects like in the IV regressions. All regression coefficients indicate a statistically significant negative relationship between particulate matter and economic output, but the coefficient is 20 times smaller in magnitudes than in the instrumental variable regressions. However, as explained above, these regression coefficients do not estimate the causal effect of pollution on economic output. Instead, they confound the impact of economic output on pollution with the impact of pollution on economic output, failing to identify either.

Table C.1. OLS estimation: Association of $PM_{2.5}$ and GDP

	(1)	(2)	(3)
	Δln(GDP per working pop)	Δln(GDP per capita)	Δln(GDP)
$\Delta PM_{2.5}$	-0.0004 **	-0.0004 *	-0.0003 *
	(0.0002)	(0.0002)	(0.0002)
Observations	16789	16789	16789
R^2	0.269	0.269	0.269

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Reduced-form results: The effect of thermal inversions on economic output

91. The reduced-form results, where we estimate the effect of thermal inversions n directly on economic output (conditional on weather and fixed effects), help to build the case for the relevance of our chosen instrumental variables. All specifications suggest that the atmospheric phenomena that we employ as instrumental variables – and which we have shown cause increases in pollution – cause negative impacts on economic activity (Table C.2). Specifically, increasing the share of summer inversion days by 1 percentage point (i.e. an additional 365/100 = 3.65 inversion days per year) is estimated to cause a 0.02% reduction in economic activity, but the coefficient is not statistically significant. However, increasing the share of winter inversion days by 1 percentage t is estimated to cause a 0.038% reduction in economic activity.

Table C.2. Reduced form: Instruments' effect on GDP

	(1)	(2)	(3)
	Δln(GDP per working pop)	Δln(GDP per capita)	Δln(GDP)
ΔSummer inversions (any)	-0.0205	-0.0214	-0.0215
	(0.0171)	(0.0171)	(0.0169)
ΔWinter inversions (any)	-0.0383 **	-0.0380 **	-0.0395 **
	(0.0156)	(0.0155)	(0.0155)
Observations	16789	16789	16789
R^2	0.269	0.270	0.270

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Annex D. Robustness checks

92. This Annex presents details of the robustness checks summarized in Section 5.2.

Weather controls

93. As emphasized above, our instrumental variables satisfy the exclusion restriction conditionally. That is, conditional on ground-level weather, both thermal inversions and wind direction should only affect economic outcomes via their effect on pollution. Because both of these variables are likely correlated with weather, which can itself impact economic outcomes, it is important to carefully control for weather. We do this in the main results using a flexible approach to controlling for temperature and wind, and including other weather variables using second-degree polynomials. In Table D.1, we show that our results are invariant to adopting an even more flexible approach to including the effect of temperature (conditioning on 70 temperature bins, rather than 20 as in the baseline, and interacting them with humidity in column 2).

Table D.1. Robustness with respect to weather controls

	(1)	(2)
	70 temp. bins	70 temp. bins & humidity interactions
Δ $PM_{2.5}$	-0.0071 **	-0.0083 *
	(0.0036)	(0.0042)
Observations	16789	16789
Weak id. stat.	11.75	10.04
Hansen J stat. p-value	0.174	0.114

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. The estimation in column (1) includes country-year fixed effects, 12 wind speed bins, 70 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity. The estimation in column (2) includes no weather controls.

Alternative instruments

94. In our main specification, we adopt (by necessity) particular definitions for the thermal inversion variables. Specifically, we use the number of days of thermal inversions between the lowest and second lowest atmospheric in winter and summer level as instruments. We re-run the analysis with different definitions for the inversions, using inversions at the surface level and splitting inversions into 4 seasons (spring, summer, fall, winter) instead of two or a single inversion variable, disregarding any seasonality. Results are shown in Table D.2. The main coefficient tends to decrease when using surface inversions or 4 seasons, but is not statistically different from the baseline.

95. Overall, our results are robust to using different sets of different instrumental variables. The main coefficient varies between -0.0056 and -0.0105 depending on the instrument, corresponding to a 0.0002 deviation from the baseline of -0.008.

Table D.2. Robustness to instrument choice

	(1)	(2)	(3)	(4)
	Inversions low (annual)	Inversions low (4 seasons)	Inversions surface (annual)	Inversions surface (4 seasons)
Δ $PM_{2.5}$	-0.0105 **	-0.0067 *	-0.0062 **	-0.0056 **
	(0.0045)	(0.0037)	(0.0031)	(0.0025)
Obs.	16789	16789	16789	16789
Weak id. stat.	15.67	5.953	34.33	17.36
Hansen J stat. p-value	-	0.227	-	0.709

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Time trends and fixed effects

96. We test the sensitivity of our results to the inclusion of alternative fixed effects and control variables. Our main research design controls for persistent heterogeneity between regions using a differencing approach, and controls for common shocks across regions within each country using country-year fixed effects. Table D.3 replicates the main results, but adding additional controls to account for heterogeneity over time and between regions that is potentially correlated with economic activity and the instruments. Column (1) adds linear NUTS3 time trends to capture potential common trends within region countries between economic activity and the instruments. Results are not impacted, showing that they are not driven but common underlying trends between instrumented pollution and GDP at the regional level. Column (2) replaces country-year fixed effects with NUTS1-year fixed effects. These control for any unobserved heterogeneity at a NUTS1-year level, and identify the impact of air pollution only from within NUTS1-year variation across NUTS3 regions in (instrumented) pollution. Column (3) combines NUTS3 time trends with NUTS1-year fixed effects. In both columns, the coefficient remains statistically significant despite the inclusion of these additional fixed effects, and increases in magnitude.

Table D.3. Robustness check with respect to fixed effects.

	(1)	(2)	(3)
	NUTS3-trends	NUTS1-year effects	NUTS3-trends & NUTS1-year effects
Δ $PM_{2.5}$	-0.0083 **	-0.0145 *	-0.0148 *
	(0.0038)	(0.0086)	(0.0087)
Observations	16789	16709	16709
Weak id. stat.	9.525	5.708	5.691
Hansen J stat. p-value	0.117	0.00447	0.00312

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

97. One of the main potential issues with using PM2.5 concentration as the measure of air pollution is that, as discussed in Section 4.2, PM2.5 is correlated with other pollutants so that the main coefficient might capture the effect of other air pollutants correlated with $PM_{2.5}$, rather than just the effect of $PM_{2.5}$. We lack the data to control for all other major air pollutants, but in Table D.4 we test the impact of controlling for SO_2 concentration, the pollutant most highly correlated with $PM_{2.5}$ and for which we could assemble data across our sample. The coefficient on PM2.5 increases in magnitude to -0.0096, suggesting that not controlling for other pollutants might in fact lead us to underestimate the impact of PM2.5. We also test the robustness of the results to controlling for lagged GDP, as a check for the conditional orthogonality of the instruments with respect to components of GDP. For example, pollution may impact investment which would only show up with a lag. Similarly, one may argue that by not controlling for health expenditures separately, we underestimate the true effect of pollution. By including the lagged GDP we control for these possibilities. We find no impact on the key coefficient.

Table D.4. Robustness with respect to the inclusion of additional controls

	(1)	(1)
Δ $PM_{2.5}$	-0.0096 **	-0.0080 **
	(0.0045)	(0.0038)
Δ SO_2	0.0396	
	(0.0254)	
Lagged ln(GDP)		-0.0019
		(0.0013)
Observations	16452	16789
Weak id. stat.	7.814	9.384
Hansen J stat. p-value		0.114

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Alternative air pollution data

98. We re-estimate the model with different air pollution data (see section 4), based both on the MERRA and the CAMS models. Results are reported in Table D.5. In both cases, we continue to find a negative and statistically significant impact of pollution on GDP, and the estimates are larger than in our baseline (but not statistically significantly so). Additionally to these satellite-based measures, we also look at the results with monitoring station data by using the European Environmental Agency's AirBase (before 2013) and AirQuality e-reporting (2013-15) database. PM2.5 monitoring is a recent practice in Europe, so the number of observations drop substantially, but the main coefficient is negative and coincides with our baseline estimate.

Table D.5. Robustness with respect to source of air pollution data

	(1)	(2)	(3)
	CAMS	MERRA	EEA monitoring data
Δ $PM_{2.5}$	-0.0147 **	-0.0135*	-0.0078
	(0.0071)	(0.0082)	(1.4292)
Observations	4951	16392	2090
Weak id. stat.	10.75	9.643	1.501
Hansen J stat. p-value	0.970	0.0951	

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors (on NUTS3 level) are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Spatial autocorrelation.

99. We test the sensitivity of our results to spatial autocorrelation. In Table D.6, columns (1) and (2) implement clustering on country-year level in addition to NUTS1 level and on NUTS2 level, respectively. These allow arbitrary correlation within country-year or within broader regions over time. The coefficient remains statistically significant (p = 0.06) as in the baseline regression.

Table D.6. Robustness checks with spatial controls

	(1)	(2)
	Clustered on NUTS3 + country-year	Clustered on NUTS2
Δ $PM_{2.5}$	-0.0080 *	-0.0080 *
	(0.0045)	(0.0047)
ΔSpatial lag of PM2.5		
ΔSpatial lag of ln(GDP)		
Observations	16789	16789
Weak id. stat.	5.688	6.532
Hansen J stat. p-value		0.167

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

100. Results are not statistically different from the baseline if one removes outliers respectively at the top and bottom 0.5%, 2.5% or 5%, and remain statistically significant (Table D.7). Including extreme values and not removing outliers increases the standard error by 30% (p-value = 0.15) but the coefficient is not statistically different from the baseline.

Table D.7. Robustness checks with respect to outliers

	(1)	(2)	(3)	(4)
	Removing top and bottom 0.5%	Removing top and bottom 2.5%	Removing top and bottom 5%	No outliers dropped
Δ $PM_{2.5}$	-0.0078 **	-0.0064 **	-0.0059 *	-0.0066
	(0.0038)	(0.0038)	(0.0035)	(0.0049)
Observations	16940	16334	15513	17085
Weak id. stat.	8.492	11.11	14.11	3.588
Hansen J stat. p-value	0.117	0.0373	0.0253	0.0468

Note: * p<0.1,** p<0.05,*** p<0.01. Clustered standard errors are in parentheses. All estimations include (first-differenced) country-year fixed effects, 12 wind speed bins, 20 temperature bins, 20 precipitation bins, second order polynomials of relative humidity and atmospheric pressure and interactions between the 20 temperature bins and both humidity and squared humidity.

Annex E. Implications for cost benefit analyses of air pollution control policies

Table E.1. Benefits from $PM_{2.5}$ emission reduction scenarios in Europe

2025 scenario (EU28)	6A	6B	6C	6D
Reduction in emissions wrt baseline	-17%	-25%	-34%	-45%
Lost working days (M€)	726	1421	2 137	2 831
Damage to built environment (M€)	53	106	145	162
Crop value losses (M€)	61	101	278	630
Healthcare costs (M€)	219	437	657	886
Total direct benefits (M€)	1 059	2 065	3 237	4 509
Total reduction in external costs of air pollution vs baseline (low valuation, M€)	14 997	29 767	44 686	59 642
Total reduction in external costs of air pollution vs baseline (high valuation, M€)	50 317	100 937	150 853	200 074

Note: Scenario 6A: 25% gap closure between baseline and Maximum Technically Feasible Reduction (MTFR); Scenario 6B: 50% gap closure between baseline and MTFR; Scenario 6C: 75% gap closure be- tween baseline and MTFR; Scenario 6D: 100% gap closure between baseline and MTFR.
Source: European Commission (2013)

Table E.2. Benefits from the US Clean Air Act Amendments

Endpoint	Valuation (million 2006 USD)
Minor restricted activity days	6 700
Work loss days	2 700
Outdoor worker productivity	170
Agricultural and forest productivity	11 000
Mortality	1 800 000

Source: US Environment Protection Agency (2011)

Table E.3. Compliance costs for $PM_{2.5}$ concentration reduction scenarios in Europe

2008 Air Quality Directive 2008/50/EC

2020 scenario (EU25)	Scenario A	Scenario B
Reduction in average urban background concentration of $PM_{2.5}$	-20%	-25%
Marginal abatement cost (M€/year)	4974.4	8079.6
Marginal abatement cost (€/person/year)	10	16
GDP	-0.03%	-0.06%

Source: European Commission (2008).

Table E.4. Abatement costs for $PM_{2.5}$ emission reduction scenarios in Europe.

2025 scenario (EU28)	6A	6B	6C	6D
Reduction in emissions wrt baseline	-17%	-25%	-34%	-45%
Marginal abatement cost (M€/year)	221	1202	4629	47007
Marginal abatement cost (€/person/year)	0.4	2.3	9	92
Abatement cost as % of GDP	0.00%	0.01%	0.03%	0.30%

Note: Scenario 6A: 25% gap closure between baseline and Maximum Technically Feasible Reduction (MTFR);
Scenario 6B: 50% gap closure between baseline and MTFR;
Scenario 6C: 75% gap closure between baseline and MTFR;
Scenario 6D: 100% gap closure between baseline and MTFR.
Source: European Commission (2013).

Table E.5. Annual compliance costs associated with the US Clean Air Act Amendments

Category	Valuation (million 2006 USD)
Electric utilities	13 000
On-road vehicles and fuel	27 200
Local controls	13 500
Others	14 800
Total costs	68 500

Source: US Environment Protection Agency (2011).