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Air Pollution Reduces Economic Activity

Evidence from India

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Abstract

Exposure to fine particulate pollution ($PM_{2.5}$) increases mortality and morbidity and reduces human capital formation and worker productivity. As a consequence, high levels of particulate pollution may adversely affect economic activity. Using a novel dataset of changes in the annual gross domestic product of Indian districts, this paper investigates the impact of changes in the level of ambient $PM_{2.5}$ on district-level gross domestic product. Using daily temperature inversions as an instrument for pollution exposure, this paper finds that higher levels of particulate pollution reduce gross domestic product. The effect is non-trivial—the median annual increase in the level of PM2.5 reduces year-to-year changes in gross domestic product by 0.56 percentage points.

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Air Pollution Reduces Economic Activity: Evidence from India*

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1 Introduction

Exposure to high levels of particulate air pollution, especially $PM_{2.5}$, has negative consequences for human health and productivity. Studies show that exposure to elevated levels of air pollution substantially decreases the rate of human capital formation (Persico and Johnson, 2020; Heissel et al., 2019; Levy et al., 2020; Molina, 2021; Zivin et al., 2020), increases mortality (Pope III et al., 2002; Krewski et al., 2009; Lepeule et al., 2012), morbidity (Tong,

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2019; Wu et al., 2020), childhood stunting (Balietti et al., 2022), decreases labor supply (Aragón et al., 2017), and reduces labor productivity (Chang et al., 2016; Fu et al., 2021). Air pollution also negatively impacts crop yields (Burney and Ramanathan, 2014a; Burney, 2020).[1]

These negative impacts closely mirror the well-documented negative impacts of exposure to high temperatures at the individual level. Exposure to high temperature increases mortality (Barreca et al., 2016), reduces labor supply (Graff Zivin et al., 2017), labor productivity (Somanathan et al., 2015), human capital formation (Garg et al., 2020; Park, 2020; Park et al., 2020), and crop yields (Schlenker and Roberts, 2009). The negative consequences of heat measured at the micro level have been shown to aggregate to substantial macro-effects. Burke et al. (2015) show that across both rich and poor countries higher temperatures reduce GDP levels. Even at current levels of heat exposure these effects are sizable, especially in lower income countries.

Despite the similarity in the micro level impacts of air pollution and exposure to extreme heat there has been limited analysis of the macro level impacts of air pollution. The consistency in the micro level impacts of heat and air pollution combined with the existence of substantial macro level effects of heat suggests that air pollution may also have macro level effects. Increased worker absenteeism, reduced job performance (reduced productivity), and reduced levels of human capital accumulation as a result of air pollution are likely to transmit to reductions in overall economic activity. These consequences of pollution exposure might be expected to reduce year-over-year changes in GDP following years with higher levels of pollution. This hypothesis finds support in recent work examining air pollution in Europe at the NUTS-3 level that finds a $1\mu g/m^3$ increase in $PM_{2.5}$ levels reduces annual changes in GDP by 0.8% (Dechezleprêtre et al., 2019) and evidence from the United States that pollution reduces GDP by 0.4% in rural counties (Avila Uribe, 2023).[2]

This paper investigates whether increasing pollution in a given year has negative consequences for economic activity in that year using a panel of district level GDP data from India covering the years 1998-2020. Existing empirical work demonstrating that pollution exposure can impact aggregate GDP is based on evidence from Europe and the United States. However, exposure to pollution in both these locations is substantially lower than average exposure across low- and middle-income countries. On average the level of $PM_{2.5}$ in the countries studied in Dechezleprêtre et al. (2019) was $10\mu g/m^3$. Average levels of exposure in India and China exceed $50\mu g/m^3$. In some districts of India the annual average level of

[1]For a recent review of the literature on the variety of negative impacts of air pollution, especially those on human capital, see Aguilar-Gomez et al. (2022).

[2]NUTS-3 is the smallest administrative unit in Europe.

$PM_{2.5}$ exceeds $100\mu g/m^3$. That is roughly 20 times the World Health Organization's (WHO) recommended levels and more than double India's own standards. Peak exposures in Delhi can exceed $500\mu g/m^3$.

Given the uniformly higher ambient pollution concentrations in most low- and middle-income countries – and the fact that levels of ambient particulate pollution are increasing in most low- and middle-income countries (Shaddick et al., 2020) – it is important to understand how the effects of pollution may vary at higher levels of pollution than are typically observed in Europe or the United States. Higher levels of pollution might suggest more severe effects. However, consistently higher levels of pollution might also induce adaptation that reduces the marginal effects of a given change in the level of pollution (Neidell, 2009).

A global analysis that examines the impact of pollution on GDP using a modified Solow model that accounts for the damages of air pollution suggests that true growth rates in India have been an average of 50 basis points lower than reported rates since 2005 due to the negative consequences of pollution (Mohan et al., 2020). This represents a substantial divergence from the experience in the largest European economies where pollution adjusted growth has slightly exceeded measured growth since 2005. These results suggest that the higher levels of pollution experienced in low- and middle-income countries may lead to more severe consequences.

Measuring the impact of changes in air pollution on GDP growth in a causal effects framework, rather than a model-based framework, is challenging because of reverse causality. GDP growth is generally strongly correlated with pollution levels because of the increase in energy demand and other polluting activities (for example, increases in traffic) that often come with GDP growth. As a result, increases in GDP have tended to drive increases in pollution.[3] Thus while increases in pollution may have negative impacts on GDP growth relative to a counterfactual world in which growth did not generate pollution, it can be difficult to measure these effects because we do not observe this counterfactual world. Instead, identifying the potential negative impacts of air pollution on GDP requires identifying exogenous changes in pollution levels whose effect on GDP growth can then be measured.

To isolate changes in air pollution that are not driven by GDP growth this paper follows several existing papers on the economic impacts of air pollution by employing an instrumental variables (IV) approach that instruments for the level of pollution with the presence of temperature (thermal) inversions (Fu et al., 2021; Chen et al., 2022; Dechezleprêtre et al., 2019). A temperature inversion is a meteorological event that occurs when temperatures

[3]This is broadly true when income per capita is at low levels (Stern, 2018; Dinda, 2004; Dasgupta et al., 2002; Cole et al., 1997; Cuaresma and Heger, 2019; Wilebore et al., 2019). The exact threshold is debated but above a certain level of per capita income GDP growth can become disconnected from pollution growth. The extent of the decoupling varies across countries and across pollutants however (Harbaugh et al., 2002).

at atmospheric levels above the surface level are higher than at the surface. Under normal conditions temperature declines monotonically as one moves up in the atmosphere away from the surface. When temperatures at higher levels in the atmosphere are higher than at the surface the air at the surface becomes stationary and trapped, which prevents the removal of pollutants by atmospheric circulation. Existing work has shown that the occurrence of these inversions increases pollution at the surface (Fu et al., 2021; Chen et al., 2022; Dechezleprêtre et al., 2019). The effects can be extreme. A temperature inversion is believed to have exacerbated the consequences of a gas leak at an industrial plant in Bhopal, India in 1984 that ultimately harmed more than 500,000 people (Boybeyi et al., 1995).

Using inversions as an instrument, our results suggest that high levels of air pollution have a negative effect on economic growth measured as the first difference of GDP at a district level. In our primary specification a $1\mu g/m^3$ year over year increase in $PM_{2.5}$ pollution reduces the year-to-year change in GDP by 0.7 percentage points. At the means in our sample this implies an increase in pollution levels that is 1 SD larger than the average year over year change reduces year-to-year GDP changes by 0.37 SD. The contemporaneous effect of pollution on changes in GDP appears to be partially offset by higher GDP in subsequent years such that the total impacts are slightly smaller than the immediate effect. Our effects are comparable to those estimated by Dechezleprêtre et al. (2019) in Europe. This despite the fact that average pollution levels in India are substantially higher than those in Europe.

Overall, our results suggest that air pollution imposes meaningful economic costs. Our estimates suggest that lowering air pollution could have led to larger year-to-year changes in India's GDP in the recent past. However, it is important to note that reducing air pollution also has significant costs and may require structural changes in India's economy. Such structural changes are likely to have direct impacts on growth rates that may be larger, and differently signed, than the impacts of reducing air pollution. Despite this, there are likely significant long-term benefits from reducing air pollution.

2 Conceptual framework

It is well documented that air pollution has negative effects on human well-being. As a result, in our conceptual framework we assume that air pollution impacts aggregate GDP primarily by changing effective labor supply. While it is possible that air pollution impacts the productivity of capital in an economy there is little current evidence to support that mechanism.[4] Air pollution could change effective labor supply by either reducing labor supply or by reducing the productivity of workers or both. We outline the evidence for each

[4]We discuss evidence that air pollution influences crop yields and power generation below.

mechanism here.

Air pollution affects labor supply decisions in the short-run primarily by increased absenteeism at work due to sickness.[5] The health effects of $PM_{2.5}$ exposure are well documented (WHO, 2013; McDuffie et al., 2021; Pandey et al., 2021). They are due to exposure over both the short term (hours, days) and long term (months, years) and include respiratory and cardiovascular morbidity, such as aggravation of asthma, respiratory symptoms and an increase in hospital admissions. Many studies find evidence of reduction in working hours due to increased pollution levels (e.g. Hanna and Oliva (2015); Hansen and Selte (2000)). In Lima, the capital city of Peru, Aragón et al. (2017) find that the impact is significantly larger at higher levels of pollution but is concentrated among households with susceptible dependents (i.e. small children and elderly adults) at moderate levels of pollution. This is consistent with evidence from the United States that finds exposure to air pollution increases student absenteeism by increasing cases of acute asthma (Komisarow and Pakhtigian, 2022). To the extent that workers have care-giving responsibilities for school children or the elderly, increases in acute incidents among these populations may translate into reductions in labor supply among the working age population.

Pollution may also impact medium-run labor supply decisions by inducing migration. Chen et al. (2017) suggest that air pollution is responsible for large changes in inflows and outflows of migration in China, and the reduction of the overall population through net out-migration by 5 percent in a given county. Khanna et al. (2021) find that pollution in China has larger effects on highly skilled workers, who are more likely to emigrate, generating large productivity impacts. Gao et al. (2023) find that migration decisions are highly responsive to an unexpected disclosure of pollution information. Pan (2023) finds that families relocate to cleaner counties after adults receive asthma diagnoses. If air pollution induces workers to migrate away from high productivity areas to lower productivity areas even internal migration may have impacts on GDP.

Air pollution not only impacts labor supply but can also impact workers' performance at the workplace. A substantial literature provides evidence of impaired cognitive and physical functions due to increased $PM_{2.5}$ levels (Aguilar-Gomez et al., 2022). Chang et al. (2016) study the effect of outdoor air pollution on the productivity of indoor workers at a pear-packing factory in Northern California. They find that a 10-unit change in $PM_{2.5}$ decreases worker productivity by roughly 6 percent at pollution levels well below current US air quality standards. Adhvaryu et al. (2019) study the effects of $PM_{2.5}$, measured at the hourly level

[5]In the long-run air pollution can reduce labor supply by changing the size of the workforce either through increased deaths (Pandey et al., 2021), reduced live births (McDuffie et al., 2021), or increased net out-migration (Chen et al., 2022; Khanna et al., 2021)

at multiple locations in an Indian garment factory, on production. Their estimates imply a roughly 0.3 percent decline in productivity (as measured by the number of garments sewn per hour) for every $10 \mu g/m^3$ increase in $PM_{2.5}$, with larger effects for more complex tasks and older workers.

Pollution impacts performance in more sectors than physically demanding activities in manufacturing. It also affects workers' ability to perform cognitive tasks. Exposure to $PM_{2.5}$ can impact decision making, educational outcomes, and productivity by impairing cognitive function and altering emotional states (Aguilar-Gomez et al., 2022). Chang et al. (2019) investigate the effect of pollution on worker productivity in the service sector by focusing on two call centers in China. They find that a 10-unit increase in the air pollution index decreases the number of daily calls by 0.35 percent, an effect that appears to occur through longer employee breaks. Heyes et al. (2016) find a significant negative impact of $PM_{2.5}$ on S&P 500 returns – a one standard deviation increase in $PM_{2.5}$ reduces same day returns by nearly 12 percent, an effect likely to be driven by decreased risk tolerance operating through pollution-induced changes in mood or cognitive function. There is a rich literature that documents student performance on exams is negatively affected by air pollution (Levy et al., 2020; Wen and Burke, 2022). Reductions in student performance may not impact contemporaneous economic activity but provides additional evidence for cognitive effects of air pollution and indicates that pollution may have long-run consequences for growth.

Higher levels of pollution also impact economic output through channels other than labor supply or productivity. These include reductions in crop yields, reductions in solar energy output, and allocation inefficiencies as funds may be diverted towards pollution-related damage reduction activities, among others (Deschenes et al., 2017). High concentrations of pollution particles can reduce the intensity of the sun's radiation reaching the Earth, decreasing direct radiation and increasing diffuse radiation. This can reduce crop yields (Burney and Ramanathan, 2014b; Behrer and Wang, 2022). Zhou et al. (2018) finds that $PM_{2.5}$ concentrations reduce average yields of wheat and corn in China. Gupta et al. (2017) assess the impact of global warming and local air pollution in India by analyzing the data of more than 200 district over 1981-2009. Their finding suggests that for a one-standard-deviation decrease in aerosol optical depth, wheat yields increase by about 4.8 percent.[6]

Reductions in the intensity of solar radiation may also impact solar generation. A recent study by Ghosh et al. (2022) finds that reductions in pollution could enhance India's annual solar production by 6-28 terawatt-hours of electrical energy, which translates to economic

[6]Aerosol optical depth (or AOD) is a measure of the number of particles in a column of the atmosphere beginning at the surface and extending to the edge of the atmosphere. Lower AOD is correlated with lower levels of particulate pollution at the surface.

benefits of USD325 million to USD845 million every year. Similar effects have been documented in eastern China (Li et al., 2017). These reductions may be driven by changes in the amount of radiation reaching the surface or by deposition of particulate matter on the solar panels, further blocking sunlight.

Model based approaches to estimating the impact of air pollution on GDP growth are an alternative to the quasi-experimental approach employed by many of the papers above and that we employ. Model based approaches start with measured GDP and attempt to aggregate all of the costs of air pollution and then subtract these costs from measured GDP and calculate a pollution inclusive measure of growth. This approach is well represented by Mohan et al. (2020) who estimate how incorporating damages from air pollution changes GDP levels in 163 countries. Their approach models the damages from pollution that occur across the economy – what they term gross environmental damage (GED) – and subtracts those damages from GDP to arrive an estimated "environmentally-adjusted value added" (EVA). This approach provides an estimate of the extent to which economic activity is drawing down stocks of natural capital (i.e. clean air) and is important for assessing whether economic growth is occurring sustainably. They find that over the last several decades India's EVA growth has been approximately 50 basis points lower than measured GDP growth.

Our approach differs as we do not attempt to explicitly estimate the full set of damages that air pollution can cause individually or in aggregate. Rather, we assume that the damage caused by year-to-year changes in air pollution will manifest as year-to-year changes in GDP. That implies that measured year over year GDP growth will be lower in years with higher levels of air pollution than it would have been absent the damages from air pollution.[7] Note that this measure will be inclusive of intra-annual adaptation measures taken to reduce the impact of air pollution on economic activity (e.g. shifting work from high pollution to low pollution days). Crucially, to the extent that air pollution has long-term effects on GDP growth (i.e. if it reduces future growth by reducing human capital formation in school aged children today) we will not detect these effects with our approach.

3 Data

3.1 GDP data

We compile real district GDP using officially published reports by state governments and CEIC (a data platform that compiles data from various official sources). The series is

[7]Note, we are not estimating the effect of pollution on long-run average growth rates, rather our outcome is the year-to-year change in GDP in percentage terms.

available for three different base years (1999-00, 2004-05, and 2011-12) starting from the fiscal year 1999-2000 until the most recently available. Given the three different base years, we construct a spliced growth rate series. The spliced GDP series is constructed by using the real GDP growth rate as implied by the latest base year; for instance, if the 2011 growth rate is available under both 2004-05 and 2011-12 base year, we use growth rate based on the 2011-12 base year. We have data for approximately 550 districts (covering around 25 states and union territories) with each having, on average, 15 observations. The available district data accounts for, on average, more than 90 percent of the respective states' GDP and based on 2015 levels, these states and union territories contribute 90 percent of India's real GDP.

The real GDP growth rate has averaged 6.9 percent over 2000-2019 for the 550 districts covered in the sample with a standard deviation of 7.2 percent (Table 1). We winzorize our GDP growth data at the 1^{st} and 99^{th} percentile. This eliminates 34 observations where the absolute growth rate exceeds 50 percent.

3.2 Inversions

To measure inversions we use data from the Modern-Era Retrospective analysis for Research and Applications (MERRA) database provided by NASA (Rienecker et al., 2011). This is a satellite based reanalysis product that provides data on temperature at each of 42 atmospheric levels on a $0.5° \times 0.625°$ grid.[8] We collect the daily aggregate mean of temperature for the first 19 levels of the atmosphere. This roughly corresponds to the levels beginning at the surface and extending 5km into the atmosphere.[9] Because MERRA indexes layers based on pressure levels, rather than consistent elevation thresholds we calculate surface temperature individually for each grid-point×day based on the temperature reported at the lowest level for that grid-point×day. We set this layer as the surface and calculate temperatures in the layers counting up from the surface layer.

We aggregate our grid-point×day temperatures to the district level by taking the weighted average across grid-points for each day with weights defined as the total population in each grid-point's unique catchment area.[10] We assign grid-points to the districts that contain them. For districts that do not contain any grid-points we use the nearest grid-point to the center of the district. We then calculate whether a district experiences an inversion on a given day based on the district×day temperature at each atmospheric level.

We use two different measures of inversions. The first considers the difference between

[8] Data available here: `https://disc.gsfc.nasa.gov/datasets/M2I3NPASM_5.12.4/summary?keywords=M2I3NPASM`

[9] The actual height varies with surface elevation and day-to-day changes in surface pressure.

[10] Catchment areas are the area around each grid-point that is closer to that grid-point than any other grid-point.

the surface temperature and the temperature in each of the two layers immediately above the surface. If the surface temperature is lower than the temperature in either the first layer *or* the second layer we classify that day as experiencing an inversion. The second compares surface temperature to the temperature in all the layers in our sample. Again, if surface temperature is lower than the temperature in *any* of these layers we classify that day as experiencing an inversion. We also split inversions into winter and summer inversions as meteorological conditions and the emissions of pollutants vary across seasons. In general winter inversions have a larger impact on pollution levels (for example because there are more emissions from burning for heating in the winter which can be trapped by inversions). We count the number of days with inversions in each district and year or season and calculate the share of days each district experienced an inversion in the whole year as well as separately by winter and summer. We also measure the strength of each inversion as the difference in temperature between the higher and lower layer on days when there is an inversion. Larger differences indicate stronger inversions (Chen et al., 2022). For each district and year or season we calculate the average inversion strength averaging across all inversions that occur in the relevant time period.

3.3 Meteorological controls

We collect weather re-analysis data from ERA5. ERA5 is produced by the European Commission's Copernicus Climate Change Service.[11] We use data from the ERA5 Land hourly product. This provides data at an hourly level on a grid of $0.1^{\circ}\times0.1^{\circ}$, which translates to a 9km resolution over India. We use data on temperature, dew point, surface pressure, wind direction, wind speed, and precipitation over the full sample. We calculate relative humidity from dew point, temperature and surface pressure. We aggregate these weather variables to the district level by averaging over all grid-points that fall within a district boundary using the same population weighting we use to calculate inversions.

3.4 Air pollution data

We use pollution data from the global data produced by the Van Donkelaar research group (Van Donkelaar et al., 2019). This provides monthly average pollution levels on a $0.01^{\circ}\times0.01^{\circ}$ grid covering the entire planet from 1998 to 2020. We calculate annual average pollution in Indian districts by assigning grid-points to their respective district and then averaging across all grid-points within a district in each month. We weight grid-points by the population

[11] Data available here: https://cds.climate.copernicus.eu/cdsapp!/dataset/reanalysis-era5-land?tab=overview

within its unique catchment area. We then average across district months within each Indian fiscal year, running from April to March.

4 Empirical approach

We estimate the impact of pollution exposure on GDP growth with an instrumental variables model instrumenting for pollution with seasonal inversions. Inversions result in plausibly exogenous changes in pollution at the surface conditional on surface weather conditions. To isolate the impact on pollution of the inversions we control flexibly for a wide range of surface level weather conditions.[12]

We estimate a first differences model so all of our variables are measured as the change from year-to-year within a district. For notational simplicity we omit the difference indicators below. All of our inversion and meteorological variables are measured as district level weighted averages where we weight the values at each grid cell within a district by the population surrounding that grid cell.

We estimate the following system of equations:

$$\begin{aligned} \text{Avg. PM}_{2.5}\text{ Conc.}_{iy} = \psi_1 &\text{Winter Inversions}_{iy} \times \psi_1 \text{Winter Inversion Strength}_{iy} \\ &+\psi_3 \text{Summer Inversions}_{iy} \times \psi_4 \text{Summer Inversion Strength}_{iy} \\ &+\delta \mathbf{X}_{iy} + \eta_y + \epsilon_i \end{aligned} \tag{1}$$

$$\text{GDP change}_{iy} = \beta \text{Avg. } \widehat{\text{PM}_{2.5}} \text{ Conc.}_{iy} + \phi \mathbf{X}_{iy} + \kappa_y + \mu_i \tag{2}$$

where we instrument for the annual average $\text{PM}_{2.5}$ concentration in district i and year y with the number of winter and summer inversions and the average strength of these inversions in district i and year y. The strength of inversion is measured as the average temperature difference across the inverted layers when there is an inversion (Dechezleprêtre et al., 2019; Chen et al., 2022). Equation 2 takes our predicted average $\text{PM}_{2.5}$ concentration and regresses it on the change in GDP growth in district i and year y. β describes how a change in our predicted level of $\text{PM}_{2.5}$ changes GDP growth. In all specifications we include $\mathbf{X}_{iy}$, a vector of meteorological controls measured at the surface. We follow Dechezleprêtre et al. (2019) and this vector controls for the number of days in one of fifteen precipitation bins, the number of days the average temperature is in one of twenty-five bins, a second order polynomial

[12] We do not control for surface level fog directly. We are unaware of any data on fog incidents that comprehensively covers the geographic and temporal span of our data. Further, research on the occurrence of fog over northern India finds that measures of relative humidity and wind speed, which we include in our broad set of weather controls, provide a close approximation of more detailed models of fog incidents (Singh et al., 2018).

of relative humidity and surface pressure, four wind speed bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. We include year fixed effects ($\eta_y \& \kappa_y$) in all regressions and because we estimate a first differences model it implicitly includes district fixed effects. We cluster errors at the district level which is the level that our outcomes and instrumental variables vary.

5 Results

Air pollution in India over our sample period is concentrated in the northwest and along the Indo-Gangetic plain (Figure 3a). In the districts in these areas the annual average pollution level can exceed the WHO recommended limits by more than ten times. But in even the least polluted districts the average annual exposure is above the average level of exposure typically experienced in wealthier countries. In the areas most exposed to pollution, exposure levels are substantially higher than in wealthier countries, with average exposure around $50\mu g/m^3$ annually (Table 1).

Exposure to $PM_{2.5}$ in India has increased significantly over time as well. During our sample period average exposures have increased by more than 50 percent, from approximately $35\mu g/m^3$ to more than $55\mu g/m^3$ (Figure 2). The impact of COVID19 lock-downs on pollution is visible as a notable decline in average pollution levels at the end of our sample period.

We see no trend in inversions over our sample period (Figure 4). There is a small spike in the final years of our sample but on average slightly less than 20 percent of days experience an inversion across all the districts in our sample. There are more inversions during the winter, with roughly 25 percent of winter days experiencing an inversion, and correspondingly fewer during the summer months.

5.1 First stage

Our measure of seasonal inversions appears to be highly predictive of pollution levels over our sample period. We show (Table 2) that a hypthetical year in which every winter day had an inversion would have pollution levels that are roughly $2.5\mu g/m^3$ higher than a year with no inversions. That represents a roughly 5 percent increase in annual average $PM_{2.5}$ levels from the mean. On average across the whole sample, 26% of winter days experience an inversion.

Summer inversions do not appear to have a meaningful impact on annual pollution levels. This could be due to differences in other meteorological conditions during the summer, for example increased monsoon rainfall that reduces pollution levels, or because there are fewer sources generating pollution (e.g. less wood-smoke from heating) to be trapped by inversions that occur during the summer. Regardless, we show that omitting the summer inversions does not appear to impact the predictive ability of winter inversions (Table 2, Columns 2-3).

One might be concerned that the predictive power of our inversions instrument is due to some artefact of the construction of our measures of pollution. These are based on satellite measurements but also include inputs from dispersion modeling. To alleviate this concern we conduct the following robustness check. For 21 cities around India we download data on daily pollution levels from the Indian Central Pollution Control Board from 2015 to 2020. This gives us an unbalanced panel of pollution (due to missing data) at the daily level across these cities. We then use our weather data to construct daily measures of inversions and ground level weather controls for each of these cities. We test whether our measure of inversions successfully predicts higher levels of pollution in these cities using this pollution dataset that is unrelated to our primary pollution data. We find that a day with an inversion leads to $PM_{2.5}$ levels that are roughly 5% (*t-stat:* 1.91) higher relative to the mean. This test, using daily data distinct from our primary pollution data suggests that the inversion instrument is both a good predictor of higher pollution levels and that this predictive power comes from true impacts in the real world rather than because of any feature of the pollution data construction.

5.2 Second stage

Our results indicate that higher levels of pollution result in smaller year-to-year changes in GDP. We find, instrumenting for pollution levels with the number of inversions during the fiscal year, a $1\mu g/m^3$ year-to-year increase in $PM_{2.5}$ pollution reduces the year-to-year change in GDP by 0.7 percentage points (Table 3). In our sample the median year-to-year change in pollution is $0.8\mu g/m^3$ and the median year-to-year change in GDP is 6.4 percent.

Our results imply that in a year where pollution levels fell by $1\mu g/m^3$ relative to the prior year – a change opposite signed than the median change we observe in our data – year over year GDP change would be 7.1 percent rather than 6.4 percent. In standard deviation terms, a decrease in pollution levels of 1 standard deviation of the typical change would result in an increase in the year over year GDP change of 0.4 standard deviations.

A $1\mu g/m^3$ change in annual average $PM_{2.5}$ relative to the prior year may not seem large, especially relative to the size of our estimated GDP effects. That is a mis-perception. A $1\mu g/m^3$ change in the average annual level of pollution implies large changes in daily pollution levels. To see this consider the following example. Assume that a given Indian district experienced daily $PM_{2.5}$ levels exactly equal to the annual national average for each day in a year. In that case, a $1\mu g/m^3$ increase in the annual average in the next year would be equivalent to increasing the daily average by 30% for an entire month. That is, a $1\mu g/m^3$ increase in the annual average is the difference between a month with daily exposure of 54 $\mu g/m^3$ and one with daily exposure of 70 $\mu g/m^3$. Or consider the level of $PM_{2.5}$ measured at the U.S. Embassy in Delhi in 2015. The annual average daily level was $170\mu g/m^3$ for 2015 with the daily average during November and December, the two worst months of the year, at $287\mu g/m^3$. A $1\mu g/m^3$ reduction in the annual average level would have been akin to reducing the peak during November and December by $\approx 10\%$.

Our results indicate that higher levels of pollution have negative consequences for economic activity that are felt in the short-run, consistent with much of the existing micro-evidence on the consequences of exposure to air pollution. These negative micro consequences appear to accumulate in ways that reduce activity across the economy, resulting in less activity relative to a counter-factual in which pollution exposure was lower. This reduction in activity results in lower rates of year over year change in GDP.

5.3 Robustness

Our results are robust to a variety of sensible specification variations and alternative clustering. We show (Table 5) that omitting the measure of inversion strength does not substantially change our results - in fact it slightly increases our point estimates. Nor does using total inversions over the whole year rather than dividing them into seasons.

To account for potential spatial correlation in weather patterns or pollution we also cluster errors at the state, rather than district level. This substantially reduces the number of clusters, from 515 to 23. Unsurprisingly this reduces our precision but our estimates remain significant at the 5 percent level.

We also test alternative sets of weather controls (Appendix Figure A1). In general our results remain very stable across a wide variety of combinations of our base weather controls. These include specifications that omit all controls except for precipitation, omit all but controls for average temperature, and define temperature as the maximum rather than the average.

To test for robustness against weak instruments we estimate a LIML version of our IV approach (Appendix Table A2). LIML models have been shown to be more robust to weak instruments than 2SLS (Stock and Yogo, 2002). Our results do not change when estimated with the LIML, rather than 2SLS approach.

The reduction in GDP due to higher levels of pollution may be offset by increases in GDP in the following year if the impacts are due to temporary reductions, for example, in labor supply that are offset by subsequent increases in labor supply. To test for such a rebound we examine the impact of changes in pollution in a lagged framework (Table 4). Including one lag makes our point estimates of the contemporaneous impact slightly smaller. Two lags moves it close to zero, as does three. The sum of the lags is never significant but including up to two lags the point estimate on the sum of the lags remains close to our original point estimates. Adding a third lag substantially reduces the point estimate, suggesting a 1 $\mu g/m^3$ increase in pollution leads to a net 0.2 percentage point reduction in year-to-year GDP growth over three years, but it remains negative.

We also examine how the impacts of pollution vary by the size of the change in pollution levels from year-to-year and by baseline levels of pollution. In both cases we find no evidence for substantial differences across quartiles of the distribution. Over the empirical support in our data we cannot reject the null that the impact of changes of pollution is linear in the size of the change. However, we note that the empirical support in our data is small relative to the average annual *level* of pollution in India. The inter-quartile range in the year-to-year change is -1.01 to 2.76. Our results do not support the conclusion that the effect of reductions in pollution levels substantially outside of this range would continue to be linear. Further, we cannot reject the null that the impact of year-to-year changes in pollution on year-to-year GDP growth is invariant to baseline levels of pollution. However, we find weak evidence that the effect of pollution on changes is GDP is most pronounced at higher baseline levels of pollution. Both of these results are somewhat counter-intuitive and we note that a necessary feature of conducting this analysis with our data is a substantial reduction in sample size. We leave additional examination of these important questions to future work.

6 Discussion and conclusion

Our IV results indicate that higher levels of air pollution reduce year-to-year GDP growth. These results are consistent with estimates of the impact of air pollution on GDP growth from Europe and the United States as well as the well-identified micro-level estimates of the negative impacts of air pollution. Air pollution has a variety of negative impacts on workers and economic sectors that manifest at the macro level in the form of reductions in economic growth. The most obvious mechanisms through which air pollution affects year-to-year changes in GDP are that pollution reduces worker productivity on the job, increases worker absenteeism due to illness, and directly harms agricultural productivity. In the long run reductions in human capital formation and migration away from the most economically productive areas due to pollution exposure loom large (Wen and Burke, 2022).

Our effect is roughly the same size as that found in Dechezleprêtre et al. (2019). This is somewhat surprising given the dramatically higher levels of ambient pollution in India when compared to Europe. On average, in their sample, the population faces annual average exposure of $10\mu g/m^3$ compared to average exposures of $50\mu g/m^3$ in our sample. But our effects are roughly double those found in Avila Uribe (2023), more consistent with the hypothesis that higher levels of exposure may lead to more severe impacts.

The effects of these differences in ambient concentrations are likely exacerbated by differences in the sources of economic activity between India and Europe and the United States, and the implied differences in vulnerability to air pollution. Data from the Reserve Bank of India suggests that as much of 50 percent of India's GDP comes from sectors that are exposed to heat - a rough approximation for the share of GDP generated by outdoor work. This is compared to less than 25 percent of European GDP generated by the same sectors based on European Central Bank figures.

Indian workers work in an environment with substantially higher levels of ambient pollution than European workers and a substantially larger share of Indian GDP is generated by workers who are likely to be frequently working in conditions – outside – that expose them to ambient pollution. Both of these facts suggest that the impact of increases in pollution on GDP should be larger in India than Europe.

On the other hand, recent work examining the mortality impacts of very high levels of air pollution using exposure to wildfire smoke in the United States suggests a strongly concave dose-response function for air pollution exposure (Miller et al., 2017). While small changes in pollution have large mortality effects at low levels of pollution, similarly small changes at higher levels of pollution have much smaller effects. This is supported by work examining the consequences of exposure to pollution on outdoor workers around the world that finds a similarly concave dose-response function (Burnett et al., 2018). It remains an open question how this dose response function for mortality translates for other outcomes but our results are consistent with the pattern being similar for labor productivity effects, for example.

Our point estimates are small relative to the overall variation in economic growth from year-to-year and across districts in our sample. A $1\mu g/m^3$ year-to-year increase in $PM_{2.5}$ pollution, roughly 25 percent larger than the median change in our sample, reduces year-to-year GDP growth by 0.16 of a standard deviation. This effect is economically meaningful but small relative to secular changes in GDP growth.

We can further benchmark our results against estimates of the direct impacts of air pollution in India on the mortality and morbidity of Indian citizens. Pandey et al. (2021) employ the methodology from the Global Burden of Disease to estimate how exposure to air pollution impacts mortality and morbidity in India. They find that the monetized reductions in mortality and morbidity amount to a loss of 36.8 billion ($USD) annually based on exposure levels in 2019.[13] They also find large inter-state variation in economic loss as a proportion of the state GDP, ranging from 0.67 percent to 2.15 percent, with the highest losses observed in the low per-capita GDP states of Uttar Pradesh, Bihar, Rajasthan, Madhya Pradesh, and Chhattisgarh. Indian GDP grew 6.26 percent from 2.7 trillion ($USD) in 2018 to 2.9 trillion in 2019. The monetized value of the mortality and morbidity costs suffered in 2019 amounts to 21.3 percent of this year over year growth. In contrast, the year-to-year change in pollution from 2016 to 2017 reduced GDP in 2017 by approximately 13 billion $USD, or roughly a third of the monetized losses from mortality and morbidity.

It is tempting to use our results to estimate how substantial reductions in pollution levels in India would impact its growth rate. For example, how reducing the average level of $PM_{2.5}$ from $55\mu g/m^3$ to the European average of approximately $10\mu g/m^3$ would impact GDP changes. Using our results in this way would be inappropriate. The effects we estimate are not calculated in a way that enables this exercise for several reasons. First, our estimates are based on generally small year-to-year fluctuations in $PM_{2.5}$ levels. We do not observe changes in our data that are of comparable magnitude to halving pollution in India. Second, although our estimates appear to be linear in the range of data we observe there are likely to be substantial non-linearities in the relationship between GDP growth and changes in pollution levels as the changes in pollution increase in magnitude. This is what we observe in the relationship between pollution exposure and mortality (Burnett et al., 2018). Extrapolation of our linear estimates fails to account for these non-linearities. Third, reductions in pollution of that magnitude may be accompanied by substantial changes to the make-up of the Indian economy. Recent work suggests that India will be unable to halve current pollution levels on its own. Rather regional cooperation will be required to achieve such reductions.(The World Bank, 2022). It is unlikely that the relationship we document here will remain the same in an economy that undergoes such changes.

A more reasonable comparison is to ask what the level of Indian GDP would be today if the average year-to-year change in $PM_{2.5}$ pollution had been half what we observe in the data. We show the results of that exercise in Figure 5. We do the following. Starting with the observe level of pollution in 1998 we assume that instead of growing at the actual rate over the sample period, pollution grows at $0.4\mu g/m^3$ less each year. That represents roughly a 50% reduction in the average year-to-year change. As we show in Panel A of Figure 5, that results in pollution levels that are just over 10% lower at the end of the period relative

[13]This study use a broader definition of air pollution including ambient particulate matter pollution, household air pollution, and ozone concentration. However, the number of deaths attributable to ambient particulate matter constitute the majority (59 percent), followed by household air pollution (37 percent) and ozone concentration (4 percent).

to what was actually observed. We then calculate, based on our estimated coefficients and this lower assumed rate of change in year-to-year $PM_{2.5}$ what the additional growth would have been in each year over the sample period. As we show in Panel B of Figure 5 these small changes accumulate over time, such that by the end of the sample period we estimate that Indian GDP would have been 4.51% higher by the end of the period if pollution had grown 50% more slowly in each year.

Our results provide evidence that the well-documented micro-level impacts of air pollution on health, productivity, labor supply, and other economically relevant outcomes aggregate to macro level effects that can be observed in year-to-year changes in GDP. These results are consistent with the fact that similar micro-effects of heat have been well-documented to generate aggregate level effects. They are also consistent with the evidence of the impacts of air pollution on GDP changes in Europe. While our results cannot be used to provide precise estimates of the benefits of large reductions in pollution in India they provide strong evidence that reducing pollution levels, all else equal, can have positive impacts on GDP.

7 Tables and Figures

7.1 Tables

Table 1: Summary statistics

	Mean	SD	Min	Max
Annual averages of pollution & growth				
Annual average PM_2.5	51.39	25.68	8.62	128.94
Annual GDP growth (%)	6.95	7.90	-16.34	36.46
Annual averages of weather measures				
Annual temperature	25.37	2.87	-6.45	29.83
Annual precipitation	1,325.93	781.49	65.31	5,711.34
Annual dew point	17.76	3.17	-11.21	24.32
Annual relative humidity	67.20	8.59	41.52	86.68
Inversions				
Share of days with a low inv	0.17	0.14	0.00	0.58
Share of days with any inv	0.17	0.14	0.00	0.58
Share with winter inversion	0.26	0.25	0.00	0.95
Share with summer inversion	0.07	0.08	0.00	0.43

Notes: All statistics are reported for the districts in our sample. All variables are population weighted averages calculated at the district level. Low inversions are days with an inversion only in the first two layers of the atmosphere. Any inversion is a day with an inversion in any layer below 5km above the surface.

Table 2: First stage

	Mean $PM_{2.5}$	Mean $PM_{2.5}$	Mean $PM_{2.5}$
Winter inversion, low	2.3865***	2.4005***	
	(0.4930)	(0.4931)	
Summer inversion, low	-1.2599		-1.5167
	(1.4048)		(1.4015)
N	8,823	8,823	8,823
Relative Effects:			
100% winter days as inversion→X% $\Delta PM_{2.5}$	5.16	5.13	
F-test of inversions:	12.47	23.70	1.17
Weather controls:			
Temperature	Y	Y	Y
Precipitation	Y	Y	Y
Relative humidity	Y	Y	Y
Surface pressure	Y	Y	Y
Wind speed	Y	Y	Y
Wind direction	Y	Y	Y
Fixed effects:			
Fiscal year	Y	Y	Y

Notes: The outcome is the first difference within a district of the annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversions are calculated comparing surface temperature to temperature in the two levels immediately above the surface. If either of these levels has a higher temperature than the surface we define it as an inversion. Winter refers to inversions between October and March. Summer refers to inversions between April and September. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four bins of wind speed, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. (* p<.10 ** p<.05 *** p<.01).

Table 3: IV results

	Inversions in first two layers
Mean $PM_{2.5}$	-0.0075**
	(0.0033)
N	6,142
Relative Effects:	
$1SD\uparrow PM_{2.5} \rightarrow$ "X" $SD\Delta GDP$ change	-0.41
Kleibergen-Paap rk Wald F statistic:	5.92
Weather controls:	
Temperature	Y
Precipitation	Y
Relative humidity	Y
Surface pressure	Y
Wind speed	Y
Wind direction	Y
Fixed effects:	
Fiscal year	Y

Notes: The outcome is the first difference within a district of the log of annual GDP measured at the district level. We instrument for annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population with inversions and inversion strength. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversion strength is the average difference in temperature when there is an inversion. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four wind speed bins, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. We winsorize GDP growth at 1%. (* p<.10 ** p<.05 *** p<.01).

Table 4: Lagged IV results

	No lags	1 lag	2 lags	3 lags
Mean $PM_{2.5}$	-0.0075**	-0.0066*	0.0022	0.0009
	(0.0033)	(0.0036)	(0.0029)	(0.0032)
N	6,142	5,628	5,114	4,596
Sum of lags		-0.008	0.009	-0.002
		(0.006)	(0.009)	(0.010)
Weather controls:				
Temperature	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Relative humidity	Y	Y	Y	Y
Surface pressure	Y	Y	Y	Y
Wind speed	Y	Y	Y	Y
Wind direction	Y	Y	Y	Y
Fixed effects:				
Fiscal year	Y	Y	Y	Y

Notes: The outcome is the first difference within a district of the log of annual GDP measured at the district level. We instrument for annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population with inversions and inversion strength. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversion strength is the average difference in temperature when there is an inversion. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four wind speed bins, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. We winsorize GDP growth at 1%. (* p<.10 ** p<.05 *** p<.01).

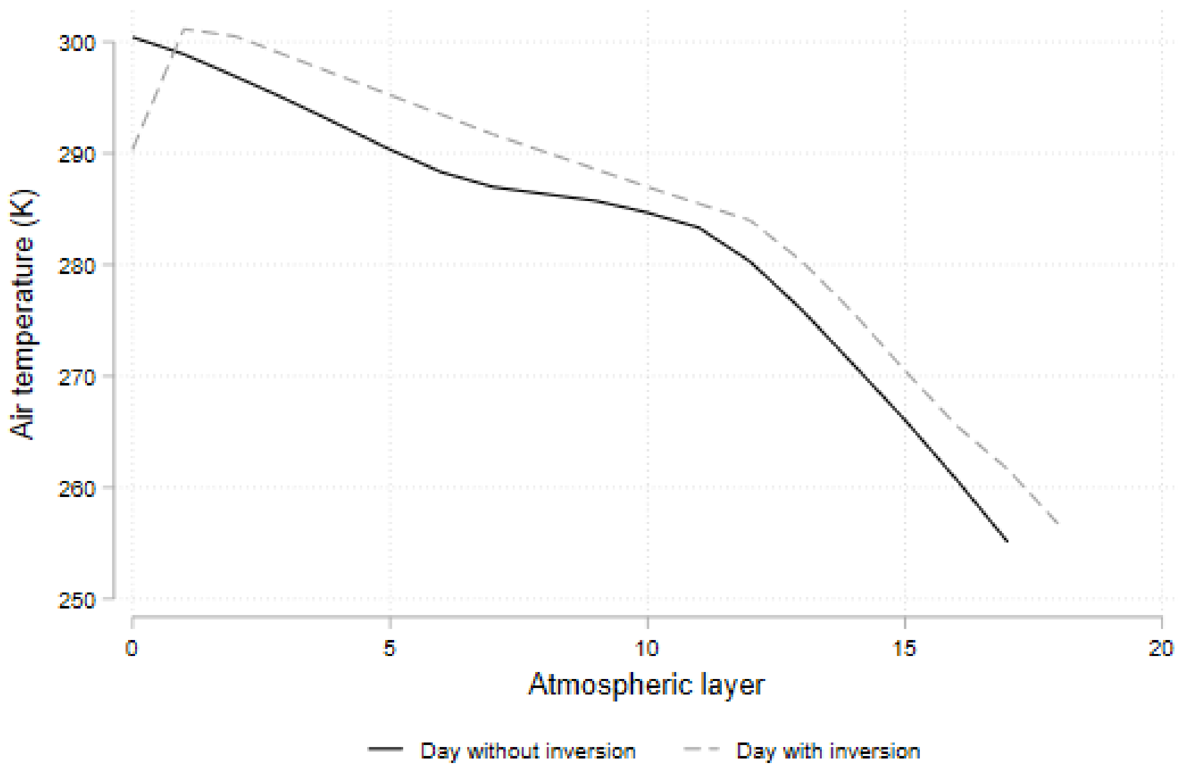
Table 5: IV results, robustness checks

	Omitting strength	Non-seasonal inversion	State clustering	Without winsored
Mean $PM_{2.5}$	-0.0090*	-0.0094	-0.0075**	-0.0085**
	(0.0050)	(0.0062)	(0.0032)	(0.0037)
N	6,142	5,575	6,142	6,069
Weather controls:				
Temperature	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Relative humidity	Y	Y	Y	Y
Surface pressure	Y	Y	Y	Y
Wind speed	Y	Y	Y	Y
Wind direction	Y	Y	Y	Y
Fixed effects:				
Fiscal year	Y	Y	Y	Y

Notes: The outcome is the first difference within a district of the log of annual GDP measured at the district level. We instrument for annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population with inversions and inversion strength. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversion strength is the average difference in temperature when there is an inversion. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four wind speed bins, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. We winsorize GDP growth at 1%. (* p<.10 ** p<.05 *** p<.01).

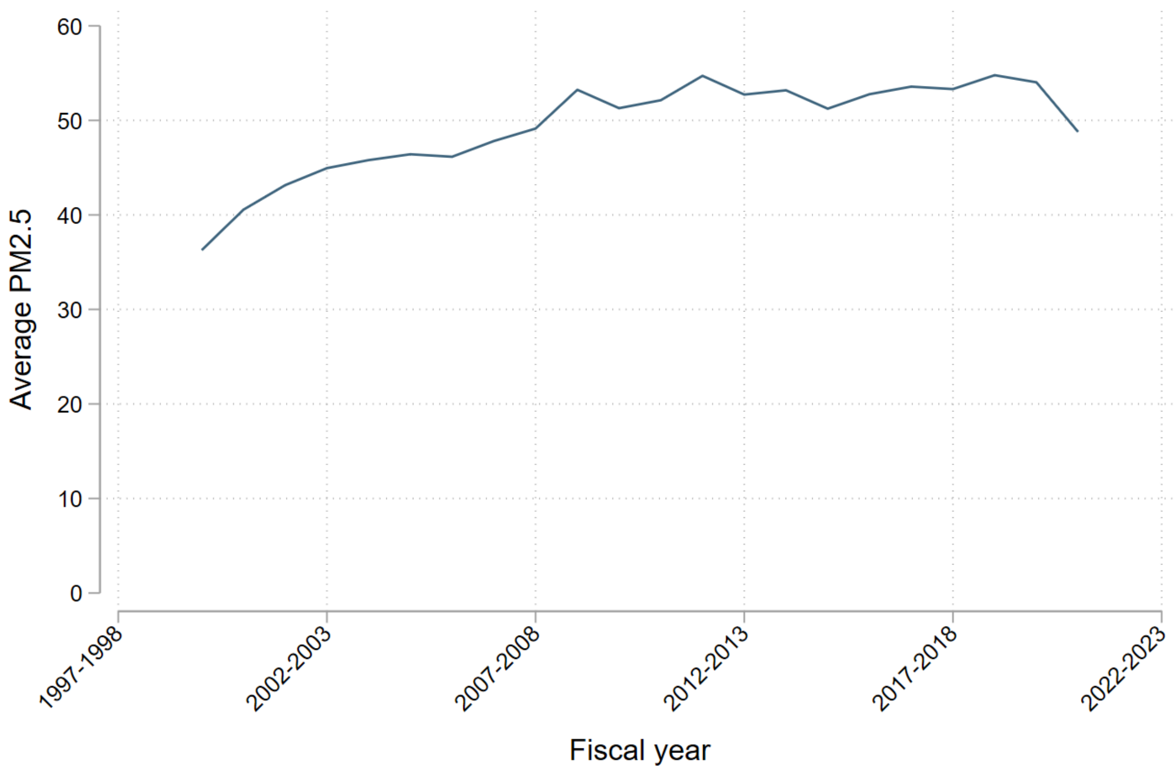
7.2 Figures

Figure 1: Example of an inversion



Notes: Inversions occur when temperature at an atmospheric level above the surface has a higher temperature than the surface. This traps air at the surface and generally raises pollution. These are the temperature profiles on two days in Mumbai in November 2005. In the dark line we show the temperature profile at atmospheric levels moving up from the surface on a day without an inversion (surface=level 0). Temperature declines monotonically as the atmospheric level increases. In the grey line we show the same profile on a day with an inversion. The clear spike in temperature at the level just above the surface is the signature of an inversion.

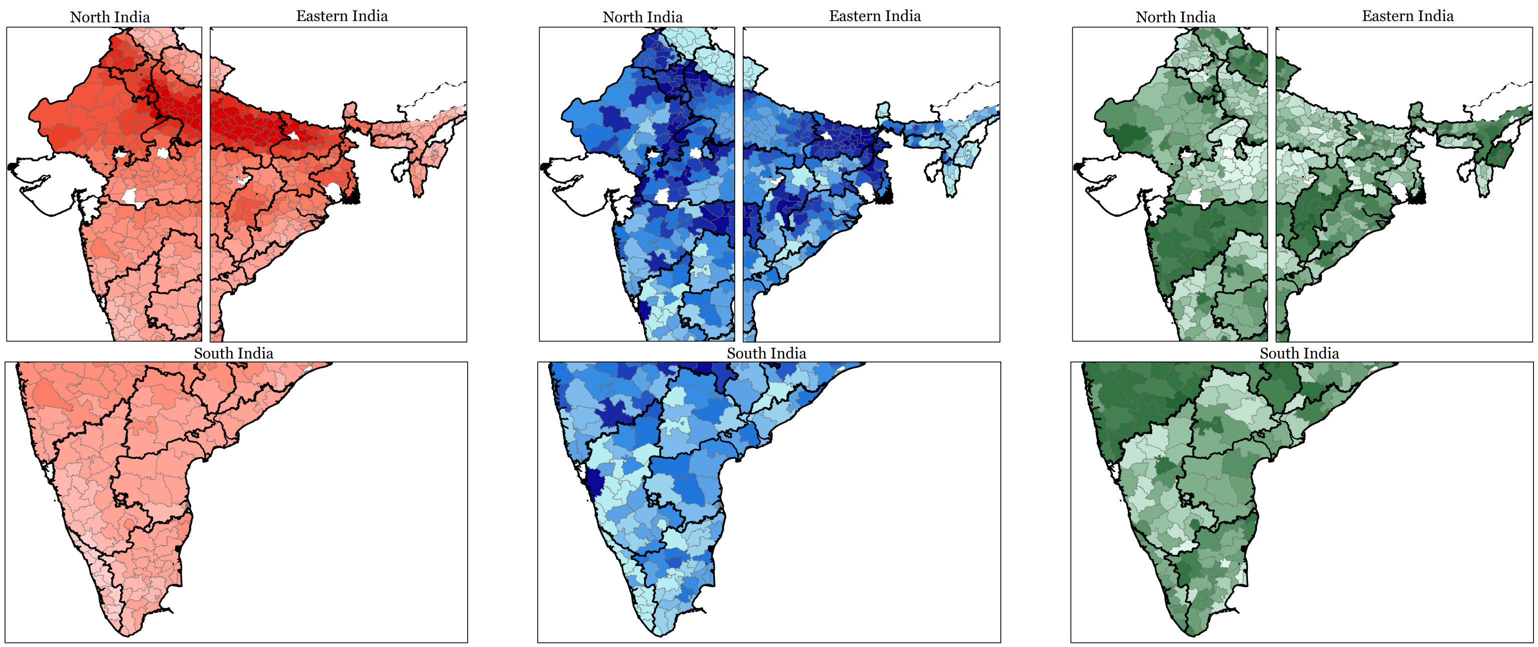
FIGURE 2: National average $PM_{2.5}$ level over time



NOTES: Weighted average $PM_{2.5}$ ($\mu g/m^3$) with averages calculated across districts in each fiscal year. District level averages are calculated by averaging across grid-points within the district and weighting each grid-point by the population of the surrounding area.

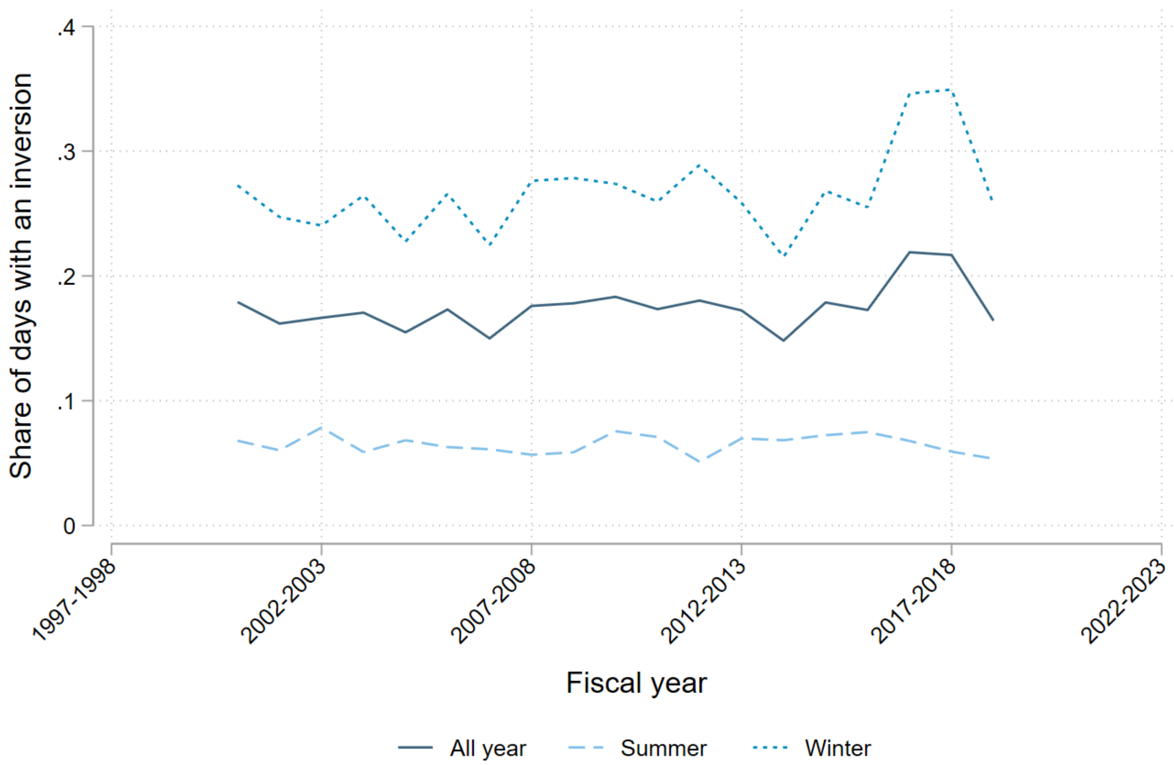
Figure 3: Geographic distribution of key variables

(a) Pollution (b) Inversions (c) GDP growth



Notes: Panel A shows the average by district of the annual level of $PM_{2.5}$ pollution ($\mu g/m^3$ by district across all years in our sample (2000-2018). Panel B shows the average share of days (0-100 percent) in a year that each district experiences an inversion over the same time period. Panel C shows annual GDP growth rates (0-100 percent). Blank districts are those for which we do not have GDP growth data. In all figures darker hues indicate higher values.

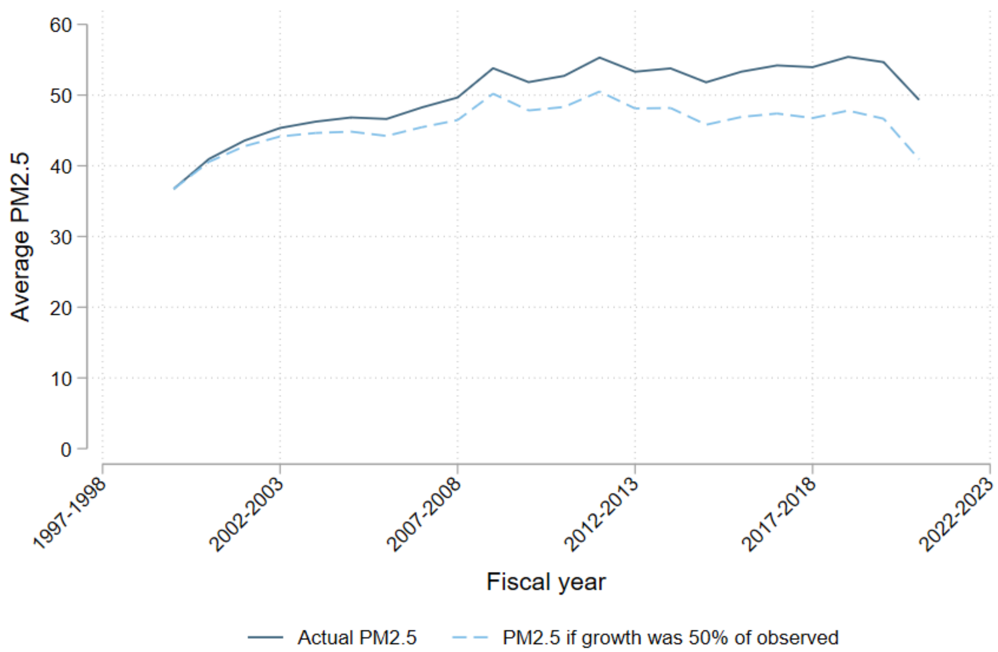
Figure 4: Share of inversions over time



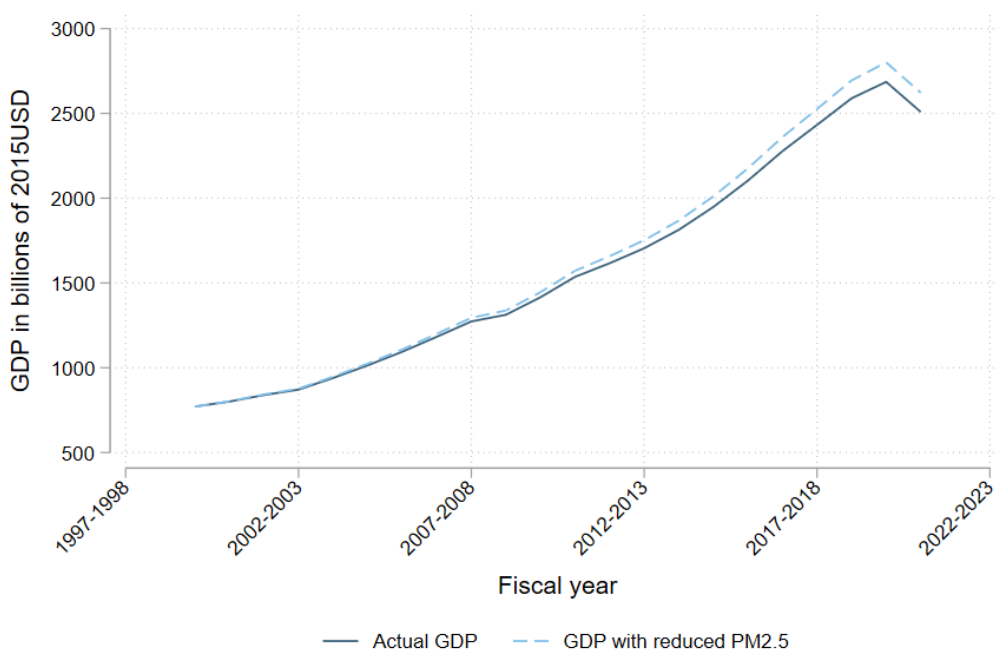
Notes: Inversions vary from year-to-year with more inversions occurring in the winter than in the summer because of differences in the angle of the sun. We show the average share of days with an inversion in each year of our sample here averaging across all the districts that are in our regression sample (i.e. those for which we have GDP data).

Figure 5: Projected pollution and GDP assuming lower pollution growth

(a) Pollution growth



(b) GDP growth



Notes: Panel A shows the observed (solid line) growth in $PM_{2.5}$ over our sample period and the projected level (dashed line) assuming that the year-to-year change was half of what we observe in the data. Panel B shows the actual growth of Indian GDP (solid line) and the projected growth if $PM_{2.5}$ changes had been lower (dashed line).

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Appendix 1 Additional Tables

Table A1: First stage, all levels

	Mean $PM_{2.5}$	Mean $PM_{2.5}$	Mean $PM_{2.5}$
Winter inversion, any	2.2200***	2.2313***	
	(0.5449)	(0.5454)	
Summer inversion, any	-1.1345		-1.2749
	(1.1784)		(1.1773)
N	8,823	8,823	8,823
Relative Effects:			
100% winter days as inversion→X% $\Delta PM_{2.5}$	5.54	5.52	
F-test of inversions:	9.05	16.74	1.17
Weather controls:			
Temperature	Y	Y	Y
Precipitation	Y	Y	Y
Relative humidity	Y	Y	Y
Surface pressure	Y	Y	Y
Wind speed	Y	Y	Y
Wind direction	Y	Y	Y
Fixed effects:			
Fiscal year	Y	Y	Y

Notes: The outcome is the first difference within a district of the annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversions are calculated comparing surface temperature to temperature in all levels below 5 km above the surface. If any level above the surface has a higher temperature than the surface we define it as an inversion. Winter refers to inversions between October and March. Summer refers to inversions between April and September. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four bins of wind speed, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. (* p<.10 ** p<.05 *** p<.01).

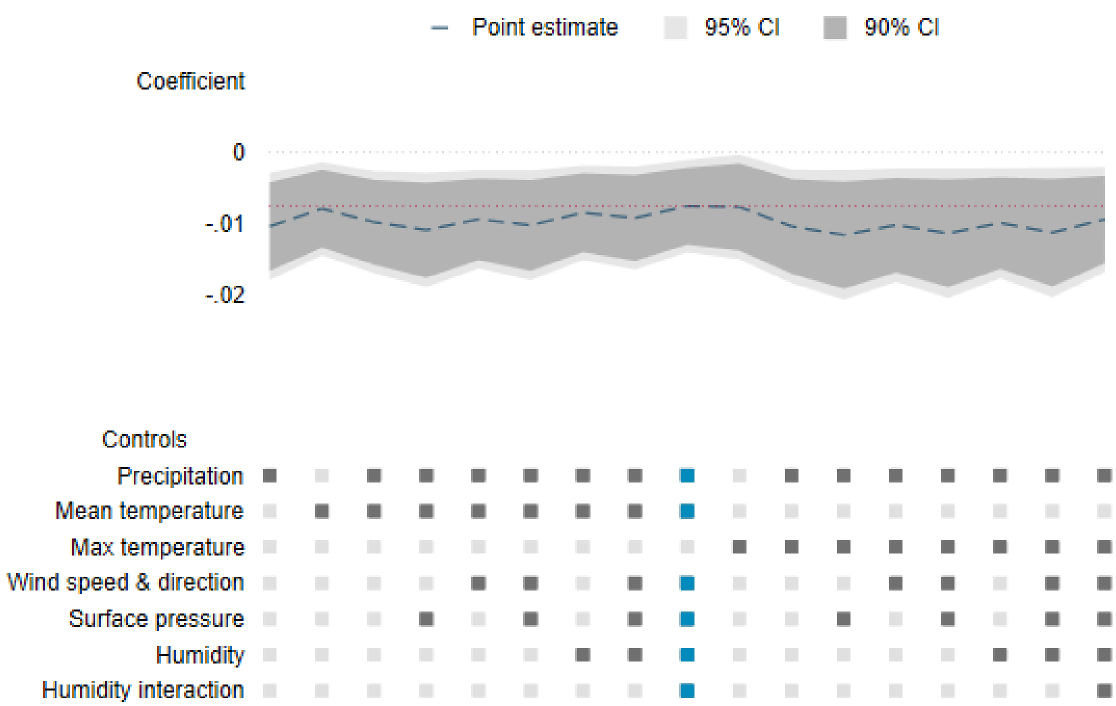
Table A2: LIML results

	Inversions in first two layers	Inversions in any layer
Mean $PM_{2.5}$	-0.0076**	-0.0084**
	(0.0033)	(0.0041)
N	6,142	6,142
First stage F-stat:	6.07e+06	4.66e+06
Weather controls:		
Temperature	Y	Y
Precipitation	Y	Y
Relative humidity	Y	Y
Surface pressure	Y	Y
Wind speed	Y	Y
Wind direction	Y	Y
Fixed effects:		
Fiscal year	Y	Y

Notes: The outcome is the first difference within a district of the log of annual GDP measured at the district level. We instrument for annual average of $PM_{2.5}$ measured at the district level during a fiscal year from April to March and weighted by population with inversions and inversion strength. Pollution data comes from the Van Donkelaar group. Inversion data comes from the MERRA re-analysis data and measures the incidents when temperature at atmospheric levels above the surface is higher than at the surface by district for each fiscal year. Inversions are measured as the share of days with an inversion. Inversion strength is the average difference in temperature when there is an inversion. All inversion data and weather controls are population weighted averages across districts. The unit of observation is the district year. In all columns we control for the first difference of the number of days in one of fifteen precipitation bins, the number of days the mean temperature is in one of twenty-five bins, a second order polynomial of relative humidity and surface pressure, four wind speed bins, ten wind direction bins, and interactions of relative humidity and the square of relative humidity with all of our temperature bins. All columns include fiscal year fixed effects. In all columns we cluster standard errors at the district level. We winsorize GDP growth at 1%. (* p<.10 ** p<.05 *** p<.01).

Appendix 2 Additional Figures

FIGURE A1: Alternative meteorological controls



NOTES: We plot the point estimates of the impact of year-to-year changes in annual average $PM_{2.5}$ on year-to-year changes in GDP growth rates from our primary IV specification with the dashed blue line. We vary how we control for surface level meteorological conditions as indicated by the squares on the bottom of the figure. Dark squares indicate a variable has been included in the regression. Blue squares indicate our primary specification. The dashed red line on the figure is the point estimate from our primary specification. 90 percent and 95 percent confidence intervals are shaded on the figure. Humidity interaction indicates that we interact our humidity measures with all temperature bins.