The effect of air pollution on US aggregate production

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August 7, 2023

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Department version at LSE Geography and Environment Discussion Paper Series (39)

Abstract

Air pollution is known to have adverse effects on individuals' health, labour market performance, and human capital accumulation, all determinants of a country's overall economic activity. So what are the effects of air pollution on aggregate economic production? To answer this, I study the effects of $PM_{2.5}$ on county-level GDP, GDP per capita, and GDP per employee in the United States (2006-2018) by exploiting a detailed dataset of yearly air pollution exposure by county and a set of instrumental variables. My main specification uses exogenous year-to-year variation in wildfire-induced $PM_{2.5}$ exposure from air trajectory simulations. Contrary to recent studies in China and the EU, which find large negative effects in all regions, my results show no such effect for the US. However, these headline results mask spatial and temporal heterogeneity. Economically relevant negative effects appear in rural areas, during working days, when base levels or air pollution are above the median, and in the trade sector and educational services. The results are robust to various alternative specifications and instruments previously used in the literature. Simple back-of-the-envelope calculations using estimates from the Clean Air Act show that its nation-wise air pollution reduction abatement costs were *half* of its benefits in rural areas' GDP. My results suggest further air pollution reduction policies would be beneficial even if we only consider short-term market costs, greatly improving their political feasibility.

Keywords — Air pollution, GDP, productivity, US, wildfires
JEL N°: R11, Q53, Q54, Q53, O44, O47, O51

Acknowledgements

I am grateful for the valuable remarks from Olmo Silva, Steve Gibbons, Laura Hospido, Felipe Carozzi, Sefi Roth, Pedro Llanos and Manuel Linsenmeier. I am thankful for the input from participants of various seminars presented at LSE, the LSE Environment Day and the Mannheim Conference on Energy and the Environment. All errors are mine. The research that gave rise to these results received the support of a fellowship from the "la Caixa" Foundation (ID 100010434), with fellowship code LCF/BQ/EU22/11930044, and from a Spanish Central Bank' (Banco de España) scholarship. The views expressed are entirely my own and not necessarily those of LSE, "La Caixa" Foundation, or Banco de España.

1 Introduction

Air pollution is globally recognised as a major threat to human health. More than 99% of the world's population live in areas where air pollution levels exceed the World Health Organisation guidelines (WHO, 2022) and 4.5 million deaths a year worldwide are attributed to ambient air pollution alone, 0.37 from ambient ozone and 4.14 from particulate matter (PM)[1] (Fuller et al., 2022).

These large health costs of air pollution have led to increasingly restrictive regulations in multiple countries, with the Clean Air Act in the United States of America (US), being a worldwide role model for environmental legislation (Holman et al., 2015). But how much pollution control is enough? The answer depends on the costs to reduce it and the size of is negative effects. As Zivin and Neidell (2018) pointed out, the effects on hospitalisations and deaths are only the tip of the iceberg, with more common (but less lethal) negative effects on labour productivity and human capital accumulation that "can add up to considerable, society-wide impacts across the globe". An estimate of these aggregated effects on health and economic production is then a valuable source of information to guide policymakers on the optimal strength of clean air policies, especially when concerned with their effects on economic growth and job creation (Morgenstern et al., 2002).

The impact of air pollution on individuals' economic outcomes is strong and wide-ranging. Air pollution has been documented to reduce labour supply and productivity in various settings and locations (Aguilar-Gomez et al., 2022; Zivin and Neidell, 2018). There is also evidence of its contemporaneous effects on human capital formation, such as lower performance in high school (Ebenstein et al., 2016; Lavy and Roth, 2014) and university examinations (Roth, 2016). Based on these results, recent research has tried to uncover the aggregate macroeconomic costs of these negative effects. Fu et al. (2021) and Dechezleprêtre et al. (2019) found strong negative macroeconomic consequences, with a 10% increase in $PM_{2.5}$ (a common air pollutant) causally reducing the GDP of China and the EU by 0.4% and 0.8%, respectively. These estimates suggest strong co-benefits from using less carbon-intensive fuels, reducing the overall cost of the efforts set in the Paris Agreement to decarbonise the economy.

On the other hand, the external validity of these studies for the US economy is nonetheless questionable as labour and health markets, levels of air pollution, and urban planning in the US differ strongly from the EU and China, potentially affecting the relationship between pollution and aggregate economic production. Sick leaves in the US are less common than in Europe, reducing a proven mechanism in which air pollution can reduce overall GDP (Holub et al., 2006; Leroutier and Ollivier, 2022). Furthermore, these air pollution-induced illnesses like asthma

[1] Particulate matter (PM) consists of small suspended particles. The most conventional measurement of PM are PM_{10} and $PM_{2.5}$. Their concentration in the air is measured in micrograms per cubic meter ($\mu g/m^3$) and the number 10 or 2.5 refers to the particle's diameter in micrometres.

might even positively affect GDP due to the US' costly and mostly private healthcare system. Finally, secondary results from Williams and Phaneuf (2019) conclude that air pollutants had no effect on manufacturing establishments, employment, or wages in the US and thus suggest its effects on overall GDP might differ from other studied regions.

The main objective of this article is to contribute to this literature and estimate the causal effect of air pollution on US macroeconomic outcomes such as local GDP, GDP per capita, and industry-specific GDP. To recover this effect, I used panel data on local economic outcomes and exposure to $PM_{2.5}$ from 2001-2018 at the US county level. The main obstacles in estimating the effect of air pollution on economic output with ordinary least squares regression are reverse causality and measurement error. Reverse causality results from air pollution being a by-product of economic and social activity. Measurement error is a feature of all studies on air pollution (Graff Zivin and Neidell, 2013). To overcome these problems, I use various instruments to create conditionally-exogenous variation in air pollution levels together with a set of fixed effects to control for constant and time-varying confounders. This is a standard estimation strategy of various previous studies on the effect of air pollution on outcomes with large geographic extent such as Dechezleprêtre et al. (2019), Borgschulte et al. (2022), Arceo et al. (2016), Fu et al. (2021), Chen et al. (2017) and Sager (2019). For this, I use year-on-year changes of two instruments: exposure to wildfire smoke and the prevalence of thermal inversions. Exposure to wildfire smoke proves to be a stronger and more consistent instrument across the US geography and is therefore chosen for the main results described below.

As anticipated, my results deviate from previous analyses from Dechezleprêtre et al. (2019) for the European Union and Fu et al. (2021) for China, finding precise and insignificant effects of $PM_{2.5}$ on overall GDP, GDP per capita, GDP per employee and population in urban regions. On the other hand, I find that air pollution has a significant negative impact on US rural areas' GDP and GDP per capita of 0.40% (SE: 0.19%) and 0.37% (SE: 0.19%) per μg/m^3 of average ambient exposure to $PM_{2.5}$, respectively. This effect in rural areas seems to be only present during working days and with air pollution levels above the median concentration (7.3 μg/m^3). Concerning individual sectors, only "Trade" and "Educational Services" experience a significant negative effect of 0.60% (SE: 0.2%) and 0.7% (SE: 0.33%) per μg/m^3, respectively. These translate to a yearly aggregate loss of 13 billion and 145 2012-equivalent dollars of GDP and GDP per capita per year. Finally, a large set of robustness tests with alternative samples, instruments, regions, pollution measures, and model specifications are performed, with no changes in the main results.

The rest of this paper is structured as follows: Section 2 discusses the current literature and how it guides my research; section 3 explains the research strategy; section 4 describes the data sources, transformation and descriptive statistics; section 5 describes the results, and section 6 concludes.

2 Background and literature review

Air pollution more generally, and $PM_{2.5}$ specifically, have been consistently found to increase the risks of death and hospitalisation for cardiovascular and respiratory diseases both in the short and long term (US EPA, 2009). As mentioned before, these strong effects have been recently shown to be only the tip of the iceberg, with less life-threatening but more common effects of $PM_{2.5}$ having deep societal consequences.

After pollution particles are inhaled, they can pass from the lungs to the bloodstream, finally affecting multiple organs such as the heart and the brain (Calderón-Garcidueñas et al., 2014; Du et al., 2016; Ranft et al., 2009). Even when it does not cause hospitalisations, short-term air pollution exposure can reduce working hours and increase sick leaves of workers (Fan and Grainger, 2019; Hoffmann et al., 2022; Holub et al., 2006; Leroutier and Ollivier, 2022; Ron Chan et al., 2022) and caregiving activities when vulnerable population, such as kids, get sick (Aragón et al., 2017; Hanna and Oliva, 2015).

On top of changes in the number of hours worked, air pollution has been shown to reduce productivity in a wide range of work types including outdoor, physical, and desk-based. Some examples include peer packers in California (Graff-Zivin and Neidell, 2012), garment factories in India (Adhvaryu et al., 2014), call centres in China (Graff Zivin and Neidell, 2013), investors in New York (Heyes et al., 2016) and Canadian members of Parlament (Heyes et al., 2019). More generally, Fu et al. (2021) looked at changes in productivity due to air pollution for a representative sample of Chinese manufacturing firms and found an elasticity of -0.44, with large effects in both high- and low-technology industries (elasticities of -0.73 and -0.33, respectively). Even more subtly, air pollution can reduce productivity while at work (Hanna and Oliva, 2015) by increasing fatigue, impairing cognition or increasing stress (Sager, 2019) and sleeplessness (Heyes and Zhu, 2019). Finally, in a more recent study for the US, Cook and Heyes (2022) show that psychological exposure, i.e. 'the thought of pollution' can also reduce willingness to work (labour supply) and work performance (labour productivity) in an experimental setting.

The literature has also studied the negative effects of air pollution on cognitive performance and human capital formation by looking at high school and university test results in the US, Israel and the UK (Gilraine and Zheng, 2022; Lavy and Roth, 2014; Roth, 2016). Less specific to students in high-stakes examinations, Zhang et al. (2018) find similar results in nationally representative cognitive tests of Chinese families, finding larger negative effects for men and low-income families. All of them coincide that air pollution can cause a decrease of cognitive performance in the studied populations.

In summary, short-term exposure to air pollution can both reduce the number of hours worked and the productivity (by hour worked) of an individual, reducing overall production and changing the determinants of local employment, wages and income. Various recent papers have looked at this question too, by focusing on the regional effects of higher average pollution levels over some months or years. This is especially relevant when we are interested in how it affects general economic outcomes in equilibrium as regional or aggregate effects are not necessarily equivalent to the sum of short-term effects due to spatial spillovers of long-run consequences. In a recent publication, Borgschulte et al. (2022) use the geographic extension of wildfire plumes to get the causal effect of air pollution changes on quarterly labour earnings, employment and labour force participation in the US. They find a 1μg increase in $PM_{2.5}$ reduced earnings by 1.8%, employment by 0.12% and LFP by 0.27%. Focusing on the firm side, Leroutier and Ollivier (2022) find that a monthly 1μg increase in $PM_{2.5}$ decreased monthly sales of French firms by 0.26% in the two months after. On the other hand, Williams and Phaneuf (2019) find no effect of SO_2 and NO_x on manufacturing establishments, employment and wages during the 1999-2003 period for US (see their online appendix).

The literature on how changes in average air pollution exposure can determine aggregate regional production and productivity is fairly recent. The two papers published on the topic, and main guidance for this project are Fu et al. (2021) and Dechezleprêtre et al. (2019) which study the case of China and the EU, respectively.

Fu et al. (2021) use data from a nationally representative sample of China's manufacturing firms from 1998 to 2007 and estimate the causal effects of air pollution on productivity and hiring. They use thermal inversions as an instrument to find that a 1μg increase in $PM_{2.5}$ decreases productivity by 0.82%. Using the differential effect between coastal and inner regions of China's access to the WTO, they estimate the effect of output on $PM_{2.5}$. Finally, they estimate the general equilibrium effects of $PM_{2.5}$ on GDP concluding that an increase of 10% in $PM_{2.5}$ ($\approx 5\mu$g) is expected to cause a decrease of 0.4% in China's GDP.

Dechezleprêtre et al. (2019) use the same methodology with thermal inversions as an instrument as Fu et al. (2021) but directly estimates the effects of air pollution on local GDP, GDP per capita and each sector's GVA. With 2000-2015 NUTS-3 data for the EU, they estimate that a 10% increase (1μg) in $PM_{2.5}$ causally decreases GDP by 0.8%, roughly the size of a small EU Member Country (such as Slovakia or Hungary) or 200€ per inhabitant per year. They conclude that 95% of this impact is due to reductions of output per worker (absenteeism or productivity) and that the largest effect is in the agricultural sector (5 times the overall effect). This is the closest work to my own and their formalisation of the effect can be applied here.

Finally, it is essential to be clear that neither this paper nor the ones just mentioned are exercises to calculate the sum of all economic costs of air pollution. GDP aggregates all market production and ignores non-market goods and externalities. Research by Muller and Mendelsohn (2007) is then an important complement to this work as it calculated the gross annual damages (GAD) of air pollution emissions.

Three major facts motivate a new study on these effects. First, only two studies have been published on the topic with no replications (that I know of). Second, their estimated effects are quite large. For example, Dechezleprêtre et al. (2019) estimate that reductions of GDP due to air pollution are two orders of magnitude larger than their respective abatement costs, as estimated by European Commission, and that "significant reductions in air pollution would easily pass a cost-benefit test, even ignoring their large benefits in terms of avoided mortality" (p. 34). It is then important to check if this also applies to the US economy. And third, the US geography, urban planning, health system and labour markets legislation differ strongly from the EU and China, potentially affecting the effect of air pollution exposure on overall GDP. For example, the US has a higher share of private (and longer) car commutes, which have been shown to experience higher air pollution levels (Chertok et al., 2004), a lower city density and a higher use of air conditioning (which filters air pollution indoors) and an overall lower exposure to $PM_{2.5}$. On the other hand, sick leaves are much less prevalent in the US than in Europe OECD (2023), this can reduce the effect of air pollution on GDP. Finally, the health system in the US is especially expensive and thus it could transform negative shocks of air pollution-induced illnesses into increases in GDP. For instance, air pollution-induced illnesses like asthma can cause medical expenses to surge. The impact of these conditions could be substantial, as approximately 15.4 million people in the US are diagnosed with asthma, with their average annual per-person medical cost being around \$3,266 for the insured and \$2,145 for the uninsured (Nurmagambetov et al., 2018).

3 Research Strategy

3.1 Econometric Specification

I start with a simple linear regression of the relation between aggregate economic output Y and average air pollution exposure P in county c in state s and year t:

$$ln(Y_{cst}) = \beta_0 + \beta_1 P_{cst} + \boldsymbol{\beta_2} f(\boldsymbol{W}_{cst}) + \gamma_c + \phi_c w_{cst} + \eta_{st} + \varepsilon_{cst} \tag{1}$$

Where Y_{cst} is a measure of economic output (GDP, GDP per capita, ...) in a given county and year, P_{cst} is the average exposure to $PM_{2.5}$ (population-weighted $PM_{2.5}$ concentration), $f(\boldsymbol{W}_{cst})$ is a flexible function that captures any surface-level weather shocks that might affect both a county's pollution and economic activity[2], γ_c are county fixed effects which capture any time-invariant

[2] It includes second-degree polynomials for atmospheric pressure and humidity, 20 bins of surface temperature, 10 bins of

differences between counties (such as geography), w_{cst} are county-specific slopes, η_{st} are state-year fixed effects which account for unobserved time-varying regional or policy shocks which might be correlated with both economic activity and pollution across states, and ε_{cst} is a random disturbance term.

To control for permanent county characteristics (γ_c) and to address the non-stationarity of the left-hand-side, I model the variables of Equation (1) in differences:

$$\Delta ln(Y_{cst}) = \beta_1 \Delta PM2.5_{cst} + \boldsymbol{\beta_2} \boldsymbol{\Delta} f(\boldsymbol{W}_{cst}) + \phi_c w_{cst} + \eta_{st} + \Delta\varepsilon_{cst} \tag{2}$$

With $\Delta X_t \equiv X_t - X_{t-1}$

In this case, the specification models the *levels* of Y_{it} (not its yearly growth) and β_1 can be interpreted as the expected change in the *contemporaneous* growth rate given an increase in the level of $PM_{2.5}$ [3].

My objective is to capture the causal effect of changes in $PM_{2.5}$ in the aggregate output level from possible changes in employment, productivity and morbidity, but various obstacles arise. First, changes in economic output can also affect the $PM_{2.5}$ concentrations as air pollution is a by-product of economic activity. This reverse causality would create a positive bias in our β_1. Furthermore, most air pollution estimates are prone to measurement errors which would bias β_1 to 0.

To overcome the issues of reverse causality and measurement error, I need a mechanism that affects exposure to air pollution exogenously. In other words, that is only related to our outcome of interest (Y) through its effect on air pollution exposure. Based on the literature, I use the dissemination of wildfire smoke by wind currents and the presence of thermal inversions as two mechanisms that serve as a natural experiment after controlling for confounders. To do this, I adopt a two-stage estimation method with instrumental variables. The first stage predicts exogenous changes in air pollution exposure with changes in wildfire smoke or thermal inversions. The second stage estimates the effect of our predicted exogenous changes in air pollution on economic output.

The first stage that estimates an exogenous variation in air pollution can be written as

$$\Delta PM2.5_{cst} = \boldsymbol{\alpha_1} \Delta \mathbf{I_{cst}} + \boldsymbol{\alpha_2} \boldsymbol{\Delta} f(\boldsymbol{W}_{cst}) + \boldsymbol{\alpha_3} \boldsymbol{\Delta C}_{cst} + \rho_c w_{cst} + \theta_{st} + \Delta\pi_{cst} \tag{3}$$

where $\mathbf{I_{cst}}$ is a set of one or more instruments constructed with the presence or strength of wildfire

rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared as suggested by Deschênes and Greenstone (2011).

[3] So $\beta_1 \approx \frac{E(Y_{cst}|P2.5_{cst+1}) - E(Y_{cst}|P2.5_{cst})}{E(Y_{cst}|P2.5_{cst})}$.

smoke drift or thermal inversions in county c and year t and $\boldsymbol{C}_{cst}$ are instrument-specific controls that help satisfy the conditional exogeneity between the instruments and Y_{cst}. θ_{st} are state-year fixed effects and π_{it} is the error term. The second step that estimates the effect of exogenous variation in $PM_{2.5}$ exposure in percentage changes of economic outcome Y can be written as

$$\Delta ln(Y_{cst}) = \beta_1 \Delta \widehat{PM2.5}_{cst} + \boldsymbol{\beta_2 \Delta} f(\boldsymbol{W}_{cst}) + \boldsymbol{\beta_3 \Delta C}_{cst} + \phi_c w_{cst} + \eta_{st} + \Delta\varepsilon_{cst} \tag{4}$$

where $\widehat{PM2.5}_{cst}$ is air pollution exposure predicted by the first stage, all other variables are defined as in Equation (1), and the error term ε is clustered at the county level. Table 1 shows the values of $\mathbf{I_{cst}}$ and $\boldsymbol{C}_{cst}$:

Table 1: Combinations of instruments and instrument-specific controls

$\mathbf{I_{cst}}$	$\boldsymbol{C}_{cst}$
Average exposure to wildfires $PM_{2.5}$ *(main specification)*	• Presence of any wildfire in the county on that year • log(share of county area burned)
Share of days with the whole county influenced by wildfire smoke *(robustness)*	• Presence of any wildfire in the county on that year • log(share of county area burned)
Share of days with thermal inversions *(robustness)*	• *None*

It is important to note that as both steps are estimated in differences, the effects are estimated by *within-county* changes in the instrument. Furthermore, including state-year fixed effects (θ_{st} and η_{st}) controls for any state-level time-specific shock such as federal legislation, differentiated impacts of the 2008 financial crisis, or the number and intensity of wildfires on that state-year. Finally, adding county-specific slopes helps to control for any general relationship between the *change in the speed of growth* of the instrument and the outcome. For example, if urban areas within a state face a higher increase in both their GDP growth rate and wildfire smoke exposure.

For my coefficients (β_1) to be representative of the whole contiguous US[4], I weigh individual counties i by their population or aggregate economic production. This is fairly common in the literature (Dechezleprêtre et al., 2019; Kalkuhl and Wenz, 2020).

The following directed acyclic graph (DAG) summarises the implied relationships between the variables in the two-step procedure:

[4]Continental US, excluding Alaska.

$$
\begin{tikzcd}
& \Delta\text{Weather}_{ct}\ \textit{and}\ \Delta\text{Controls}_{ct} \arrow[dl, bend right] \arrow[d] \arrow[dr, bend left] & \\
\Delta\text{Instrument(s)}_{ct} \arrow[r, "\alpha_1"] & \Delta\text{Air Pollution}_{ct} \arrow[r, "\beta_1"] & \Delta\text{Economy}_{ct} \arrow[l, bend left] \\
& \text{State}\times\text{Year FE}_{st}\ \textit{and}\ \text{County slopes}_{c} \arrow[ul, bend left] \arrow[ur, bend right] &
\end{tikzcd}
$$

Using an instrumental variable addresses the reverse causality issue and changes the nature of the other two primary sources of bias: omitted variable bias and measurement error in air pollution. For omitted variable bias to be a concern before using an instrument (equation 2), the non-controlled correlation had to be between economic output and air pollution, two closely related variables. The use of an instrument corrects for the measurement error bias while the omitted-variable bias could only emerge from non-controlled correlations between economic output and thermal inversions or wildfire smoke drift within states, both of which are clearly less plausible or relevant. Nonetheless, the use of an instrumental variable requires additional assumptions to hold and can lead to new types of biases. These are explained in the following subsection.

3.2 Instrumental variables

The two-stage method requires one (or more) instrumental variables that (1) affect air pollution exposure (i.e., are relevant), and (2) that they are not caused by pollution or economic activity and only affect the dependent variable through their effect on air pollution concentrations (i.e., that they are exogenous). In the following paragraphs, I will explain how exposure to $PM_{2.5}$ from wildfire smoke drift, my preferred instrument, can satisfy both conditions in the two-stage method shown above. To test for the robustness of my estimates, I also use exogenous changes in the frequency of thermal inversions, which I explain in detail in Appendix A.

Like other sources of air pollution, the combustion of vegetation creates particulate matter and other contaminants such as ozone, carbon monoxide, atmospheric mercury, and a variety of volatile organic compounds (VOCs). This pollution is then ejected into the atmosphere and dispersed by wind currents. While exposure to wildfire smoke is understood to operate similarly to other sources of air pollution, its composition may be different and thus, it can be more (or less) harmful to human health per unit of measured particulate matter. I explore this in depth and conclude that daily changes in wildfire-induced $PM_{2.5}$ concentrations in my sample have an almost-zero correlation with SO_2, CO and NO_2 concentrations and have a similar correlation with O_3 as non-wildfire-induced $PM_{2.5}$ ($\hat{\rho} = 0.09$). These results coincide with previous atmospheric science literature (Langmann et al., 2009) and allows my results to show the effects of particulate matter isolated from other usual co-pollutants in the literature such as SO_2, CO and NO_2. A table with pairwise correlations between by-source $PM_{2.5}$ and other pollutants is available on Table B.3 in the appendix.

In addition to the literature mentioned above, large increases in wildfire smoke have been shown to produce various behavioural responses, including spending more time indoors, running air conditioners for longer times, and missing work (Langmann et al., 2009). Burke et al. (2022) record a wide range of awareness and behaviour changes in response to a large increase in wildfire smoke, including mobility, sentiment, and health-protective behaviours. This contrasts with smaller (and more common) changes in urban air pollution created by other factors. In our data, wildfire smoke creates both small and large increases in daily PM2.5, with small changes being much more common[5] (Figure B3 in the appendix).

Wildfires account, on average, for around 17% of the $PM_{2.5}$ emitted in the United States in the last 20 years[6]. Wind currents then carry these emissions for thousands of kilometres (Langmann et al., 2009), a process that depends on current weather conditions such as moisture, rain and heat. Thanks to satellite-based plume identification and other information on the trajectory of pollution, it is possible to infer the average exposure to $PM_{2.5}$ that originated from wildfires in each county and day. That makes the relevance of this instrument straightforward as it is on the same units as the endogenous variable ($PM_{2.5}$ exposure). On the other hand, it is convenient to think about its exogeneity to local economic activity in detail. For that, I distinguish between two types of wildfire smoke:

First, let us assume that the origin of the smoke is sufficiently far away that its only effect on local economic outcomes is through the change in air pollution it generates. In that case, various concerns might arise. Unobserved local characteristics might be correlated with being down or upwind of wildfire-prone areas, but as our specification is in differences we consider only the *changes* in local characteristics, such as prevailing wind patterns. Also, various large scale weather shocks can affect economic activity while increasing the range of wildfire drift from far away locations, such a dry season or changes in wind speed (Langmann et al., 2009). State-year fixed effects would account for any such deviations from the regional average.

Second, we can focus on the case where the origin of the smoke is close enough to affect local economic outcomes through other channels. These could be direct fire damages to property and amenities, emergency responses or visible dust expenditure of other pollutants which, as pointed out before, can cause their own behavioural responses. For these local effects, I include variables

[5]We look if small or large *changes* in pollution have different effects by unit of $PM_{2.5}$ both by looking at non-linearities in our coefficient and by interacting the increase in $PM_{2.5}$ with the number of days that a given county experienced large changes in the wildfire-induced pollution. All results suggest this is not the case.

[6]Own calculation with data from the EPA (2022).

that control for the presence and scale of a wildfire within a given county[7]. Finally, even if we consider the occurrence, strength, and impact of wildfire events in local air pollution levels to be fully determined by the random within-state variation of weather conditions (wind, rain dryness, heat)[8], these might affect economic activity by themselves. For that, I control for weather conditions non-parametrically with large set of flexible weather controls as in Deschênes and Greenstone (2011)[9].

4 Data

To study the causal effect of $PM_{2.5}$ exposure on aggregate economic variables with the methods described in the Research Strategy section, I aggregate multiple sources of $PM_{2.5}$ concentrations and emissions, economic variables, weather variables and population density rasters on a county-by-year panel data. In the following paragraphs, I explain in detail the data sources, modifications, aggregations and cleaning procedures to construct the final panel data structure ready for analysis.

4.1 Data sources

I start with the local economic outcomes and demographics such as overall and sector real GDP and population. All of these are from the US Bureau of Economic Analysis (BEA)[10] and are yearly (2001-2018) estimates by county[11]. All other estimates of control values are spatially aggregated to these geographic and time units.

To look at the average exposure to air pollution for each county, I use the pollution estimates constructed by Hammer et al. (2020). They consist of yearly (2000-2018) estimates of surface $PM_{2.5}$ mean concentration, and its components, in a 0.01º x 0.01º grid (approx. 1km^2 at the equator). These estimates were constructed using both satellite and monitor data from the EEA Air quality E-reporting, are used extensively in the literature, and cover the contiguous United States[12]. I use this data source that combines satellite and ground measurements for my main specification for two main reasons: first, it provides me with complete spatial coverage at a fine resolution, and thus it allows me to create population-weighted exposure to pollution. Secondly, Mu et al. (2022) documented how local governments of 14 metro areas in the US had tended to skip air pollution monitoring when they expected air quality to deteriorate. As wildfire smoke increases can be easily predicted, the satellite measurements would avoid the resulting bias from

[7]The main results are also robust to excluding county-year pairs that had a wildfire.

[8]Although it is hard to know the causes of wildfires, less than 1% of fires are considered due to Arson in the data.

[9]Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 12 bins of wind speeds and interactions between the temperature bins and humidity.

[10]Source: CAGDP9 and CAINC4 datasets from https://www.bea.gov/data/employment/employment-county-metro-and-other-areas

[11]The total number of counties in my sample is around 1% less than the official number as some 'combination areas' in Virginia are taken as one county. These consist of "one or two independent cities with 1980 populations of less than 100,000 combined with an adjacent county."

[12]Source: https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V4.NA.03

this endogenous measurement error. For an alternative measure of local air pollution, I also use the county-level pollution estimates from Borgschulte et al. (2022), taken directly from monitor stations. Although they are only available for around half of the counties, they still represent over 85% of the U.S. population. For the emissions of $PM_{2.5}$ I use the estimates of Global Air Pollutant Emissions from the EDGAR database (v5.0) from Crippa et al. (2020)[13].

To have information on the exposure to wildfire $PM_{2.5}$, my main instrumental variable, I use a new dataset by Childs et al. (2022)[14] of ambient wildfire-smoke-attributable $PM_{2.5}$ on a daily $10km^2$ grid for the contagious US (2006-2018). This data is created by combining information from satellite-based smoke plume identification and simulations of air trajectories from fire locations to identify when smoke is detected in the air by monitors or satellite and reanalysis products. This is a more detailed dataset relative to the one used by Borgschulte et al. (2022), mentioned above, as it not only gives information of the geographic extent of wildfire smoke, but its quantity measured in $PM_{2.5}$[15]. Finally, to get additional information on the location and extent of wildfires, I also use a combination of the wildfire datasets for the United States done by the Forest and Rangeland Ecosystem Science Center (Welty and Jeffries, 2019)[16], which provides polygons of wildfires by day together with additional metadata on their documented causes.

Weather measurements are used to create the thermal inversion instrument and construct the surface weather controls. To this end, I use data on temperature, pressure, wind speed and humidity from NASA's MERRA 2[17] at an hourly rate for a 0.50º x 0.625º grid (Randles et al., 2017) and daily precipitation data (interpolated from monitors) from the NOAA CPC on a 0.25ºx0.25º definition[18]. Thermal inversions are constructed based on data from NASA's MERRA 2[19] which provides estimates of air temperature a in a 0.50º x 0.625º grid at multiple heights (pressure levels). The construction of the instrument is detailed in the next section. Finally, I use $1km^2$ estimates of population density from the 2010 US census by CIESIN (2017) to create population-weighted averages for each county of $PM_{2.5}$ emissions and concentrations[20]. An illustrative example of this procedure is available in Figure B9.

4.2 Construction of the final panel data

The construction of the final panel data consists in the transformation of 6 data sources into the county-year format of aggregate economic data: Economic outcomes, weather control variables, the share of days with temperature inversions, average historical emissions and exposure to

[13] Source: https://edgar.jrc.ec.europa.eu/gallery?release=v50_AP&substance=PM2.5&sector=TOTALS
[14] Source: https://www.stanfordecholab.com/wildfire_smoke
[15] I use Borgschulte et al. (2022) classification as an alternative instrument for a robustness test.
[16] Source: https://www.sciencebase.gov/catalog/item/5ee13de982ce3bd58d7be7e7
[17] Specifically the M2T1NXSLV_5.12.4 files: https://disc.gsfc.nasa.gov/datasets/M2T1NXSLV_5.12.4/summary
[18] Source: https://psl.noaa.gov/data/gridded/data.unified.daily.conus.html
[19] Specifically the M2I3NPASM_5.12.4 files https://disc.gsfc.nasa.gov/datasets/M2I3NPASM_5.12.4/summary
[20] For a variable X and county c, we have: $\bar{X}_c = (\sum_{g \in G} X_g \times Population_g)/population_c$, with g being a raster grid and G being the set of grids inside that county.

$PM_{2.5}$, the proportion of area burnt by wildfires and average wildfire-induced $PM_{2.5}$ exposure. I explain each one of them in the following paragraphs and illustrate the hole process in Figure 1.

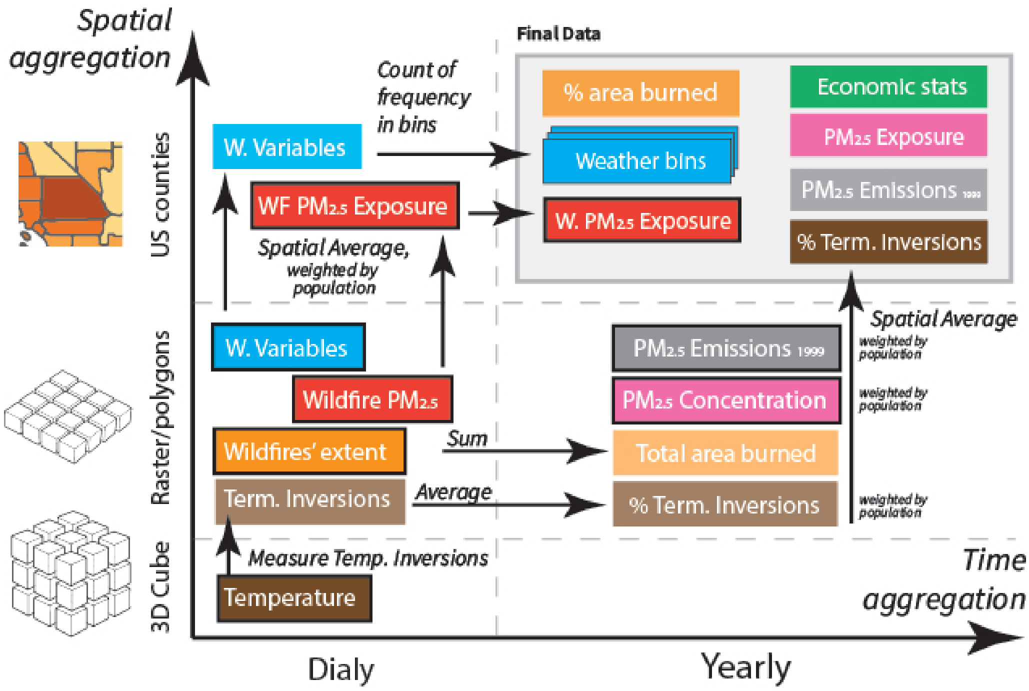


Figure 1: Summary of the construction of the final panel data. Different data sets (marked with black rectangles) begin with different spatial and temporal dimensions and are joined in the 'Final Data' format through various transformations (arrows).

First, the economic outcomes are not changed as they already start as county-year observations dimension. Estimates for the average exposure and emissions of $PM_{2.5}$ in a given county are constructed from a population-weighted average of 1km^2 or 10km^2 grids of yearly estimates, thus reducing the measurement error.

The data to construct the weather controls starts with a set of daily weather rasters of surface measurements (such as precipitation, temperature, humidity, and atmospheric pressure) which are aggregated by county using population-weighted averages. To flexibly control for weather variables, I follow Deschênes et al. (2017) and create counts of the number of days an average measurement falls inside a given bin (see the econometric specification in Research Strategy for further details).

I then go to construct the two instruments used to generate quasi-random variation in the exposure to pollution. First, I use population weights to get the daily exposure to wildfire smoke for each county and day, from which I create yearly averages. As I want to distinguish between the effects of air pollution from wildfires and other effects they might have on neighbouring economic activity, I create indicators of the proportion of area burned by year in each county. This comes from daily polygons of wildfire extent that are aggregated by year and then averaged by county.

The second instrument used is the prevalence of thermal inversions. As a dataset of this phenomenon is not readily available, I construct my own measure from NASA's MERRA-2 database. Air temperature measurements are available in a 3-hourly 3D raster (with layers of altitude 200-1000m wide). Given that a thermal inversion happens when temperature increases with altitude, the instrument is constructed by comparing the temperature of overlapping layers in a unique coordinate grid. This can be done in multiple ways by looking at the presence or the 'strength' of thermal inversions. I focus on the definitions presented by Dechezleprêtre et al. (2019) and Chen et al. (2017), which look at the differences the closest possible to the surface. First, I average all measurements to the day, and then I count a day-grid as having a thermal inversion if the temperature at the lowest level is lower than the one just above it. An extensive explanation of how exactly this is constructed and possible alternatives is available in Appendix 1.

After having a daily indicator of thermal inversions, I count the proportion of days a given grid had a thermal inversion each year. Finally, these grids are averaged for each county using population weights[21].

After having a unified dataset with all the necessary variables, I check the data for outliers. The distribution of year-on-year changes in average county $PM_{2.5}$ exposure and growth levels of GDP, GDP per capita, GDP per employee and population have a small number of observations showing extreme changes, most probably due to extreme local events in the case of economic variables and measurement error or large wildfires in the $PM_{2.5}$ estimates[22]. To discard these observations, I exclude all observations of the top and bottom 0.5% of these 5 variables, ensuring that the remaining data is not driven by extreme values[23], this excludes 3% of all observations. For sector regressions, all observations that exhibit an extreme growth in the top or bottom 0.5% on any sector are also discarded ($\approx$ 7%).

4.3 Descriptive Statistics

Here I present some descriptive statistics and maps to describe the variation (Table 2) and geographical distribution (Figure 2) of the variables used.

From the first map on average GDP per county (the main independent variable), it is clear that economic production is strongly concentrated few counties and has a very strong variation (see that the legend is in a logarithmic scale of thousands of US$). This clearly illustrates why my estimates are weighted by county production or population. The second map shows the average

[21] Figure B10 provides an illustrative example of this aggregation in the case there are no raster centroids in a county.

[22] Some examples are decreases of 80% of the population, 89% of GDP per capita and 85% of air pollution concentrations or increases of 42% in population, 279% in GDP per capita and 184% in air pollution concentrations.

[23] counties of St Bernard Parish, St. John the Baptist Parish and Kemper county are completely excluded from the sample due to their substantial relative changes in population and GDP due to extreme weather events and very large infrastructure constructions (hurricane Katrina and the Kemper Project power plant)

exposure to $PM_{2.5}$ (main explanatory variable) over the sample period (2001-2018). We see that there is also wide heterogeneity between regions with the east side of the contiguous US having higher levels of air pollution and the area of Los Angeles having the highest exposures in the country. The third map shows the urban and rural categories used. The fourth map shows the average Agricultural GDP of each county in the US. As the other indicators of sectorial GDP, it is highly concentrated in some counties and has a fair proportion of counties with no data.

After excluding observations with extreme changes in average air pollution or economic output I end up with a panel data of 3077 counties and 18 years (2001-2018). Nevertheless, the measure of average wildfire exposure to $PM_{2.5}$ is only available for 12 years (from 2006) and one year of data is lost when treating the outcomes in differences.

For this final data, Table 2 describes the main variables' overall (x_{it}), between ($\bar{x_i}$) and within ($x_{it} - \bar{x_i} + \bar{x}$) variation. We can first see the extreme differences in GDP levels between counties, also visible in Figure 2. The growth of GDP, GDP per capita and GDP per employee show much less heterogeneity. Although some regions grew at an average of 30% a year and others shrank at

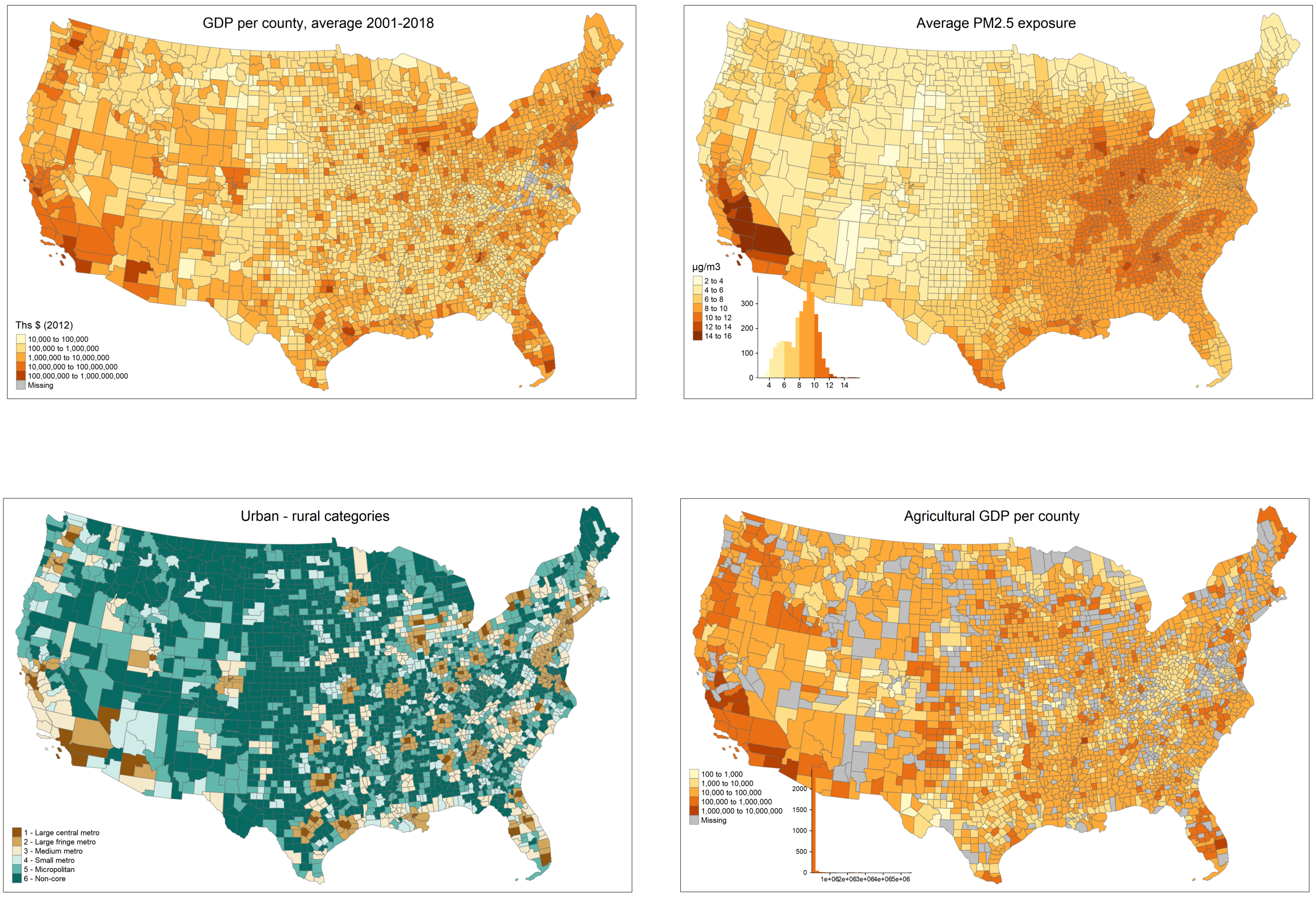


Figure 2: Regional variation of overall GDP, $PM_{2.5}$ exposure, Urban-Rural categories and Agricultural GDP by US counties

Table 2: Panel descriptive statistics

Variable	Panel	Mean	Sd	Min	Max	Observations
GDP (M, 2012)	Overall	5158.8	21868.26	9.95	710893.3	N = 53779
	Between		21456.65	15.37	588194.3	n = 3077
	Within		2646.6	-106141.3	132720.4	$\bar{T}$ = 17.48
Δ ln(GDP)	Overall	0.02	0.07	-0.29	0.39	N = 50702
	Between		0.02	-0.07	0.3	n = 3077
	Within		0.07	-0.34	0.38	$\bar{T}$ = 16.48
Δ ln(GDP/capita)	Overall	0.01	0.07	-0.29	0.38	N = 50369
	Between		0.02	-0.08	0.25	n = 3054
	Within		0.07	-0.36	0.39	$\bar{T}$ = 16.49
Δ ln(GDP/employee)	Overall	0.01	0.07	-0.29	0.37	N = 50369
	Between		0.02	-0.08	0.26	n = 3054
	Within		0.07	-0.35	0.39	$\bar{T}$ = 16.49
Δ ln(Population)	Overall	0	0.01	-0.04	0.05	N = 50369
	Between		0.01	-0.02	0.05	n = 3054
	Within		0.01	-0.05	0.06	$\bar{T}$ = 16.49
Avg. $PM_{2.5}$	Overall	8.35	2.7	2.07	42.48	N = 53779
	Between		2.3	2.73	33.01	n = 3077
	Within		1.51	-2.41	18.65	$\bar{T}$ = 17.48
Δ Avg. $PM_{2.5}$	Overall	-0.19	0.92	-3.01	3.14	N = 50702
	Between		0.14	-0.74	0.46	n = 3077
	Within		0.91	-3.44	3.32	$\bar{T}$ = 16.48
Avg. wildfire $PM_{2.5}$	Overall	0.41	0.36	0	7.01	N = 38848
	Between		0.18	0.04	1.8	n = 3077
	Within		0.32	-1.28	5.9	$\bar{T}$ = 12.63
Δ Avg. wildfire $PM_{2.5}$	Overall	0.03	0.41	-4.78	4.95	N = 35150
	Between		0.06	-0.47	0.64	n = 3076
	Within		0.41	-4.95	4.78	$\bar{T}$ = 11.43
% burned area	Overall	0	0.01	0	0.64	N = 53779
	Between		0.01	0	0.19	n = 3077
	Within		0.01	-0.19	0.6	$\bar{T}$ = 17.48
Prop. inv. days	Overall	0.23	0.09	0	0.64	N = 53761
	Between		0.09	0	0.55	n = 3076
	Within		0.02	0.14	0.47	$\bar{T}$ = 17.48
Δ Prop. inv. days	Overall	0	0.03	-0.14	0.24	N = 50685
	Between		0	-0.01	0.02	n = 3076
	Within		0.03	-0.14	0.22	$\bar{T}$ = 16.48
Avg. $PM_{2.5}$ emis (1999)	Overall	48.59	95.68	0.81	1749.63	N = 53779
	Between		94.95	0.81	1749.63	n = 3077
	Within		0	48.59	48.59	$\bar{T}$ = 17.48

an average of 7%, the variation is strong both within and between counties. Average air pollution exposure shows significant variation both in levels and changes, with much of the heterogeneity on the changes in $PM_{2.5}$ exposure happening within counties. The variation in the instruments is also large, especially within counties and not between them. This shows that the instrument is strong within counties while being homogeneous in space, which is crucial for interpreting of the final coefficients as causal effects representative of the whole sample. Figures B2 and A2 in the Appendix show the spatial distribution of the changes in wildfire smoke and thermal inversions, respectively.

5 Results:

We start with a simple linear model looking at the correlation between an increase in average exposure to $PM_{2.5}$ and changes in GDP growth, as described in equation 4 above. The results, available in Table 3, show that there is no significant positive or negative correlation between these two variables.

Table 3: Linear model

	All counties	Urban counties	Rural counties
	(1)	(2)	(3)
	Δ ln(GDP)	Δ ln(GDP)	Δ ln(GDP)
Δ PM2.5 exposure	-0.00052	-0.00084	-0.00047
	(0.00054)	(0.00073)	(0.00071)
Nº obs	49629	12906	36689
Nº of counties	3074	788	2284
R^2	0.42	0.56	0.30

Standard errors in parentheses

Clustered SE by county (BEA) and weighted by population. Regressions include state-year fixed effects and county-specific slopes. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 12 bins of wind speeds and interactions between the temperature bins and humidity

* $p < 0.1$, ** $p < .05$, *** $p < .01$

But clearly, these estimates are expected to be biased. As explained above in detail, air pollution emissions are a by-product of economic activity. To correct for the intrinsic reverse causality between changes in air pollution exposure and economic growth and move to causal estimates, I use the two-stage method described in section 3. In the first stage, I use the exposure of $PM_{2.5}$ from wildfire plumes to predict average $PM_{2.5}$ exposure while controlling for the presence and size of local wildfires as in equation 3[24]. The results of this first stage are shown in column (1) of Table 4, where, as expected, a 1μg/m^3 increase in $PM_{2.5}$ exposure from wildfire smoke is almost exactly equivalent to a 1μg/m^3 increase in overall exposure[25]. It would be possible, and even equivalent, to use the created measure of $PM_{2.5}$ exposure from wildfires in a simple reduced-form linear regression specification. Nevertheless, I keep the IV setup to be consistent with the

[24]The residual variance in wildfire $PM_{2.5}$ exposure and thermal inversions after including their respective controls can be seen in Figure B8 in the appendix.

[25]Other alternative instruments are also explored in the Appendix on Table B.2, showing the first stage) for each one of them and including the ones used by Borgschulte et al. (2022), Dechezleprêtre et al. (2019) and Fu et al. (2021).

literature and continuously show the strength and validity of this new instrument.

The second stage estimates the aggregate causal effect of $PM_{2.5}$ in economic output are presented in columns 2-5 of Table 4 with their respective Kleibergen-Paap F statistic (larger than 400). Second-stage coefficients for GDP, GDP per capita, GDP per employee and Population are almost identical to zero and not statistically significant, even if the standard errors are equivalent or smaller to the previous literature.

Table 4: Effect of $PM_{2.5}$ on economic output

	First stage	(2)	(3)	(4)	(5)
	Δ $PM_{2.5}$ exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ $PM_{2.5}$ exposure		-0.0011	-0.00078	0.00035	-0.00032
		(0.0023)	(0.0024)	(0.0024)	(0.00023)
Δ Wildfire $PM_{2.5}$ exp.	1.04^{***}				
	(0.049)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.76	0.45	0.44	0.32	0.84
Kleibergen-Paap F		458.9	463.1	463.1	463.1

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size $\rightarrow$ F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

On the other hand, these null effects on economic outcomes can hide effects that are more specific to a specific sector, geography or time. I perform various alternative specifications and tests to explore this heterogeneity and give a notion of the possible mechanisms behind any effect.

Sector-specific GDP: The results on how increases in $PM_{2.5}$ affects different sectors are shown in Figure B5. As the geographical distribution of these industries varies widely, counties are weighted by the average level of each sector's GDP over the whole sample period. Contrary to previous research by Dechezleprêtre et al. (2019) for Europe, I find no significant effects on the GDP of most sectors. Only *Trade* and *Educational Services* return significant results, with a 1μg increase in ambient exposure to $PM_{2.5}$ decreasing Trade's GDP by 0.6% and Educational Service's GDP by 0.7%. For some of these sectors (such as Mining, Agriculture, Information or Manufacturing) it could well be that large standard errors make sizeable effects statistically insignificant but for others such as Health Services, Government Expenditure or Transportation, the results suggest no causal effect. These significant results are merely indicative, as only 13% (2 out of 15) of the coefficients are statistically significant at the 5% level and after adjusting for multiple hypothesis testing, all become insignificant. It then is advisable to treat the statistical significance of these estimates with caution.

Urban vs. rural counties: To look at heterogeneities between geographies, Table 5 divides the main results between urban and rural counties, using the NCHS Urban-Rural Classification

Scheme for Counties (see Figure 2) and defining "large and medium metros" as urban and "small metros, micropolitan and non-core-areas" as rural. The first stage is strong in both samples, although the results differ. As the main results, urban counties have no significant effects in any of the outcomes. On the other hand, for rural counties, air pollution levels negativelly affected both GDP and GDP per capita, but not GDP per employee or population numbers. The coefficients suggest a 1μg increase in average ambient exposure to $PM_{2.5}$ decreased GDP and GDP per capita levels by 0.40% and 0.37%, respectively. These translate to a yearly aggregate loss of 13 billion dollars of GDP and 145 dollars of GDP per capita[26]. The results coincide with previous research suggesting the effect of pollution to be larger in rural areas in Europe. On the other hand, the results are half the size of those brought forward by Dechezleprêtre et al. (2019), with no significant reduction in GDP per employee.

Table 5: IV results for urban and rural areas

	First stage Δ Avg. $PM_{2.5}$ exposure	(1) Δ ln(GDP)	(2) Δ ln(GDP/capita)	(3) Δ ln(GDP/employee)	(4) Δ ln(Population)
Large and medium metros					
Δ Avg. $PM_{2.5}$ exposure		0.000342	0.000665	0.00138	-0.000348
		(0.00303)	(0.00310)	(0.00322)	(0.000297)
Δ Wildfire $PM_{2.5}$ exp.	1.086***				
	(0.0817)				
Nº obs	8530	8530	8457	8457	8457
Nº of counties	729	729	720	720	720
R^2	0.790	0.598	0.586	0.428	0.880
Kleibergen-Paap F		176.8	177.3	177.3	177.3
Small metros, micropolitan and non-core areas					
Δ Avg. $PM_{2.5}$ exposure		-0.00398**	-0.00369*	-0.00188	-0.000323
		(0.00193)	(0.00195)	(0.00185)	(0.000309)
Δ Wildfire $PM_{2.5}$ exp.	0.906***				
	(0.0517)				
Nº obs	26595	26595	26470	26470	26470
Nº of counties	2344	2344	2330	2330	2330
R^2	0.779	0.331	0.320	0.273	0.745
Kleibergen-Paap F		306.7	308.4	308.4	308.4

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

So air pollution does not have a significant effect on urban counties, which represent 73% of the population according to the 2010 census and an 80% of GDP in 2001, while it has some negative impacts on rural counties. Given this is a prevalent feature of the results, all other tests of heterogeneity are performed separately for both samples of urban and rural regions.

[26] 2012 US$-equivalent, base estimates multiplied by the sum of average GDP of rural counties over the study period.

Working days vs. weekends: Another way to understand the mechanisms by which air pollution can affect economic outcomes is to look at weekends and working days separately, as the types of economic activities performed differ significantly between these two periods. Working days are characterised by active realisation and coordination of the productive process, while weekends are more focused on consumption and leisure activities. Furthermore, air pollution levels in weekends are smaller on average.

To explore whether the effects of air pollution on the economy differ between the two periods, I construct yearly averages of exposure to wildfire $PM_{2.5}$ during weekends or working days, and use these two new instruments separately. Their second stages show the effect of an increase in average $PM_{2.5}$ exposure during these periods. The results (in Table 6) show that the adverse effects of air pollution are concentrated during working days in rural areas and air pollution increases on weekends do not affect aggregate economic output.

Table 6: IV results for weekends and weekdays for both rural and urban counties

	First stage	(1)	(2)	(3)	(4)
	Δ Avg. $PM_{2.5}$ exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
			Large and medium metros		
Δ $PM_{2.5}$ exposure		0.0000073	0.00029	0.0015	-0.00031
		(0.0032)	(0.0033)	(0.0034)	(0.00030)
Δ Wildfire $PM_{2.5}$ exp.	1.01^{***}				
Workday	(0.077)				
Δ $PM_{2.5}$ exposure		-0.0013	-0.0010	-0.00044	-0.00032
		(0.0028)	(0.0029)	(0.0030)	(0.00035)
Δ Wildfire $PM_{2.5}$ exp.	0.83^{***}				
Weekend	(0.057)				
Nº obs	9206	9206	9124	9124	9124
Nº of counties	788	788	778	778	778
R^2 (min)	0.78	0.58	0.57	0.41	0.88
Kleibergen-Paap F (min)		172.9	173.4	173.4	173.4
			Small metros, micropolitan and non-core areas		
Δ $PM_{2.5}$ exposure		-0.0041^{**}	-0.0037^{*}	-0.0024	-0.00039
		(0.0019)	(0.0019)	(0.0018)	(0.00031)
Δ Wildfire $PM_{2.5}$ exp.	0.82^{***}				
Workday	(0.048)				
Δ $PM_{2.5}$ exposure		-0.0035	-0.0032	-0.0022	-0.00033
		(0.0021)	(0.0022)	(0.0021)	(0.00034)
Δ Wildfire $PM_{2.5}$ exp.	0.70^{***}				
Weekend	(0.036)				
Nº obs	25907	25907	25791	25791	25791
Nº of counties	2284	2284	2271	2271	2271
R^2 (min)	0.77	0.33	0.32	0.28	0.72
Kleibergen-Paap F (min)		290.4	293.0	293.0	293.0

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Non-linearities with respect to background concentrations: A prevalent finding of previous work is that the effect of air pollution can be non-linear with respect to background concentrations (Aragón et al., 2017; Dechezleprêtre et al., 2019). To test if this is also the case for US aggregate output, I divide the urban and rural counties into 2 equal samples by their air pollution levels during that specific year and compare their results, displayed below in Table 7.

Table 7: IV results for various levels of background PM2.5. Urban and rural counties.

[Min Mean Max]	*Stats*	(1) Δ ln(GDP)	(2) Δ ln(GDP/capita)	(3) Δ ln(GDP/employee)	(4) Δ ln(Population)
		Large and medium metros			
Δ Avg. $PM_{2.5}$ exposure	Nº obs: 4544	-0.0032	-0.0032	-0.0013	-0.000040
[2.9 7.1 8.4]	F = 180.3	(0.0022)	(0.0021)	(0.0023)	(0.00047)
Δ Avg. $PM_{2.5}$ exposure	Nº obs: 4524	0.0011	0.0014	0.0026	-0.00040
[8.4 10.3 37.6]	F = 57.8	(0.0049)	(0.0049)	(0.0048)	(0.00047)
		Small metros, micropolitan and non-core areas			
Δ Avg. $PM_{2.5}$ exposure	Nº obs: 12736	0.00012	-0.00011	-0.00042	0.00023
[2.2 5.7 7.3]	F = 257.4	(0.0033)	(0.0034)	(0.0031)	(0.00051)
Δ Avg. $PM_{2.5}$ exposure	Nº obs: 12791	-0.0088***	-0.0086**	-0.0053	-0.00045
[7.3 9.0 36.5]	F = 308.6	(0.0034)	(0.0035)	(0.0035)	(0.00049)

Standard errors in parentheses. Kleibergen-Paap F reported.
Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes. First stages are not displayed for simplicity but are all highly significant.
Stock-Yogo weak ID test critical value: 10% maximal IV size F = 19.93
* $p < 0.1$, ** $p < .05$, *** $p < .01$

The results coincide very strongly with the ones in Table 5, with average $PM_{2.5}$ exposure decreasing GDP and GDP per capita only on rural areas. On top of this we can see that the previous average effect of 0.40% (Table 5) is concentrated on county-years with average air pollution levels above the median [7.3μg/m^3], doubling its effect to 0.80% of GDP and GDP per capita. These effects are large in scale but coincide with previous findings such as Dechezleprêtre et al. (2019)'s 1.0% negative effect for European regions with high pollution. Additionally, these effects are for concentrations with an average of 9μg/m^3, showing that increases of air pollution can have large negative effects even when levels are way below the EPA yearly standard of 12μg/m^3. The results are consistent when the instrument exploits the variation of air pollution on either working days or weekends. So if air pollution is high enough it can cause GDP reductions in rural counties irrespective of its timing.

5.1 Robustness tests

To check the robustness and heterogeneity of my results, I conducted a series of robustness checks and alternative specifications, summarised in Table 8. The complete results of individual regressions for the main variables and sectors can be found in the appendix (tables B.4-B.22).

Changes in instruments: To review that my results are not sensitive to the selection of the instrument, I use various specifications. I use (1) yearly thermal inversions interacted with historic emissions, (2) summer and winter thermal inversions[27] from Fu et al. (2021) and Dechezleprêtre et al. (2019), and (3) the share of days county covered by smoke plumes used by

[27] April 15th to October 14th being Summer and October 15th to April 14th being Winter

Table 8: Robustness tests and alternative specifications

Changes in...	Δln(GDP)	Δln(GDP/capita)	Δln(GDP/employee)	Δln(Population)	#Counties / (F)
Instruments					
Share of days with TI interacted with 1999	0.0028	0.0039	0.00079	−0.00071	3073
county $PM_{2.5}$ emissions	(0.0026)	(0.0028)	(0.0027)	(0.00057)	(16)
Winter and summer TI, as Fu et al. (2021)	0.0021	0.0024	0.00091	0.000079	3073
and Dechezleprêtre et al. (2019).	(0.0030)	(0.0031)	(0.0029)	(0.00056)	(19)
Share of days county covered by smoke plumes	0.00012	−0.00029	0.0024	−0.00011	3071
polygons as Borgschulte et al. (2022).	(0.0054)	(0.0054)	(0.0053)	(0.00043)	(103)
Saturday-Sunday Smoke $PM_{2.5}$	−0.0013	−0.00082	0.000053	−0.00043	3074
	(0.0021)	(0.0022)	(0.0023)	(0.00026)	(374)
Monday-Friday Smoke $PM_{2.5}$	−0.0011	−0.00074	0.00057	−0.00037	3074
	(0.0024)	(0.0025)	(0.0025)	(0.00023)	(389)
Geography					
East of population centroid	−0.00116	−0.000855	−0.00215	−0.000363	1219
	(0.00249)	(0.00261)	(0.00243)	(0.000503)	(320)
West of population centroid	−0.00119	−0.000775	0.000809	−0.000413	1832
	(0.00267)	(0.00274)	(0.00283)	(0.000287)	(299)
North of population centroid	−0.00114	−0.000469	−0.000902	−0.000663**	1509
	(0.00204)	(0.00201)	(0.00193)	(0.000287)	(233)
South of population centroid	−0.000050	0.00027	0.00205	−0.000293	1561
	(0.00335)	(0.00342)	(0.00348)	(0.000305)	(157)
Weighted by county GDP	−0.00085	−0.00063	0.00080	−0.00026	3074
	(0.0029)	(0.0029)	(0.0030)	(0.00023)	(369)
Not weighted by county population	−0.0066 ***	−0.0062 ***	−0.0043 **	−0.00046	3074
	(0.0022)	(0.0022)	(0.0022)	(0.00030)	(915)
Sample					
Including economic outliers	−0.0014	−0.0014	−0.00048	−0.000027	3076
	(0.0013)	(0.0014)	(0.0014)	(0.00017)	(684)
Excluding county-year pairs with	−0.0029	−0.0022	−0.0012	−0.00074 *	2864
active wildfires	(0.0041)	(0.0041)	(0.0039)	(0.00041)	(186)
Excluding Great Recession (2008-2011)	−0.0013	−0.0011	0.00021	−0.00020	3069
	(0.0015)	(0.0015)	(0.0014)	(0.00037)	(200)
Excluding San Francisco area	−0.0015	−0.0013	−0.0000046	−0.00026	3070
	(0.0025)	(0.0025)	(0.0026)	(0.00023)	(454)
Others					
With monitored $PM_{2.5}$ measurements from	−0.00086	−0.00053	0.00075	−0.00035	1614
Borgschulte et al. (2022) as $PM2.5_{cst}$	(0.0030)	(0.0030)	(0.0031)	(0.00027)	(75)
Without county-specific slopes	0.00059	0.00055	0.0018	0.000015	3075
	(0.0018)	(0.0019)	(0.0019)	(0.00038)	(479)
Without county-specific slopes and only	0.00679***	0.00600***	0.00501**	0.000804**	3076
year FE	(0.00231)	(0.00233)	(0.00225)	(0.000329)	(491)
Without weather controls	−0.0047 **	−0.0044 **	−0.0030	−0.00037	3074
	(0.0020)	(0.0020)	(0.0020)	(0.00027)	(954)

Standard errors in parentheses. Kleibergen-Paap F for $\Delta ln(GDP)$ regression reported as it is quite stable though outcomes.
Clustered SE by county (BEA). Weighted by county population (unless stated). # of counties corresponds to the $\Delta ln(GDP)$ regression.
Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.
* $p < 0.1$, ** $p < .05$, *** $p < .01$

Borgschulte et al. (2022), finding the same null results. As in the section before, I look at differentiated impacts on weekends and working days for the whole set of counties, but the results continue to be insignificant in this case.

Changes in regions: To look at heterogeneity between different regions of the contiguous US, I divide counties between the North, South, East or West of its population centroid (so each sample includes around half of the population). Although all the results are not significantly different from the main estimates, the effect on population is significantly negative for counties north of the centroid. Finally, I change the regression weights as to explore this geographical heterogeneity. I first weigh counties by GDP instead of population levels: thus, the results can be interpreted as "the average effect to a unit of GDP". Secondly, I remove all regression weights to interpret the results as "the average effect to a county" in the contiguous US. From this last regression, a strong negative effect of $\text{PM}_{2.5}$ on GDP, GDP per capita, and GDP per employee is clear with a $1\mu g/\text{m}^3$ increase in $\text{PM}_{2.5}$ concentrations causing a 0.67%, 0.60% and 0.50% decrease in each of them, respectively. This is a clarifying result as shows that the changes in $\text{PM}_{2.5}$ do affect aggregate output, but this effect is concentrated on counties with small population and GDP.

Changes in sample: All changes in sample yield no different results to the main specification. First, including all counties (even if they had very large changes in GDP, productivity, or population) only increases the standard error of the estimates. We also exclude of the years of the Great Recession (2008-2011), which reduces the standard errors but keeps the estimates reasonably similar. Finally, we exclude the San Francisco area given its aggregate importance in GDP and the large wildfire events it has experienced on recent years and find the same robust results.

Other changes: Additionally, I explore the results with four additional changes in specification. First, I execute my main specification using Borgschulte et al. (2022)'s measure of local air pollution, which they derive exclusively from monitor stations. The results are equivalent to my main specification[28]. Finally, I ran the analysis without county-specific slopes or state-year FE to test if these controls were necessary to attain my main results and thus as a guide of possible biases for future research. Omitting county-specific slopes does not change my results significantly. However, only having year fixed effects (instead of state-year) in addition to differenced outcomes produces biased results as it fails to control for unobserved time-specific regional shocks such as state-level legislation, differentiated impacts of the 2008 financial crisis, or the number and intensity of wildfires on that state-year.

Placebo tests and long-term effects: Finally, I regress changes in exogenous pollution in time t, $\Delta P\widehat{M2.5}_t$, on past (lags) and future (leads) changes of GDP. I focus on rural counties, as the main negative effects of air pollution are for this sub-sample. The regressions with lags of GDP changes perform a simple placebo test as we would not expect these shocks to causally change *past* GDP. The results, visible on Figure B6 in the appendix, show all estimates being statistically insignificant. Another interesting question to explore is if an air pollution shocks affect GDP changes in *future* years. The results, also in figure B6 do not point to that conclusion and suggest the impact might be limited to only one year.

[28]The number of counties included is slightly lower and represents counties with a higher population as not all counties had enough data to create their measure.

6 Conclusions

The primary goal of this article was to evaluate the causal influence of air pollution on macroeconomic outcomes in the United States: local GDP, GDP per capita, and industry-level GDP. To recover this impact, I employed a panel data set of local economic outcomes and $PM_{2.5}$ exposure at the county level from 2001 to 2018, as well as two instrumental variables to account for reverse causality and measurement error: Year-on-year variations in exposure to wildfire smoke and the occurrence of thermal inversions.

My main findings suggest $PM_{2.5}$ had no substantial effects on overall GDP, GDP per capita, GDP per employee, and population in urban areas even when considering only working days or years with high baseline air pollution. This is contrasts with previous studies by Dechezleprêtre et al. (2019) for the European Union and Fu et al. (2021) for China. On the other hand, air pollution has a considerable negative impact on rural regions' GDP and GDP per capita of 0.40% and 0.30% per μg/m^3 of average ambient exposure to PM2.5, respectively. These go in line with previous research in Europe by Dechezleprêtre et al. (2019) and on the effect of $PM_{2.5}$ on crop production employment in the US by Borgschulte et al. (2022). As expected, these effects seem to be more salient when pollution increases during working days or in counties with an already high level of air pollution, For this last case, a 1μg/m^3 increase of average ambient exposure to $PM_{2.5}$, when its level is above 7.3μg/m^3, can cause up to a 0.8% reduction in local yearly GDP and GDP per capita. Looking at individual sectors, only "Trade" and "Educational Services" GDP seem to exhibit a substantial decrease of 0.40% and 0.37% per μg, respectively. These results are robust to a large number of alternative sample limits, instruments, geographies, pollution indicators, and model specifications.

Finally, it is important to note that GDP should not be considered as a complete measure of social cost as it does not capture non-market assets such as leisure or clean air, can result in double counting since investment today results in a stream of future consumption benefits, and may even increase when welfare decreases. The EPA's Scientific Advisory Board provides a detailed discussion on this (SAB, 2017).

The policy implications of this work can be viewed from two perspectives. First, economically, they depend on the size of air pollution costs (here measured in aggregate production) relative to its abatement costs through policy. With regards to the costs of air pollution, and although I find no negative effects in urban counties, I do find that a 1μg/m^3 increase in rural areas creates a yearly aggregate loss of 13 billion 2012 dollars of rural GDP and 158 dollars of GDP per capita.We can get a simple back-of-the envelope calculation of the abatement costs for the US using the compliance costs and reduction of pollution estimates from the US Clean Air Act Amendments conducted by the US Environment Protection Agency (EPA, 2011). With their sample period from

2000 to 2020, we get an average yearly compliance cost of 8.6 billion 2012 dollars per μg/m^3 reduced of $PM_{2.5}$. With this figure, it is simple to see that the increase in GDP in rural areas due to the average reduction of pollution is around twice as large as its costs. With an average reduction of 6.1μg/m^3, the aggregated net benefits of the policy (without considering the reduction of other pollutants and other benefits not accounted in contemporaneous GDP changes) would be around 540 billion 2012 US dollars over the 2000-2020 period.

Second, and focusing on public policy, this study provides additional information to policymakers. The current federal legislation on air quality was last updated in 2012. It thus was conceived with a much more limited knowledge of the economic costs of air pollution, including the estimates brought forward by this paper. This should lead to a reconsideration of current policy and stricter limits on air pollution levels. These limits would be most effective when the negative impact of air pollution on local GDP is particularly pronounced in the US context, such as in rural areas during working days, or when pollution levels are large enough to affect aggregate GDP (above 7.3μg/m^3 in rural areas). Only the last of these three factors is included in the current legislation which limits yearly averages of $PM_{2.5}$ to 12μg/m^3.

In summary, this study contributes to the ongoing debate on the causal effect of air pollution on economic outcomes by using a panel data set from the United States and a robust econometric methodology. The results suggest that the impact of air pollution on US aggregate production is heterogeneous across regions and time. Moreover, these findings highlight the importance of further research on the effects of air pollution on the economy, as well as the need for effective and evidence-based air pollution policies.

Appendices

A Thermal Inversions

A.1 Relevance and exogeneity

Under normal atmospheric conditions, air temperature decreases with altitude (up to the end of the Troposphere, $\approx$ 11 km above sea level). This creates a natural convection flow called 'atmospheric ventilation' that rises and dissipates air from the surface which tends to be hotter and more polluted. Thermal inversions are a temporal deviation from this rule and occur when a mass of air happens to be below a warmer mass of air. This breaks the convection cycle and thus traps the pollution closer to the surface (Trinh et al., 2019; Wallace and Kanaroglou, 2009) making them a relevant instrument.

It is important to note that this effect does not create air pollution and depends on the local emissions of air pollutants. If there are no local emissions, thermal inversions do not affect the concentration of air pollutants. Figure A1 shows this empirical relationship for counties above and below the median emissions level, with high-emission counties having a much steeper relationship between the number of inversions and air pollution exposure. This heterogeneity is the main reason why this instrument is not included in the main results, as it is not strong enough in rural areas where emissions per area are much lower than in big cities. To account for this heterogeneity when modelling, the equivalent of equation 3 for Thermal Inversions includes an interaction between thermal inversions and the population-weighted emissions from 1999 to predict $\Delta P\widehat{M2}.5_{cst}$[29].

Thermal inversions occur mainly through atmospheric conditions and large movements of air masses. For example, the large-scale movement of air masses throughout the atmosphere typically forms thermal inversions at its leading edge, as warm air masses rise over cooler air masses. Thermal inversions also form in winter at higher latitudes, as the air higher in the atmosphere gets more heat from the low-angle sun than the ground-level air or when precipitated snow cools the ground-level air. It is important to note that thermal inversions work with different mechanisms in winter and in summer and "summer inversions tend to happen during the morning, whereas winter inversions usually take place in the afternoon, having different effects on the pollution levels" (Hicks et al., 2016). This is why I differentiate between summer and winter inversions in some alternative specifications.

[29] As I include implicit county fixed effect by taking differences on the right-hand side, we should not worry that 1990 emissions are correlated with thermal inversions, breaking the exclusion restriction.

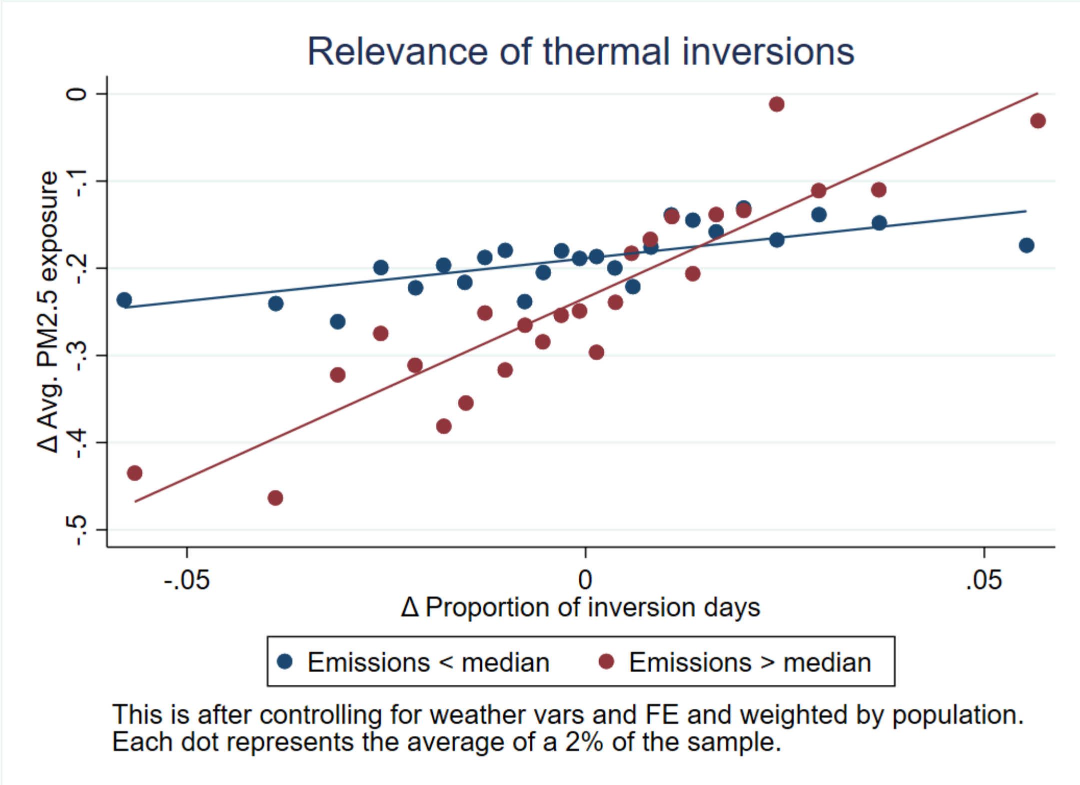


Figure A1: Descriptive relation between changes in the proportion of thermal inversions in a year and the average exposure to PM2.5.

The assumption of **exogeneity** can only be viable if thermal inversions are not affected by air pollution concentrations or economic activity. First, I have found no studies that show or hypothesise that air pollution might cause thermal inversions. Secondly, air pollution and thermal inversions should not be simultaneously affected by something else. On this, yearly changes in surface temperature are usually assumed to be exogenous in the climate economics literature (Burke et al. (2015); Dell et al. (2008); Kalkuhl and Wenz (2020) so it is fair to argue that the air temperature at higher levels that causes thermal inversions, is also exogenous.

Even though thermal inversions affect the concentration of air pollution exogenously, they also can be linked with weather, which can potentially influence economic activity on the ground (Burke et al., 2015). Thermal inversions can determine cloud formation, reduce precipitation, increase temperatures and reduce visibility (Encyclopedia Britannica, 2020). This is why I flexibly control for on-the-ground weather conditions as to rule out these potential correlations as Dechezleprêtre et al. (2019) and Fu et al. (2021). Finally, $PM_{2.5}$ is also (positively and negatively[30]) correlated with other pollutants that are also likely to be affected by thermal inversions. As other research that uses this same instrument (Chang et al., 2018), the estimates include the effects of other air pollutants correlated with local concentrations of $PM_{2.5}$.

[30]Table B.3 gives my results for the US while Dechezleprêtre et al. (2019) finds similar results for Europe. This is not the case for wildfire-induced $PM_{2.5}$, which is very weekly correlated with other pollutants.

If thermal inversions create exogenous variation in air pollution, it is possible to use them as a natural experiment. And the quality of the results will strongly depend if the variation it creates is correctly modelled by the first-stage specification (equation 3). The literature usually assumes this (Dechezleprêtre et al., 2019; Fu et al., 2021). Other alternative instrument specifications are shown in Table B.2, in the appendix.

First, thermal inversions and air pollution emissions are not necessarily homogeneous across large extents of land such as the US, Europe or China. This implies that some regions will have a higher influence in the results than others with the final results being the “average effects for subpopulations that are induced by the instrument to change the value of the endogenous regressors.” or local average treatment effect (LATE) (Imbens and Wooldrige, 2007). To have understand the degree of this heterogeneity, Figure A2 shows the average absolute change in the prevalence of thermal inversions ($\overline{\boldsymbol{\Delta TI}_c}$) and the log of tons of $PM_{2.5}$ emissions per 10km in 1999 (E_c). Figure A2 shows that most counties are in the centre of the distribution of both variables and that, in general, there are no large regions where the instrument is way stronger than others. A possible exception is the San Francisco Bay, where the instrument is especially powerful. Thanks to this, and its economic relevance, I do specifications with and without it and find no significant differences in results.

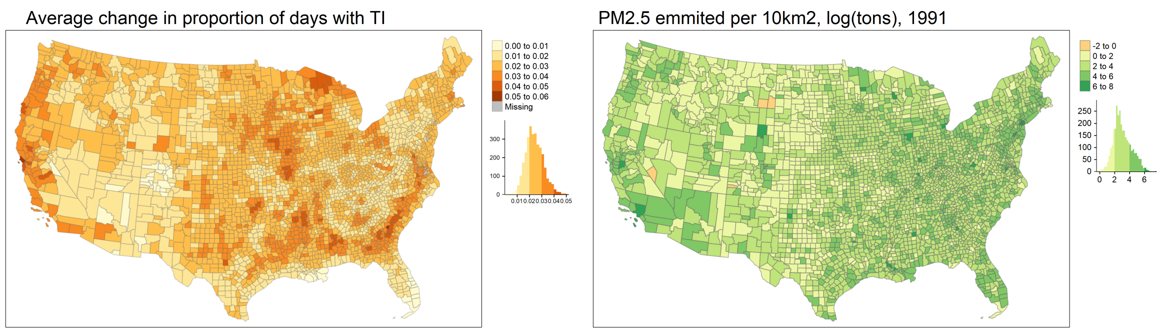


Figure A2: Identifying variation of the thermal inversion instrument.

A.2 Construction

To construct a measure of the prevalence or strength of thermal inversions I follow Chen et al. (2017) and Dechezleprêtre et al. (2019). As thermal inversions are a deviation from the monotonic declining relationship between altitude and air temperature. The data on air temperature is a 3D raster in which, for each coordinate pair, there are temperature measurements for a set of altitude layers. Layers are separated by 200m (roughly). These depend slightly on the temperature and the initial height as they are defined by pressure levels (hPa), with the lowest layer representing the first 200m above the surface. As I am interested in those that affect surface air pollution I have constructed 3 different measures of thermal inversions:[31]

1. If the temperature of the second layer is higher than that of the surface. This is closer to the adopted by Chen et al. (2017), Dechezleprêtre et al. (2019) and this study on my specifications that use thermal inversions.

2. If the temperature at any layer below the first 1000m is higher than the that of the surface

3. If the temperature at any layer below the first 1000m is higher than the layer below it

All 3 are strong instruments in urban areas that attain very similar results on the effect on GDP, GDP per capita, GDP per employee and population size.

[31] I also create measures of the strength of those differences (in ºC)

B Additional Figures and Tables

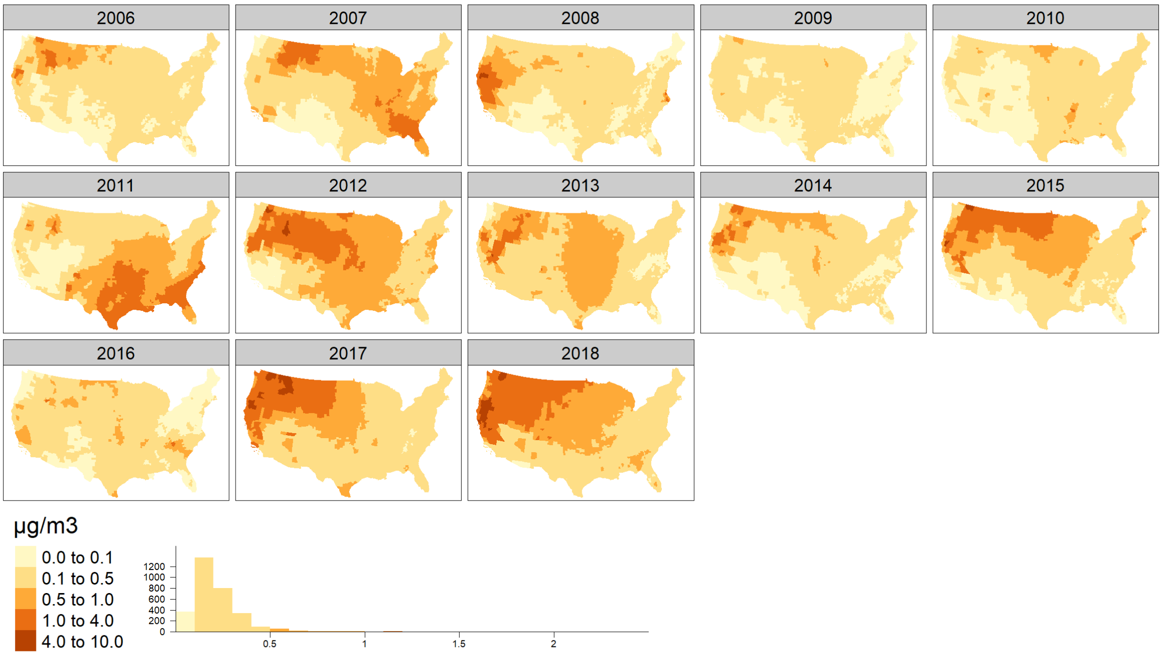


Figure B1: Geographical distribution of yearly exposure to Wildfire PM2.5

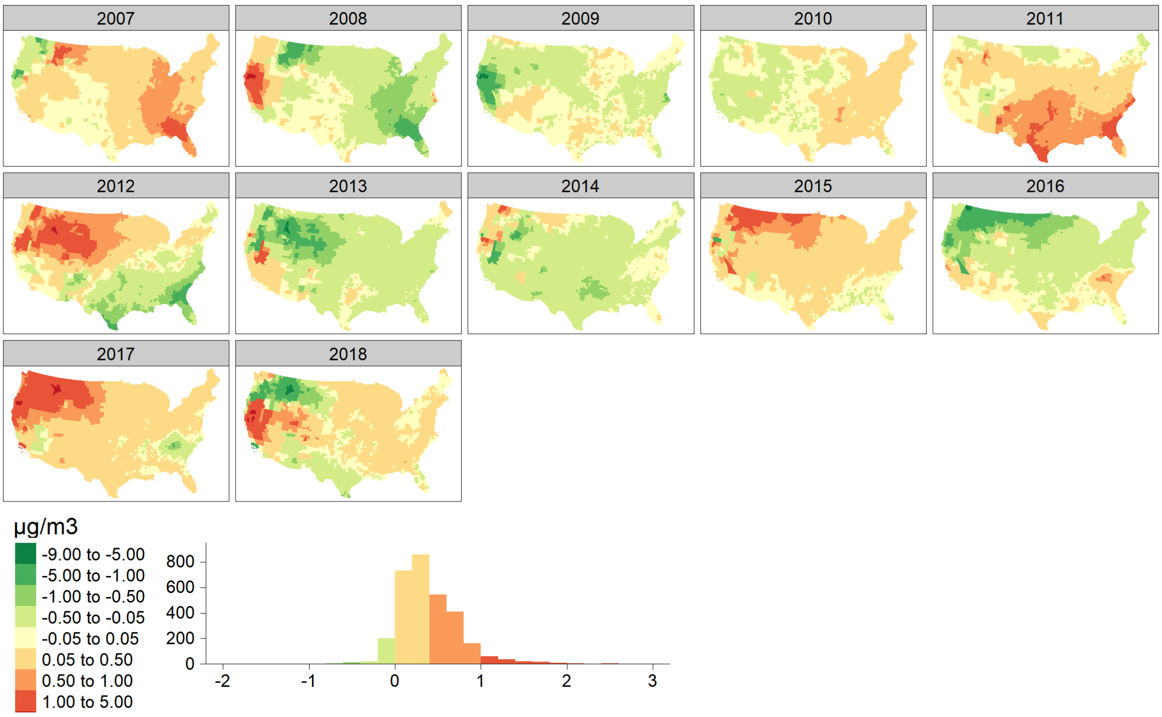
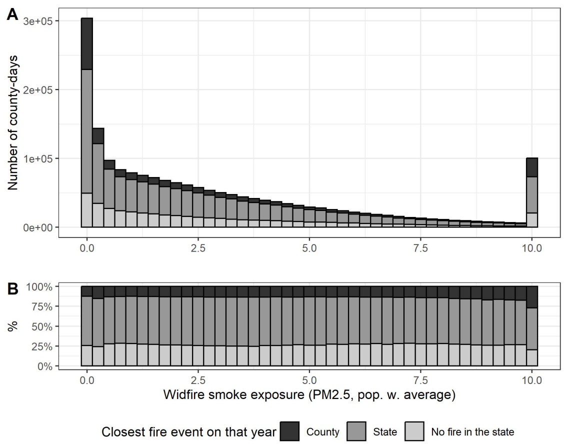
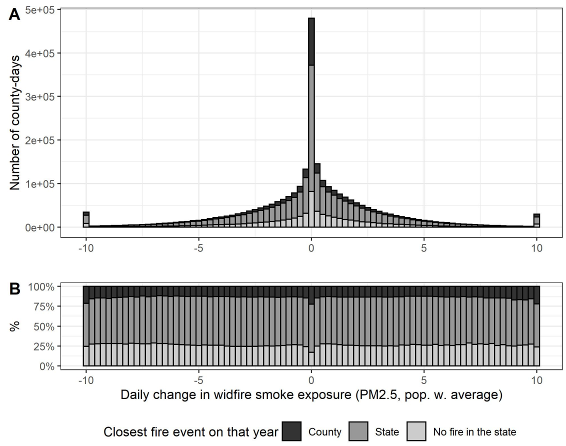


Figure B2: Geographical distribution of yearly *changes* of exposure to Wildfire PM2.5



(b) Daily values



(d) Daily changes

Figure B3: Distribution wildfire $PM_{2.5}$ exposure relative to the closeness of wildfires on that year. **A** and **B** display the absolute and relative frequencies, respectively. Distributions capped at [-10, 10].

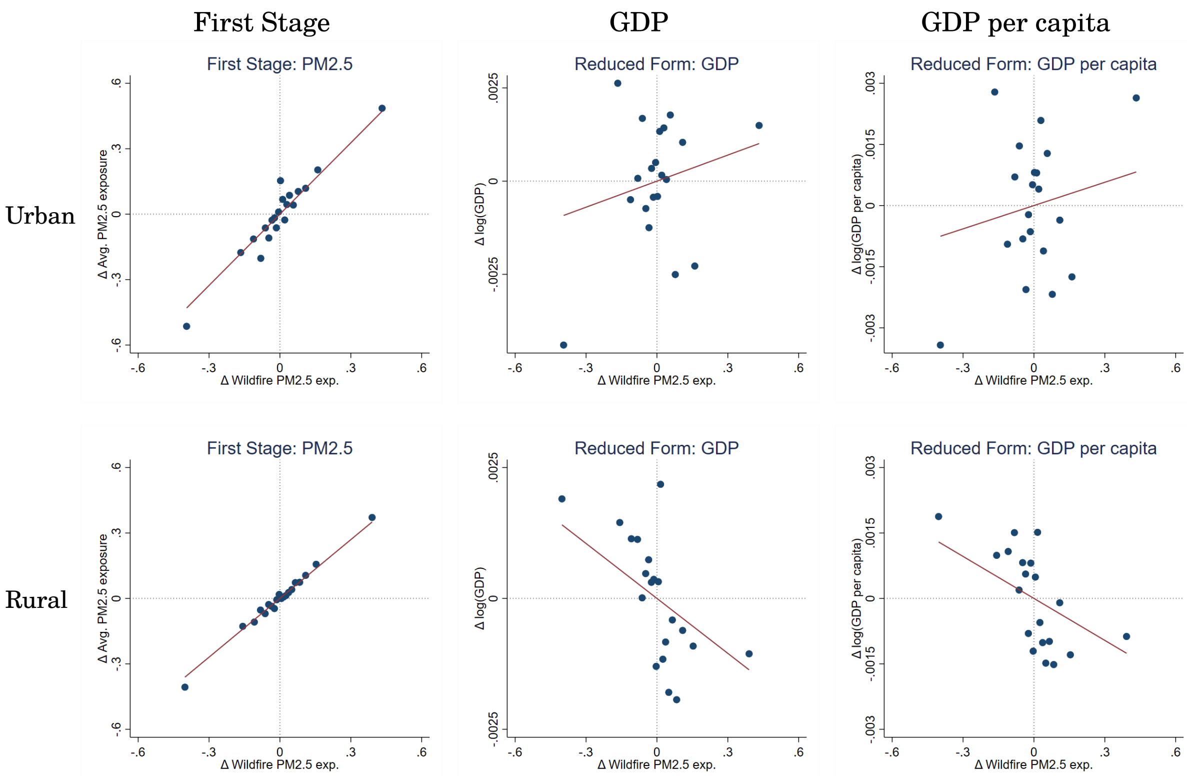


Figure B4: Binscatters of the first stage and reduced form for urban and rural counties reported in Table 5. Each dot represents a 5% of the counties, population-weighted. Outcomes and $PM_{2.5}$ exposure are cleaned of all influence of fixed effects and control variables.

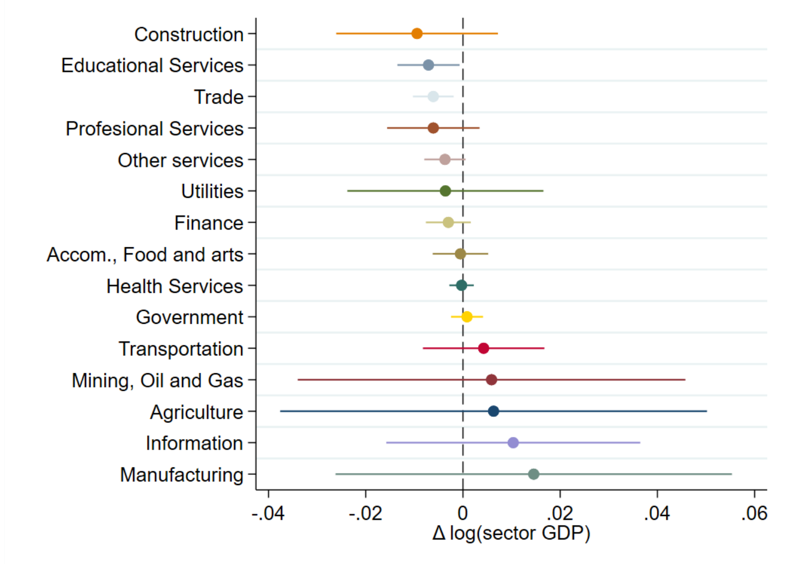


Figure B5: Summary of the impact of an 1μg increase in $PM_{2.5}$ on sector-level GDP with 95% CI. Full results are available in Table B.1, in the Appendix. Not corrected for multiple hypothesis.

Table B.1: Effect of $PM_{2.5}$ on the output of economic sectors

	(1)	(2)	(3)	(4)	(5)
	Δ ln(Agriculture)	Δ ln(Mining)	Δ ln(Utilities)	Δ ln(Construction)	Δ ln(Manufacturing)
Δ PM2.5 exposure	0.0063	0.0059	-0.0036	-0.0094	0.015
	(0.022)	(0.020)	(0.010)	(0.0085)	(0.021)
Nº obs	24530	26935	26588	29824	30117
Nº of counties	2726	2623	2817	2867	2847
R^2	0.23	0.51	0.32	0.50	0.46
Kleibergen-Paap F	133.6	257.7	188.4	402.4	371.0
	(6)	(7)	(8)	(9)	(10)
	Δ ln(Transportation)	Δ ln(Trade)	Δ ln(Information)	Δ ln(Finance)	Δ ln(Prof.Services)
Δ PM2.5 exposure	0.0043	-0.0061***	0.010	-0.0030	-0.0061
	(0.0064)	(0.0021)	(0.013)	(0.0024)	(0.0048)
Nº obs	20873	25195	26604	33406	26189
Nº of counties	2310	2632	2669	3067	2854
R^2	0.39	0.76	0.64	0.60	0.59
Kleibergen-Paap F	286.8	325.3	164.5	313.9	256.7
	(11)	(12)	(13)	(14)	(15)
	Δ ln(Educ.Services)	Δ ln(Heal.Services)	Δ ln(Acom.Food.Arts)	Δ ln(OtherServices)	Δ ln(Government)
Δ PM2.5 exposure	-0.0071**	-0.00028	-0.00051	-0.0037*	0.00084
	(0.0033)	(0.0013)	(0.0029)	(0.0022)	(0.0017)
Nº obs	20788	20109	29989	29873	33451
Nº of counties	2347	2259	2978	2925	3069
R^2	0.56	0.55	0.59	0.56	0.60
Kleibergen-Paap F	220.0	310.3	366.5	341.4	298.8

Standard errors in parentheses
Clustered SE by county (BEA). Weighted by average county sector's GDP over the whole sample. Counties with the 0.5% more extreme growth in any sector are excluded. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.
Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Alternative first stage specifications

	(1) Δ PM2.5	(2) Δ PM2.5	(3) Δ PM2.5	(4) Δ PM2.5	(5) Δ PM2.5	(6) Δ PM2.5	(7) Δ PM2.5
Δ Wildfire PM2.5 exp. *(main instrument)*		1.030^{***}					
		(0.0470)					
Δ Prop. days with inv.	3.384^{***}	4.158^{***}	-2.829^{**}			-2.530^{***}	3.380^{***}
	(0.650)	(0.682)	(1.142)			(0.886)	(0.647)
Δ Prop. days with inv.^{2}			11.72^{***}				
			(2.433)				
Δ Prop. days with inv. (Winter)					1.824^{***}		
					(0.298)		
Δ Prop. days with inv. (Summer)					1.518^{***}		
					(0.420)		
Δ Prop. days with wildfire smoke				0.0220^{***}			
				(0.00217)			
Δ Prop. days with inv. × log(avg. emis)						1.306^{***}	
						(0.269)	
Surface Pressure × Prop. days with inv.							-0.00685
							(0.00465)
Nº obs	49612	35125	49612	32252	49612	49612	49612
Nº of counties	3073	3073	3073	3071	3073	3073	3073
R^2	0.741	0.768	0.744	0.728	0.741	0.742	0.741

Standard errors in parentheses
Clustered SE by county (BEA). Weighted by county population. Includes state-year fixed effects and county-specific slopes. Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared.
* $p < 0.1$, ** $p < .05$, *** $p < .01$

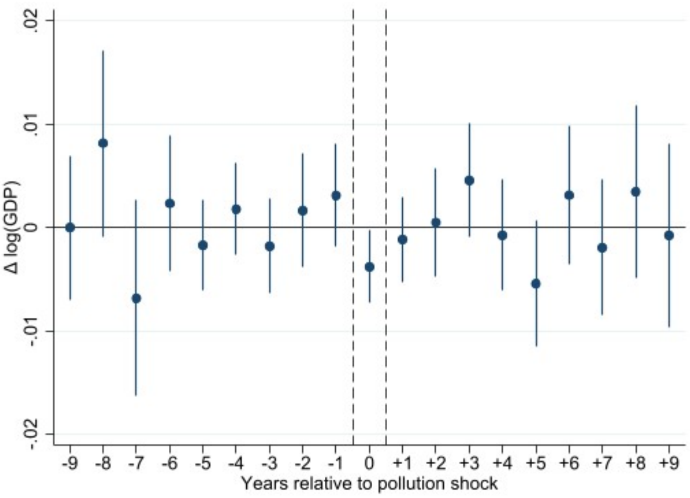


Figure B6: Estimated coefficients of β_1 For the effect of $\Delta PM_{2.5,t=0}$ on ΔGDP_t for $t \in \{-9, ..., 0, ..., +9\}$ in rural areas with 95% C.I., $t = 0$ corresponds with the effect in rural areas from Table 5.

Table B.3: Correlation of daily *changes* in $PM_{2.5}$ concentrations and other common pollutants.

	Wildfire $PM_{2.5}$	$PM_{2.5}$	PM_{10}	SO_2	NO_2	CO	O_3
Non-wildfire $PM_{2.5}$	-0.09	0.92	0.43	0.14	0.38	0.39	0.06
Wildfire $PM_{2.5}$	1	0.28	0.11	0.02	0.04	0.07	0.09
$PM_{2.5}$	0.28	1	0.47	0.14	0.38	0.40	0.09

Daily concentrations of $PM_{2.5}$, SO_2, NO_2, CO and O_3 are taken form Borgschulte et al. (2022). "Wildfire $PM_{2.5}$" corresponds to my measure of daily exposure to $PM_{2.5}$ from wildfire smoke and Non-wildfire $PM_{2.5}$ is equal to $PM_{2.5}$ − Wildfire $PM_{2.5}$. All correlations are significant to the 1% level.

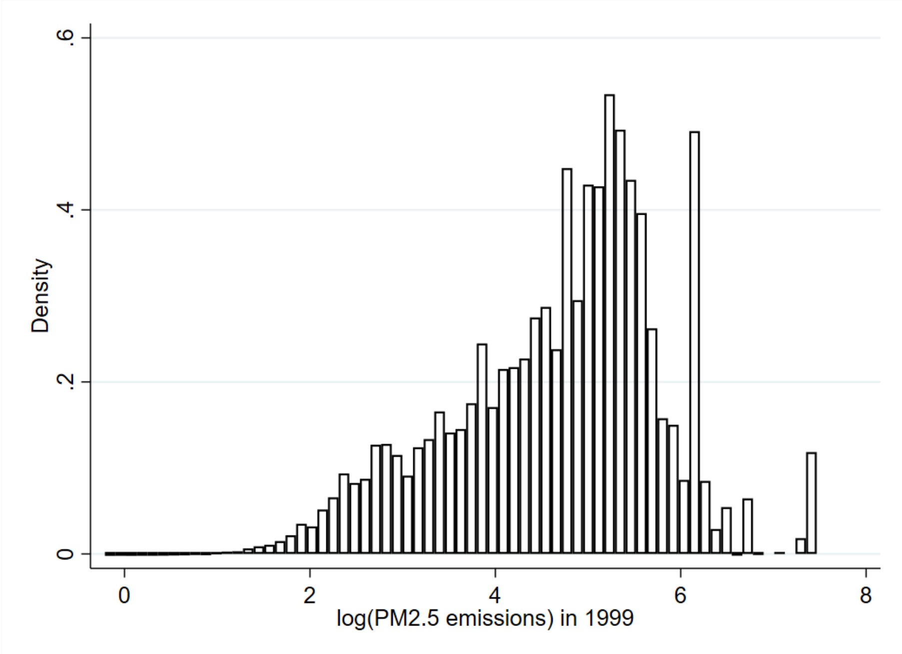
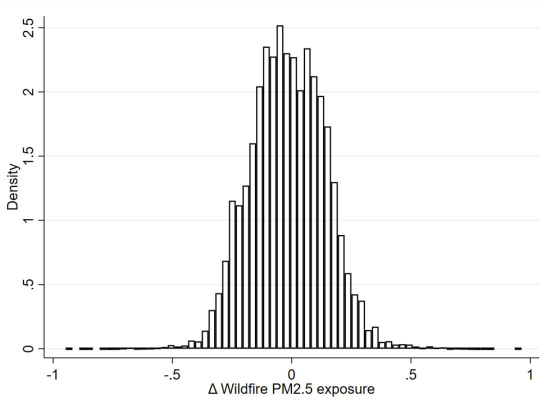
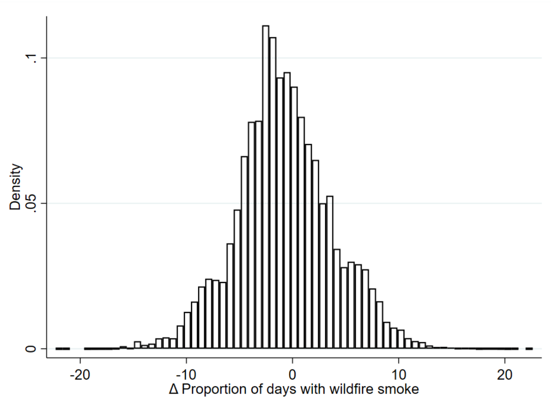


Figure B7: Histogram of log(Emissions) in 1999 (E_c), weighted by population

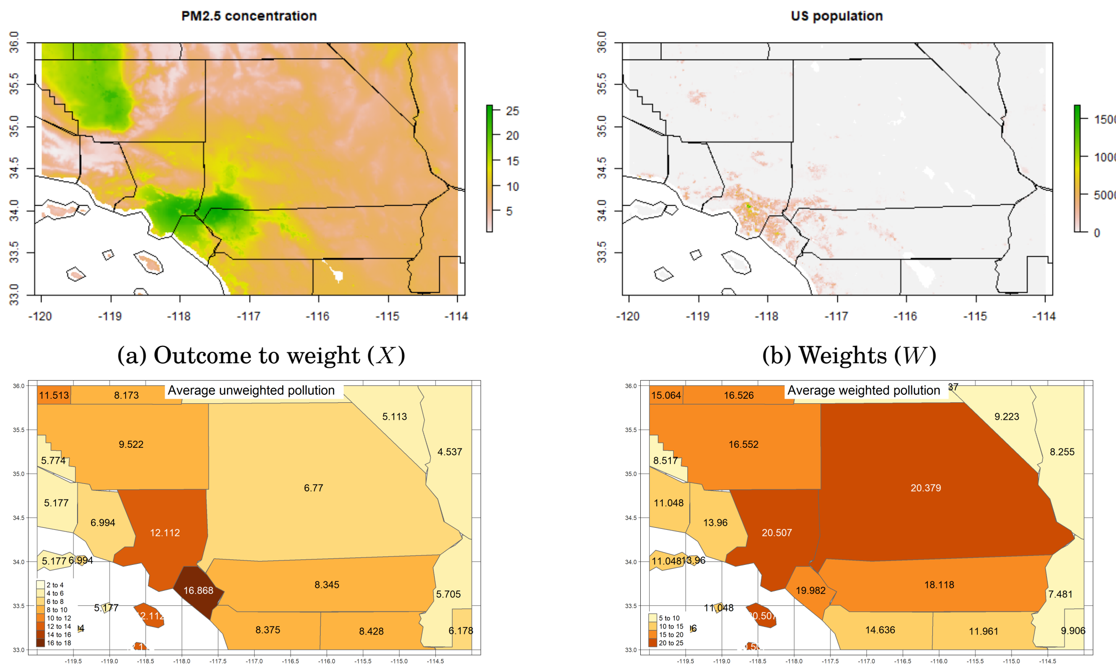


Yearly wildfire $PM_{2.5}$ exposure



Wildfire smoke

Figure B8: Histogram of residual variation in the instruments after including controls. Weighted by county population



(a) Outcome to weight (X)

(b) Weights (W)

(c) Average with no population weights ($\bar{X}$)

(d) Average with population weights ($\bar{XW}$)

Figure B9: Illustrative example of population weighting within counties. This is especially relevant in areas such as Las Vegas where population, emissions, and air pollution are spatially clustered.

Table B.4: Main results, with proportion of days with thermal inversions interacted with log(emissions) from 1999 as instruments

	(1)	(2)	(3)	(4)	(5)
	Δ PM2.5 exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ PM2.5 exposure		0.0028	0.0039	0.00079	-0.00071
		(0.0026)	(0.0028)	(0.0027)	(0.00057)
Δ Pro. inv.	-2.61***				
	(0.90)				
Δ Pro. inv. × log(emissions)	1.33***				
	(0.28)				
Nº obs	49612	49612	49321	49321	49321
Nº of counties	3073	3073	3050	3050	3050
R^2	0.74	0.42	0.38	0.30	0.82
Kleibergen-Paap F		16.3	15.4	15.4	15.4
Hansen J		0.25	1.27	0.025	.
p-value		0.62	0.26	0.87	

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.5: Main results, with Winter and Summer inversions as instruments

	(1)	(2)	(3)	(4)	(5)
	Δ PM2.5 exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ PM2.5 exposure		0.0021	0.0024	0.00091	0.000079
		(0.0030)	(0.0031)	(0.0029)	(0.00056)
Δ Pro. S inv.	1.52***				
	(0.43)				
Δ Pro. W inv.	1.85***				
	(0.30)				
Nº obs	49612	49612	49321	49321	49321
Nº of counties	3073	3073	3050	3050	3050
R^2	0.74	0.42	0.39	0.30	0.82
Kleibergen-Paap F		19.3	18.4	18.4	18.4
Hansen J		0.14	0.24	0.037	.
p-value		0.71	0.62	0.85	

Standard errors in parentheses
Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.
Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93
* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.6: Main results,number of days the county is covered by a smoke plume as instrument (same as Borgschulte et al. (2022)).

	(1)	(2)	(3)	(4)	(5)
	Δ PM2.5 exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ PM2.5 exposure		-0.00012	-0.00029	0.0024	-0.00011
		(0.0054)	(0.0054)	(0.0053)	(0.00043)
Δ Prop. days smoke	0.022***				
	(0.0022)				
Nº obs	32252	32252	32071	32071	32071
Nº of counties	3071	3071	3048	3048	3048
R^2	0.73	0.47	0.45	0.33	0.86
Kleibergen-Paap F		103.1	107.2	107.2	107.2

Standard errors in parentheses
Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.
Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93
* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.7: Main results, average wildfire-induced $PM_{2.5}$ for **Saturday and Sunday** as instrument.

	(1)	(2)	(3)	(4)	(5)
	Δ Avg. PM2.5 exp.	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ Avg. PM2.5 exp.		-0.0013	-0.00082	0.000053	-0.00043
		(0.0021)	(0.0022)	(0.0023)	(0.00026)
(mean) smokePM$_{Weekend}$	2.82***				
	(0.15)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.75	0.45	0.44	0.32	0.84
Kleibergen-Paap F		374.9	377.0	377.0	377.0

Standard errors in parentheses
Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.
Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93
* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.8: Main results, average wildfire-induced $PM_{2.5}$ for **Monday to Friday** as instrument.

	(1) Δ Avg. PM2.5 exp.	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Avg. PM2.5 exp.		-0.0011	-0.00074	0.00057	-0.00037
		(0.0024)	(0.0025)	(0.0025)	(0.00023)
(mean) smoke$PM_{Workday}$	1.34^{***}				
	(0.068)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.75	0.45	0.44	0.32	0.84
Kleibergen-Paap F		389.0	392.1	392.1	392.1

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.9: Main IV results for counties with centroid **east** of the US median population point

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Wildfire PM2.5 exp.	0.985^{***}				
	(0.0550)				
Δ Avg. PM2.5 exposure		-0.00116	-0.000855	-0.00215	-0.000363
		(0.00249)	(0.00261)	(0.00243)	(0.000503)
Nº obs	14604	14604	14406	14406	14406
Nº of counties	1242	1242	1219	1219	1219
R^2	0.818	0.518	0.505	0.384	0.842
Kleibergen-Paap F		320.5	329.2	329.2	329.2

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size $F = 19.93$

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.10: Main IV results for counties with centroid **west** of the US median population point

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Wildfire PM2.5 exp.	1.037^{***}				
	(0.0600)				
Δ Avg. PM2.5 exposure		-0.00119	-0.000775	0.000809	-0.000413
		(0.00267)	(0.00274)	(0.00283)	(0.000287)
Nº obs	20531	20531	20531	20531	20531
Nº of counties	1832	1832	1832	1832	1832
R^2	0.741	0.414	0.401	0.289	0.831
Kleibergen-Paap F		299.0	299.0	299.0	299.0

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size $F = 19.93$

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.11: Main IV results for counties with centroid **north** of the US median population point

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Wildfire PM2.5 exp.	1.038^{***}				
	(0.0680)				
Δ Avg. PM2.5 exposure		-0.00114	-0.000469	-0.000902	-0.000663^{**}
		(0.00204)	(0.00201)	(0.00193)	(0.000287)
Nº obs	17210	17210	17183	17183	17183
Nº of counties	1513	1513	1509	1509	1509
R^2	0.821	0.450	0.432	0.343	0.844
Kleibergen-Paap F		233.0	233.2	233.2	233.2

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size $F = 19.93$

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.12: Main IV results for counties with centroid **south** of the US median population point

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Wildfire PM2.5 exp.	1.010^{***}				
	(0.0804)				
Δ Avg. PM2.5 exposure		-0.0000502	0.000271	0.00205	-0.000293
		(0.00335)	(0.00342)	(0.00348)	(0.000305)
Nº obs	17927	17927	17756	17756	17756
Nº of counties	1561	1561	1542	1542	1542
R^2	0.762	0.469	0.455	0.315	0.817
Kleibergen-Paap F		157.8	157.1	157.1	157.1

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size $F = 19.93$

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.13: Main IV results, regression weighted by average county GDP levels

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Avg. PM2.5 exposure		-0.00085	-0.00063	0.00080	-0.00026
		(0.0029)	(0.0029)	(0.0030)	(0.00023)
Δ Wildfire PM2.5 exp.	1.06^{***}				
	(0.055)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.78	0.49	0.47	0.37	0.84
Kleibergen-Paap F		369.1	374.7	374.7	374.7

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 12 bins of wind speeds and interactions between the temperature bins and humidity Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.14: Main IV results, with no population weights

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Avg. PM2.5 exposure		-0.0066***	-0.0062***	-0.0043**	-0.00046
		(0.0022)	(0.0022)	(0.0022)	(0.00030)
Δ Wildfire PM2.5 exp.	0.89***				
	(0.029)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.77	0.28	0.28	0.25	0.66
Kleibergen-Paap F		915.8	916.4	916.4	916.4

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.15: Main results, including economic outliers (counties with extreme changes in GDP, population or GDP/capita)

	(1) Δ PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ PM2.5 exposure		-0.0014	-0.0014	-0.00048	-0.000027
		(0.0013)	(0.0014)	(0.0014)	(0.00017)
Δ Wildfire PM2.5 exp.	1.11***				
	(0.042)				
Nº obs	36912	36912	36636	36636	36636
Nº of counties	3076	3076	3053	3053	3053
R^2	0.76	0.39	0.38	0.27	0.82
Kleibergen-Paap F		684.1	685.6	685.6	685.6

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.16: Main results, excluding county-year pairs with active wildfires.

	(1) Δ PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ PM2.5 exposure		-0.0029	-0.0022	-0.0012	-0.00074*
		(0.0041)	(0.0041)	(0.0039)	(0.00041)
Δ Wildfire PM2.5 exp.	1.02***				
	(0.075)				
Nº obs	28724	28724	28563	28563	28563
Nº of counties	2864	2864	2844	2844	2844
R^2	0.82	0.45	0.43	0.35	0.86
Kleibergen-Paap F		186.3	188.2	188.2	188.2

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.17: Main IV results, Excluding the Great Recession years (2008-2011)

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Avg. PM2.5 exposure		-0.0013	-0.0011	0.00021	-0.00020
		(0.0015)	(0.0015)	(0.0014)	(0.00037)
Δ Wildfire PM2.5 exp.	1.06***				
	(0.075)				
Nº obs	23488	23488	23322	23322	23322
Nº of counties	3069	3069	3046	3046	3046
R^2	0.75	0.46	0.41	0.38	0.87
Kleibergen-Paap F		200.5	200.5	200.5	200.5

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

$^* p < 0.1$, $^{**} p < .05$, $^{***} p < .01$

Table B.18: Main results, excluding countiers from the San Fancisco area

	(1) Δ Avg. PM2.5 exposure	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Δ Avg. PM2.5 exposure		-0.0015	-0.0013	-0.0000046	-0.00026
		(0.0025)	(0.0025)	(0.0026)	(0.00023)
Δ Wildfire PM2.5 exp.	1.03***				
	(0.048)				
Nº obs	35089	35089	34891	34891	34891
Nº of counties	3070	3070	3047	3047	3047
R^2	0.76	0.44	0.43	0.31	0.84
Kleibergen-Paap F		454.1	458.2	458.2	458.2

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

$^* p < 0.1$, $^{**} p < .05$, $^{***} p < .01$

Table B.19: Main results, With monitor-based $PM_{2.5}$ measures from Borgschulte et al. (2022)

	(1) Monitored PM2.5	(2) Δ ln(GDP)	(3) Δ ln(GDP/capita)	(4) Δ ln(GDP/employee)	(5) Δ ln(Population)
Monitored PM2.5		-0.00086	-0.00053	0.00075	-0.00035
		(0.0030)	(0.0030)	(0.0031)	(0.00027)
Δ Wildfire PM2.5 exp.	1.02***				
	(0.12)				
Nº obs	14934	14934	14827	14827	14827
Nº of counties	1614	1614	1600	1600	1600
R^2	0.68	0.56	0.55	0.40	0.90
Kleibergen-Paap F		75.0	74.7	74.7	74.7

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

$^* p < 0.1$, $^{**} p < .05$, $^{***} p < .01$

Table B.20: Main results, without county-specific slopes

	(1)	(2)	(3)	(4)	(5)
	Δ Avg. PM2.5 exp.	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ Avg. PM2.5 exp.		0.00059	0.00055	0.0018	0.000015
		(0.0018)	(0.0019)	(0.0019)	(0.00038)
Avg. wildfire PM2.5	1.06^{***}				
	(0.048)				
Nº obs	35138	35138	34940	34940	34940
Nº of counties	3075	3075	3052	3052	3052
R^2	0.74	0.30	0.30	0.18	0.37
Kleibergen-Paap F		479.2	483.5	483.5	483.5

Standard errors in parentheses

Clustered SE by county (BEA). Weighted by county population. Weather controls include atmospheric pressure and himidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.21: Main IV results, without county-specific slopes and only year FE

	(1)	(2)	(3)	(4)	(5)
	Δ Avg. PM2.5 exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ Avg. PM2.5 exposure		0.00679^{***}	0.00600^{***}	0.00501^{**}	0.000804^{**}
		(0.00231)	(0.00233)	(0.00225)	(0.000329)
Δ Wildfire PM2.5 exp.	0.802^{***}				
	(0.0362)				
Nº obs	35150	35150	34952	34952	34952
Nº of counties	3076	3076	3053	3053	3053
R^2	0.512	0.159	0.176	0.0734	0.0322
Kleibergen-Paap F		491.1	492.2	492.2	492.2

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size -¿ F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$

Table B.22: Main IV results, without weather controls

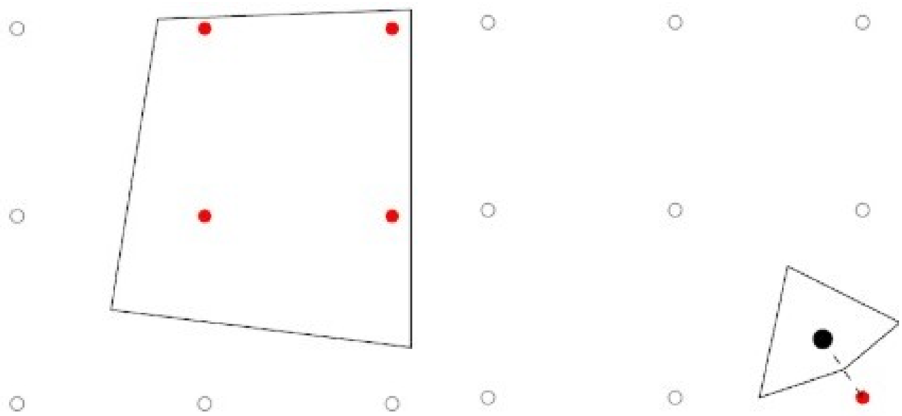
	(1)	(2)	(3)	(4)	(5)
	Δ Avg. PM2.5 exposure	Δ ln(GDP)	Δ ln(GDP/capita)	Δ ln(GDP/employee)	Δ ln(Population)
Δ Avg. PM2.5 exposure		-0.0047^{**}	-0.0044^{**}	-0.0030	-0.00037
		(0.0020)	(0.0020)	(0.0020)	(0.00027)
Δ Wildfire PM2.5 exp.	0.93^{***}				
	(0.030)				
Nº obs	35137	35137	34939	34939	34939
Nº of counties	3074	3074	3051	3051	3051
R^2	0.75	0.28	0.27	0.25	0.66
Kleibergen-Paap F		954.3	953.9	953.9	953.9

Standard errors in parentheses

Clustered SE by county (BEA). Weather controls include atmospheric pressure and humidity squared, 20 bins of temperature, 10 bins of rain, 10 bins of snow, 12 bins of wind speeds and interactions between the temperature bins and both humidity and humidity squared. Includes state-year fixed effects and county-specific slopes.

Stock-Yogo weak ID test critical value: 10% maximal IV size → F = 19.93

* $p < 0.1$, ** $p < .05$, *** $p < .01$



(a) With centroids inside a region (b) With no centroids inside a region

Figure B10: Imputation of raster values to counties (image from Dechezleprêtre et al. (2019))

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