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Abstract

In the first chapter, we examine the impact of temperature on manufacturing production in India and the underlying mechanisms. Using plant-level manufacturing data and satellite-based temperature estimates from 1998-2007, we find that the relationship between temperature and output exhibits an inverted U-shape, with especially large losses occurring at extreme cold and hot temperatures. Such nonlinearity provides valuable insight into the potential welfare consequences of climate change. Back-of-the-envelope calculations suggest that a 1°C shift in the annual distribution of daily temperature would lead to net losses in manufacturing output of 1.3% or USD 0.6 billion, equivalent to a 0.5% reduction in India's GDP 2007 through the manufacturing sector alone. The estimated temperature-output relationship is driven by the joint effects of temperature on total factor productivity and capital. This finding has important implications for adaptation. The manufacturing sector can adapt to changing climate by reducing the sensitivity of labor productivity to temperature and by making investments in machinery. Labor-related adjustments can also contribute to adaptation by offsetting direct productivity losses or facilitating labor reallocation. Guided by these strategies, India's manufacturing can achieve climate change policy goals without compromising its growth and development perspectives.

In the second chapter, I reexamine empirical evidence on the effectiveness of environmental regulations in India from a study by Greenstone and Hanna (GH, 2014). GH report that the city-level air pollution control policies in India were effective in improving air quality but had a modest and statistically insignificant effect on infant mortality. These somewhat counterintuitive findings are likely to stem from the limited availability of ground-based air pollution data used in GH and the absence of critical meteorological confounders. I leverage recent advances in satellite technology and GH's methodology to test the sensitivity of their findings to revised air pollution outcomes, an extended number of observations, and meteorological controls. Despite striking differences between the two datasets, reexamination using satellite-based data broadly confirms the conclusions drawn from GH's data. The effects of the policies are, however, substantially weaker. The study urges further research on the

effectiveness of environmental regulations in developing countries and the use of satellite-based estimates in the examination of this important question.

In the third chapter, I estimate the impact of the sharp reduction in particulate air pollution driven by the Global Financial Crisis of 2008 on district-level infant mortality in India. Utilizing plausibly exogenous geographic variation in the crisis-induced changes in air quality and novel data from household surveys and satellite-based sources, I find that the infant mortality rate fell by 24% more in the most affected districts, implying 1338 fewer infant deaths than would have occurred in the absence of the crisis. Analysis of the mechanisms indicates that air pollution reductions affected infant mortality mainly through respiratory diseases and two biological mechanisms: in-utero and post-birth exposure. Heterogeneity analysis further emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution and justifies the need for interventions targeting low-income households. Calculations suggest that the estimated decline in infant mortality translates into a three-year after crisis total of USD 312.5 million. The resulting health benefits could be used as a benchmark for assessing the effectiveness of the policies designed to improve air quality in India.

Abstrakt

V první kapitole zkoumáme dopad teploty na výrobní produkci v Indii a související mechanismy. Využitím výrobních dat na úrovni závodu a satelitních odhadů teplot z let 1998-2007 jsme zjistili, že vztah mezi teplotou a výrobou vykazuje tvar obráceného U, přičemž zvláště velké ztráty nastávají při extrémně nízkých a vysokých teplotách. Taková nelinearita poskytuje cenný pohled na potenciální důsledky změny klimatu na blahobyt. Výpočty naznačují, že posun o 1 °C v roční distribuci denní teploty by vedl k čistým ztrátám ve výrobě ve výši 1,3 % nebo 0,6 miliardy USD, což odpovídá 0,5% snížení HDP Indie v roce 2007 pouze prostřednictvím výrobním sektoru. Odhadovaný vztah mezi teplotou a výrobou je řízen společnými účinky teploty na celkovou produktivitu faktorů a kapitál. Toto zjištění má důležité důsledky pro adaptaci. Výrobní sektor se může přizpůsobit měnícímu klimatu snížením citlivosti produktivity práce na teplotu a investicemi do strojního zařízení. Úpravy související s pracovních sil mohou také přispět k přizpůsobení tím, že vyrovnají přímé ztráty produktivity nebo usnadní přerozdělení pracovních sil. Na základě těchto strategií může Indická výroba dosáhnout cílů politiky v oblasti změny klimatu, aniž by ohrozila její růst a perspektivy rozvoje.

Ve druhé kapitole znovu zkoumám empirické důkazy o účinnosti environmentálních předpisů v Indii ze studie Greenstone a Hanna (GH, 2014). GH uvádí, že politiky omezování znečištění ovzduší na úrovni města v Indii byly účinné při zlepšování kvality ovzduší, ale měly mírný a statisticky nevýznamný dopad na kojeneckou úmrtnost. Tato poněkud kontraintuitivní zjištění pravděpodobně pramení z omezené dostupnosti údajů o znečištění ovzduší z pozemních zdrojů používaných v GH a z absence kritických meteorologických kontrolních proměnných. Využívám nedávné pokroky v satelitní technologii a metodologii GH k testování citlivosti jejich zjištění na revidovaná měření znečištění ovzduší, rozšířený počet pozorování a zahrnutí meteorologických kontrolních proměnných. Navzdory výrazným rozdílům mezi těmito dvěma datovými soubory, opětovné přezkoumání pomocí satelitních dat široce potvrzuje závěry vyvozené z dat GH. Účinky politik jsou však podstatně slabší. Studie nabádá k dalšímu výzkumu účinnosti ekologických předpisů v rozvojových zemích a využití satelitních dat při zkoumání této důležité otázky.

Ve třetí kapitole odhaduji dopad prudkého snížení znečištění ovzduší způsobeného globální finanční krizí v roce 2008 na kojeneckou úmrtnost na úrovni okresu v Indii. Využitím věrohodně exogenních geografických variací ve změnách kvality ovzduší způsobených krizí a nových údajů z průzkumů domácností a satelitních zdrojů jsem zjistil, že kojenecká úmrtnost klesla o 24 % více v nejvíce postižených okresech, což znamená o 1338 méně úmrtí kojenců než by nastaly, kdyby stalo bez krize. Analýza mechanismů ukazuje, že snížení znečištění ovzduší ovlivnilo kojeneckou úmrtnost především prostřednictvím respiračních onemocnění a dvou biologických mechanismů: vystavení znečištěnému ovzduší zatímco v děloze a po porodu. Analýza heterogenity dále zdůrazňuje roli výchovy rodičů při zmírňování nepříznivých důsledků vystavení kojenců znečištěnému ovzduší a odůvodňuje potřebu intervencí zaměřených na domácnosti s nízkými příjmy. Výpočty naznačují, že odhadovaný pokles kojenecké úmrtnosti se promítne do celkové výše 312,5 milionu USD za tři roky po krizi. Výsledné zdravotní přínosy by mohly být použity jako měřítko pro hodnocení účinnosti politik určených ke zlepšení kvality ovzduší v Indii.

Introduction

This thesis consists of three chapters that examine the effects of climate change, environmental externalities, and regulations on health, wellbeing, and economic development in India. Specifically, I create unique datasets by combining large administrative datasets with satellite-derived estimates and spatial information to study the impact of temperature on output, productivity and factor inputs of manufacturing plants, reexamine the effectiveness of environmental regulations, and quantify the effects of air pollution on infant mortality. My studies include a policy-relevant component so that my research outcomes could inform policymakers aimed at finding cost-efficient solutions for the most pressing global challenges.

In the first chapter, Tong Liu and I study the impact of temperature on manufacturing production in India and the underlying mechanisms. This is critical for designing effective climate change adaptation strategies, especially for developing countries with a sizable population exposed to extreme temperatures and limited capacity for adaptation.

Exploiting plausibly exogenous variation in a plant's exposure to temperature, we arrived at two main findings. First, the relationship between temperature and manufacturing output is non-linear and exhibits an inverted U-shape. The output losses are especially large at extreme temperatures. Detected nonlinearity provides valuable insight into the potential welfare consequences of climate change. There is a possibility that, due to replacing cold days with hot, the reduced negative impact of climate change due to fewer cold days can offset, at least partially, the increased negative impact due to more hot days. However, this is not the case for India. Our calculations suggest that a 1°C rise in temperature would lead to net losses in manufacturing output of 1.3% or USD 0.6 billion, equivalent to a 0.5% reduction in India's 2007 GDP through the manufacturing sector alone.

Second, the estimated temperature-output relationship is driven by the joint effects of temperature on total factor productivity (TFP) and capital. Heterogeneity analyses further reveal that temperature affects TFP through its impact on labor productivity and that machinery is the most suitable for the adaptation category of capital. We also find suggestive evidence of labor reallocation between seasonal manufacturing industries and between economic sectors. These findings have important implications for adaptation. The manufacturing sector in India can adapt to changing climate by reducing the sensitivity of labor productivity to temperature and by investing in capital, prioritizing investments in machinery. Labor-related adjustments can also contribute to adaptation by either offsetting direct productivity losses or facilitating reallocation.

In the second chapter, I reexamine empirical evidence on the effectiveness of environmental regulations in India from a study by Greenstone and Hanna (GH, 2014). GH report that air pollution control policies in India were effective in improving air quality but had a modest and statistically insignificant effect on infant mortality. A likely explanation for GH's findings might stem from the scarcity of reliable air pollution measures and the effects of unaccounted confounding factors. I show that GH's dataset, which was constructed using readings from a spatially sparse network of public air pollution monitors, suffers from high interannual variability in sample size, inaccurate measures of air pollution, and the absence of critical meteorological confounders. Ignoring these limitations could potentially lead to misleading conclusions about the effectiveness of air pollution mitigation efforts. Coupled with the prominence of GH's study, this conclusion motivates a reexamination of GH's findings using alternative data sources.

Using satellite-based estimates for air quality and meteorological conditions, I test the sensitivity of GH's findings to revised air pollution outcomes, an extended number of observations, and meteorological controls. Three findings emerge. First, air pollution outcomes constructed using GH's and satellite-based data demonstrate opposite trends. While concentrations of air pollutants were falling in GH, concentrations of the revised air pollution outcomes are continuously increasing. Second, GH's findings are highly sensitive to the revised air pollution outcomes and the extended number of observations. There is little empirical support in satellite-derived data for the effectiveness of the air pollution control policy found in GH to be strongly associated with air quality improvements. Third, meteorological controls matter. Additionally controlling for meteorological confounders revealed similar effects of policies on air pollution to those reported in GH. Likewise, the estimated impact on infant mortality confirms that regulation-induced improvements in air quality do not necessarily result in improved health. However, the qualitative patterns estimated using GH's and satellite-derived data differ substantially. Further, the effects of policies estimated using satellite-derived data are not robust across various data-sample combinations and specifications. Based on the complementary empirical evidence, it seems reasonable to broadly confirm GH's findings and interpret air pollution control policies in India as effective, although with substantially weaker effects on air pollution.

In the third chapter, I examine the effects of ambient air pollution on infant mortality in India to address a broader policy question of whether and to what extent improvements in air quality in developing countries lead to improvements in health outcomes and associated health benefits. I take advantage of the economic slowdown in India caused by the Global Financial Crisis of 2008 and exploit the episode of synchronous decline in industrial production, reduction in air pollution, and improvement in infant mortality. Economic slowdown affected Indian districts differentially, based on their pre-crisis industrial structure and industry-specific pollution intensities. Evidence suggests that Indian districts with larger shares of the manufacturing, mining, construction, or energy sectors experienced a more substantial decline in air pollution than districts without these pollution-intensive sectors.

Utilizing plausibly exogenous geographic variation in the crisis-induced changes in air quality and data from household surveys and satellite-based sources, I find that the crisis-induced reductions in PM2.5 pollution led to a statistically significant decline in district-level infant mortality rates. Regression coefficients indicate that the infant mortality rate in the treated districts fell by about 24% more than in the control districts between pre- and post-crisis periods. The estimates are robust to a variety of specifications and falsification tests. Studying transmission channels through which reductions in air pollution affect infants' health, I examine the impact of the changes in PM2.5 concentrations on the mortality of infants at different ages and from various diseases. My findings suggest that the PM2.5 reductions affected infant mortality mainly through respiratory diseases and two biological mechanisms: in-utero and post-birth PM2.5 exposure. Heterogeneity analysis further emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution and justifies the need for interventions targeting low-income households. Finally, I use the quantified relationship to measure health benefits and monetary gains from the crisis-induced episode of PM2.5 pollution reduction. My calculations suggest that 1338 infant lives were saved, implying a contribution of 11% to the overall decline in infant mortality during the post-crisis period and leading to monetary benefits of USD 312.5 million. The resulting health benefits could be used as a benchmark for assessing the effectiveness of policies designed to improve air quality in India.

1 Temperature and Manufacturing Production in India: Plant-Level Evidence for Adaptation Strategies (co-authored with Tong Liu)

1.1 Introduction

Climate change is projected to increase the average annual temperature and alter the number of days with extreme temperatures worldwide (Climate Impact Lab, 2019; U.S. EPA, n.d.b), thus affecting nature and humans in many aspects, including health, productivity, and behavior.[1] There is also growing evidence that the average annual temperature can significantly affect economic activity. Several macro-level studies document the negative and nonlinear impact of temperature on aggregate economic output, with the temperature effects varying widely across geographical regions and extending to both agricultural and non-agricultural sectors (Hsiang, 2010; Dell, Jones, and Olken, 2012; Burke, Hsian, and Miguel, 2015; Carleton and Hsiang, 2016; Berg, Curtis, and Mark, 2021). Thus, understanding the impact of the climate-induced temperature changes on economic activity and the underlying mechanisms is critical for the design of effective climate change adaptation strategies, but relevant evidence remains scarce (Burke et al., 2015; Heal and Park, 2015; Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021).

This study examines the effects of temperature on manufacturing production in India, one of the largest developing countries with a sizable population exposed to extreme temperatures and limited capacity to adapt to a changing climate (Somanathan et al., 2021). We combine detailed plant-level data from the formal manufacturing sector for 1998-2007 with high-resolution satellite-based estimates for meteorological conditions and air pollution and aggregate them to the district-year level. Exploiting plausibly exogenous variation in a plant's exposure to temperature, we document a significant inverted-U relationship between temperature and manufacturing output, with especially large output losses at extreme high and low temperatures. Specifically, an

[1] For evidence on heat-related diseases and mortality, see Curriero et al. (2002), Sachs and Malaney (2002), Deschênes and Moretti (2009), Gasparrini et al. (2015); for evidence on productivity, see Graff Zivin and Neidell (2014), Zhang et al. (2018), Adhvaryu et al. (2020), Somanathan et al. (2021); for evidence on behaviors, see Field (1992), Miguel, Satyanath, and Sergenti (2004), Jacob, Lefgren, and Moretti (2007).

additional extremely hot day with a temperature above 33°C decreases output by 0.12% or USD 3,749 relative to a day in the optimal temperature interval. The comparable estimate for an additional extremely cold day with a temperature below 8°C is a decrease of 0.27% and USD 8,435, respectively. The output loss is most prominent during India's hottest pre-monsoon season, with a 1°C increase in the seasonal average temperature reducing manufacturing output by 2.2%, which is consistent with most literature.

To pin down the mechanisms, we decompose the estimated temperature-output relationship into the temperature effects on the components of the production function: total factor productivity (TFP), labor and capital factor inputs. We find that the temperature impact is mainly driven by the joint effects of temperature on TFP and capital, contributing roughly 30% and 70%, respectively. The response of TFP to temperature closely follows the response of output, while the response of capital mirrors the response of output only to higher temperatures. Relative to the optimal temperature interval, an additional day above 33°C decreases TFP and capital by 0.04% and 0.08%, respectively. Heterogeneity analyses further reveal that TFP losses are associated with a reduction in labor productivity rather than capital productivity, consistent with workers' exposure to thermal stress suggested in the literature (Hsiang, 2010; Somanathan et al., 2021). We also find suggestive evidence that temperature changes induce seasonal fluctuations in employment, both between seasonal manufacturing industries and between economic sectors. For capital, our analyses show that machinery is most suitable for the climate change adaptation category of fixed assets. Additionally, the lagged temperatures significantly impact the current-year machinery stock, implying that the previous-year extreme temperatures lead to faster destruction, carrying over the necessity of increasing machinery stock into the current year.

This study makes several contributions. First, it is among the first to document nonlinearity in the temperature-output relationship with the adverse effects of both extreme high and low temperatures. This finding complements the existing economic literature, which has to date focused mainly on the negative impact of heat (e.g., Somanathan et al. 2021). It also provides valuable insight into the potential welfare consequences of climate change. Generally, climate change is expected to shift the daily temperature distribution to the right, replacing cold days with hot. Thus, it may be possible that the reduced negative impact due to fewer cold days will offset, at least partially, the increased negative impact due to more hot days. However, back-of-the-envelope calculations suggest that a 1°C shift in the annual distribution of daily temperature would lead to net losses in manufacturing output of 1.3% or USD 0.6 billion, equivalent to a 0.5% reduction in India's 2007 GDP through the manufacturing sector alone.

Second, this study provides novel insights into the mechanisms behind the temperature effects on manufacturing output and its determinants. Despite the growing macro-level evidence of the negative impact of temperature on aggregate economic output, much less is known about the country-specific micro-level mechanisms behind the temperature-output relationship and their potential role in climate adaptation. As the manufacturing sector accounts for a larger share of national GDP in many countries, we establish and quantify the role of the sector in the transmission of the negative temperature shocks to India's economy, complementing a recent study by Somanathan et al. (2021). Our study is also among the first to quantify the relative importance of TFP, labor, and capital in the temperature-output relationship and to highlight the possibilities for climate change adaptation strategies at the level of the manufacturing sector.

Third, we provide useful insights into climate change policies in India and other countries exposed to extreme temperatures with limited capacity for adaptation, mitigation, and resilience. As the TFP response to temperature follows the output response closely, productivity-related adjustment can be a universal adaptation strategy, with a focus on reducing the responsiveness of labor productivity to high temperatures. Other labor-related adjustments can include reallocation between seasonal manufacturing industries or between economic sectors. In addition, at extreme high temperatures, India's manufacturing sector should prioritize capital-related adjustments, such as investments in machinery, when possible because of the larger contribution of the temperature-capital effects to the overall temperature-driven output losses. In all cases, the manufacturing sector should consider the seasonal responses of the specific adjustments and the timing of the expected effects to ensure effectiveness.

Lastly, the optimal temperature interval uncovered in our study, from 18°C to 23°C, can also play an important role in designing optimal adaptation strategies (Hallegatte, 2009; Dell, Jones, and Olken, 2014; Chen and Yang, 2019). The identified optimal interval is consistent with the interval reported in similar studies that examine the temperature-output relationship for designing climate change adaptation policies in developing countries (Chen and Yang, 2019), but it is higher than the interval documented in studies focusing on developed countries (Deryugina and Hsiang, 2014). This finding may imply that developed and developing countries have different optimal temperature zones, likely due to adaptation to baseline temperatures. Thus, the transferability of the estimated temperature effects from developed to developing countries may be unjustified for designing climate change adaptation policies. Comparing our findings with evidence from other large emitters such as China (Zhang et al. 2018; Chen and Yang, 2019) would provide a better ground for developing climate change mitigation and adaptation strategies with potentially global impact.

The rest of this chapter is organized as follows. Section 2 introduces the manufacturing sector in India and the related literature. Section 3 presents a simple framework and explains our empirical strategy. Section 4 describes the data sources and provides summary statistics. Section 5 reports our results. Section 6 discusses the implications for the plant-level climate change adaptation strategies and concludes.

1.2 Background

1.2.1 Climate and Manufacturing in India

India provides an appealing setting to study climate impacts and policies for several reasons. First, the country is projected to experience substantial climate change-induced changes in the current weather patterns by the end of the century, especially in temperature. The average annual temperature will increase by 4°C, from about 24°C to 28°C (Climate Impact Lab, 2019), which is much higher than the 0.6°C rise in the previous century (Rajeevan and Nayak, 2017). In a similar vein, the number of extremely hot days is expected to increase substantially. On average, India will likely experience eight times more days per year with a temperature higher than 35°C (Climate Impact Lab, 2019). India has also witnessed more extremely cold days in recent years. The incidence of cold wave days increased by 506% between 2010 and 2018, peaking with a record of 276 days in 2017, the highest since 1980 (Pandey, 2019; Sengupta, 2020). The number of such days is expected to increase, especially in Northern India, where 50% of such days occur (Ratnam et al., 2016; Mahapatra et al., 2018). While people in India may have adapted to the relatively hot days because they are already used to higher temperatures, cold days can cause significant losses. Changing temperature patterns may place substantial pressure on India's economy, including increasing damage experienced by the manufacturing sector, particularly if the adoption of industrial air-conditioning systems remains very limited (Somanathan et al., 2021). Such temperature effects have not been thoroughly examined by policies or the literature, specifically for cold temperatures (Sengupta, 2020).

Second, despite its vulnerability to climate change, India is one of the world's largest emitters of greenhouse gases. India's emissions grew at an annual average rate of 5-6% between 1990 and 2019, leading to an increase in its share of total global emissions from 2% to 7%, almost equivalent to that of all of Europe (Cail and Criqui, 2021; Convery and Sterner, 2021). Importantly, the manufacturing sector is the largest consumer of India's commercial energy and the leading source of emissions after the energy sector, contributing a quarter of overall emissions (Cail and Criqui, 2021; Choragudi, 2021). This suggests a potentially central role of the sector in mitigation and adaptation to rising temperature under climate change.

Nevertheless, the role of the sector in India's climate policy remains underrepresented. Policies have been focused on sectors with direct and immediate effects, such as electricity generation, coal, transport, electric vehicles, and appliances. By contrast, policies for most manufacturing industries have been considered challenging, accompanied by uncertain agendas and time specificity of goals (Biswas et al., 2019; Choragudi, 2021; Chakravarty, 2021). One reason is the lack of knowledge about the sector's potential for mitigation and adaptation, which stems from its complexity and the inherent industry-specific heterogeneity in responses to temperature fluctuations. Exploiting the empirical relevance of adjustments in productivity and factor inputs in mitigating temperature-driven output losses would allow India to achieve its climate change policy goals without compromising growth and development perspectives.

Lastly, the rich history of India's industrial data collection combined with advances in satellite technology provides a rare opportunity to overcome critical data limitations in a key developing country by exploiting the best available micro-level panel data.

1.2.2 Related Literature

An extensive literature has documented a nonlinear negative relationship between temperature and aggregate economic outcomes, such as national or regional output, in different parts of the world using macro-level data (e.g., Hsiang, 2010; Dell et al., 2012; Burke et al., 2015). On average, a 1°C increase in average annual temperature decreases national output by 1-3%. The studies also attempt to uncover the potential mechanism by documenting the association of higher temperatures with a reduction in both agricultural and non-agricultural output. As the associations are highly heterogeneous across countries and it is difficult to separate various factors such as diverse climates, institutions and incomes, more disaggregated analyses of the mechanisms are called for.

Another growing literature investigates the temperature-output mechanisms using micro-level data and focusing on human capital and agricultural production. Because of the direct dependence of the agricultural sector on atmospheric conditions, many papers examine the effects of temperature on agricultural output (Mendelsohn, Dinar, and Sanghi, 2001; Schlenker et al., 2005, 2006; Schlenker and Roberts, 2009). These studies generally show that high temperatures are associated with severe damage to specific crop yields. A large body of health economics studies demonstrates that the increase in the number of heat-related diseases and mortality rates could be another link between lower economic output and temperature (Curriero et al., 2002; Sachs and Malaney, 2002; Deschênes and Moretti, 2009; Gasparrini et al., 2015). Other papers suggest that crime and social unrest occur more frequently during the hot years and indirectly cause the decline in economic output (Field, 1992; Miguel, Satyanath, and Sergenti, 2004; Jacob, Lefgren, and Moretti, 2007). However, neither of these channels can fully explain the negative temperature effects on aggregate economic output.

Although the industrial sector accounts for a larger share of national GDP than the agricultural sector[2], only a few studies examine the impact of temperature on the industrial sector and underlying mechanisms. Zhang et al. (2018) and Chen and Yang (2019) estimate the impact of temperature on the output of manufacturing firms in China and detect an inverted U-shaped relationship, while Somanathan et al. (2021) find a negative relationship between hot days and manufacturing output of Indian factories. Zhang et al. (2018) is the first paper that disentangles the effect of temperature on output by assessing temperature-driven effects separately on TFP and factor inputs of manufacturing firms. The paper concludes that the TFP channel is the primary driver behind the temperature-output relationship. With regard to TFP, the literature focuses

[2] For example, the shares of agriculture in the GDP of the U.S., China, and India are 1%, 10% and 16%, respectively, while the industrial sector contributes 12%, 32% and 30% of each country's GDP (U.S. BEA, 2013; NBS, 2014; MOSPI, 2019).

mainly on the temperature effects on labor productivity (Adhvaryu et al., 2020; Somanathan et al., 2021). The effects on capital productivity remain understudied despite evidence from engineering studies that temperature could also affect capital productivity (Zhang et al., 2018). Concerning the factor inputs, Graff Zivin and Neidell (2014) and Somanathan et al. (2021) show that heat stress can reduce labor supply in the U.S. and India. Capital can also be negatively affected by temperature, especially temperature extremes, exposure to which can lead, for example, to machinery wearing and tearing at a faster rate. However, the temperature effects on capital are not well documented.

Our study is most closely related to Zhang et al. (2018) and Chen and Yang (2019). We build on these studies when we design our empirical strategy.[3] Our estimates of the temperature effects on output and productivity of manufacturing plants partially overlap with those from Somanathan et al. (2021). While Somanathan et al. (2021) use the same plant-level data, our studies differ in a number of key aspects. First, whereas we comprehensively analyze the temperature effects on output, TFP and factor inputs, Somanathan et al. (2021) specifically focus on productivity and labor supply. Second, we examine temperature effects along the whole range of the temperature distribution, while Somanathan et al. (2021) focus on the effects of high temperatures. Third, our weather data are from satellite-based reanalysis data with high resolution, which can reduce the measurement errors in the station-based interpolated data used in Somanathan et al. (2021). We also measure our key variables differently: value-added output vs. total output, average temperature vs. maximum temperature, fixed assets vs. value of equipment and machinery, respectively in our study and in Somanathan et al. (2021). Our studies are also based on different sample periods. Finally, we use different specifications of the transformed Cobb-Douglas production function, in which we strictly follow the approach from Zhang et al. (2018). Our specifications allow us to focus specifically on the effects of extreme temperatures and isolate the mechanisms underlying the temperature-output relationship in a manner comparable with the evidence of Zhang et al. (2018) on China. Our specifications also differ by the number of bins, selection of the optimal temperature interval, sets of control variables and their functional forms, and sets of fixed effects. Despite these differences, the estimated magnitudes of the effects on output induced by the high temperatures within comparable temperature intervals are similar in

[3] Chen and Yang (2019) apply the same combination of approaches to examine whether the temperature affects industrial output but does not attempt to disentangle the temperature-driven impact between the components of a production function. In contrast, Zhang et al. (2018) take over this examination using just a binned-variable approach.

our studies.[4] However, Somanathan et al. (2021) conclude that the temperature-induced output losses are driven by the decline in labor productivity rather than by temperature effects on factor inputs. Given that we document similar output responses, the discrepancy between our results and Somanathan et al. (2021) may be due to the difference in the specifications of the production function used in the analysis of the mechanisms.

1.3 Empirical Strategy

Our purpose is to examine the effects of temperature on the output of manufacturing plants and to understand the mechanism underlying the temperature-output relationship. This section exploits a simple framework to demonstrate the channels through which temperature can affect output. We then explain our empirical strategy guided by this framework.

We consider a standard Cobb-Douglas production function as a natural starting point to lay out our empirical strategy:

$$Q=(A_L L)^{(\sigma_L)}(A_K K)^{(\sigma_K)} \tag{1}$$

where Q, L, K are manufacturing output, labor, and capital, respectively; A_L, A_K are labor and capital productivity; σ_L, σ_K are output elasticities for labor and capital. Rewriting Eq. (1) in log-linearized form brings us to Eq. (2):

$$\ln Q=\ln TFP+\sigma_L \ln L+\sigma_K \ln K \tag{2}$$

where $\ln TFP=\sigma_L \ln A_L+\sigma_K \ln A_K$ is the log total factor productivity (TFP) defined as the weighted average of labor and capital productivity with the elasticities of each input as weights.

Eq. (2) demonstrates that the impact of temperature on output can be decomposed into the temperature-induced effects on TFP and factor inputs: labor and capital. Establishing and

[4] For example, the coefficient estimate of -0.0012 for the bin with temperatures above 33°C in our study is comparable with the coefficient estimates -0.0016 and -0.019 for the temperatures within (30°C, 35°C) and (35°C, 45°C) intervals in Somanathan et al. (2021).

quantifying these channels has considerable importance for policymaking. If the estimated temperature-TFP relationship is close to the estimated temperature-output relationship in magnitude and shape, the temperature-output impact is primarily driven by the temperature effect on TFP. In such a case, adjustments in factor inputs play a minor role in offsetting negative temperature effects on manufacturing output, and policies should focus on lowering the sensitivity of productivity to temperature. In the opposite case, if the estimated temperature-inputs relationship closely follows the estimated temperature-output relationship, factor reallocation may play an important role in offsetting negative temperature impact on manufacturing output, and policies should focus on reducing the costs of factor adjustment. Overall, Eq. (2) shows that reducing the sensitivity of productivity to temperature and lowering the cost of factor adjustments are two important margins for the adaptation of the manufacturing sector to the warming climate.

To estimate the temperature-driven effects on manufacturing output and each component of the production function in Eq. (2), we employ the following regression:

$$Y_{idt} = \sum_m \alpha_0^m Temp_{dt}^m + \beta_0 W_{dt} + \delta_0 PM_{dt} + \gamma \Psi_t^j + \psi_i + \varepsilon_{idt} \tag{3}$$

where i indexes micro-level manufacturing unit (a plant or factory), d indexes district, t indexes year, and j indexes industries. Y_{idt} is the outcome that takes the form of $\ln Q_{idt}, \ln TFP_{idt}, \ln L_{idt}, \ln K_{idt}$. A micro-level manufacturing output (Q_{idt}) is measured by value-added output. Total factor productivity (TFP_{idt}) is estimated using the Olley-Pakes (1996) approach.[5] Labor (L_{idt}) is measured by total employment, and capital (K_{idt}) is measured by fixed capital stock.

Because previous studies have documented the nonlinear relationship between temperature and various economic outcomes, we model temperature, $Temp_{dt}^m$, using a standard non-parametric binned approach (Deschênes and Greenstone, 2011; Deryugina and Hsiang, 2014; Burgess et al., 2017; Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021; Colmer, 2021). It

[5] The Olley-Pakes (1996) estimator addresses simultaneity bias by using investment to proxy for unobserved productivity shocks, and addresses selection bias by using firms' survival probabilities. This estimator is one of the most widely used in the literature. The method is implemented using the Stata command by Yasar, Raciborski, and Poi (2008).

transforms the annual distribution of daily temperatures into a set of temperature bins and allows flexible estimation of nonlinear temperature effects across daily temperature values. The binned-variable approach preserves the daily variation in temperature and also allows to estimate the effects of daily temperatures on annual outcomes (Hsiang, 2010; Burgess et al., 2017; Zhang et al., 2018).[6]

$Temp_{dt}^{m}$ denotes the number of days in year t with daily average temperatures in district d that fall into the mth temperature bin, m =1,2,…,7. We divide daily average temperatures, measured in °C, into seven bins, each of which is 5°C wide. For example, $Temp_{dt}^{1}$ is the number of days in district d during year t with daily temperature below 8°C. Then, $Temp_{dt}^{7}$ is the number of days with temperature above 33°C. To avoid collinearity, the temperature bin (18°C, 23°C) is set as an omitted, reference category. We select this bin to correspond to the optimal temperature interval[7], the one outside of which the temperature becomes harmful for output. The coefficient of interest, a semi-elasticity α_0^m, can be interpreted as the marginal effect on output of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin.

The binned-variable approach makes three assumptions about the estimation of the daily temperature effects on the outcomes (Burgess et al., 2017; Colmer, 2021). First, the effects are determined by the daily average temperature alone since the approach does not count for the intra-day temperature variations. Second, the effects of the daily average temperature are constant within specific temperature bins. Third, the sequence of days with relatively higher and lower temperatures is irrelevant for the length of exposure of the annual outcomes to hot and cold days since the approach uses the total number of days in each bin in each year as a regressor.

To isolate the role of temperature, we include a rich set of control variables. W_{dt} is a vector of the district-level weather controls, including precipitation, humidity, atmospheric pressure, and wind speed. We use annual averages of weather controls, except for precipitation constructed as annual sums. As air pollution is correlated with weather (Zhang et al., 2018; Li et al., 2019; He at al., 2019) and affects productivity (Graff Zivin and Neidell, 2012; Lichter, Pestel, and Sommer,

[6] It is an important advantage of the binned-variable approach because our plant-level data are available annually.

[7] Following Chen and Yang (2019), we iteratively estimate Eq. (3) with the log of value added as the outcome, setting each temperature bin in turn as a reference category. Non-positive coefficients on other temperature bins when the particular bin is omitted identify the reference category and the critical temperature threshold. Temperature bin (18°C, 23°C) is the only temperature interval that satisfies this condition.

2017), we also control for the annual average air pollution at the district level. PM_{dt} refers to particulate matter less than 2.5 micrometers in diameter (PM2.5), which is often considered a general air pollution indicator (Greenstone and Hanna, 2014). Weather and pollution are modeled quadratically to account for the potential nonlinear relationship.

We further incorporate plant fixed effects ψ_i to control for any unobserved plant-specific time-invariant characteristics. We also use year-by-two-digit-industry fixed effects Ψ_t^j to control for any unobserved factors common to all plants in a given year but different across industries, such as industry-specific policy, technological, and input-output price changes. Standard errors are clustered at both plant and district-year levels to allow for serial correlation within plants and spatial correlation across plants within a particular district and year.

The binned-variable approach does not examine the dynamics of the temperature effects and potential adjustments of production below the year level. The effects and adjustments may vary by season. For example, labor may relocate from hot to cooler seasons to reduce the temperature effects on production. India is very diverse geographically and climatically, with a designation of four seasons (Dey et al., 2020; Bali, Dey, and Ganguly, 2021). The winter season lasts from December through February, the summer or pre-monsoon season includes March, April, and May, the monsoon season begins in June and ends in September, and the post-monsoon season lasts from October through November. Exploring the seasonal variations could offer additional insights into the mechanisms and adaptation policy, while still allowing to detect the presence of nonlinearity. As such, we complement the binned-variable approach with a seasonal-variable approach following Chen and Yang (2019):

$$Y_{idt} = \alpha_0 Temp_{dt}^s + \beta_0 W_{dt}^s + \delta_0 PM_{dt} + \gamma \Psi_t^j + \psi_i + \varepsilon_{idt} \qquad (4)$$

We construct seasonal temperature variable $Temp_{dt}^s$ with superscript s indicating seasons as the temperature averages for each season: $Temp_{dt}^{Winter}$, $Temp_{dt}^{Pre-monsoon}$, $Temp_{dt}^{Monsoon}$, and $Temp_{dt}^{Post-monsoon}$. We also incorporate seasonal averages of humidity, atmospheric pressure, wind speed, and a seasonal sums of precipitation. These weather controls are denoted by W_{dt}^s in Eq. (4). Outcomes Y_{idt}, pollution control PM_{dt}, plant fixed effects ψ_i, year-by-two-digit-industry fixed effects Ψ_t^j, and error terms ε_{idt} are defined and modeled the same way as in Eq. (3). Given the semi-log form of Eq. (4), the coefficients of interest α_0 can be interpreted as the percentage changes in the outcomes caused by an increase in average temperature in a particular season by 1 °C.

Finally, we modify Eq. (3) and Eq. (4) to examine whether the fluctuations in temperature in prior years affect current-year manufacturing output. To date, there is considerable disagreement among economists about the lagged temperature effects. For example, Dell et al. (2012) and Chen and Yang (2019) show that the current year's output can be substantially affected by temperature changes in prior years, while Hsiang (2010), Deryugina and Hsiang (2014) and Zhang et al. (2018) find limited effects of lagged temperatures. To further explore this relationship in the context of India, we estimate Eq. (3) and Eq. (4) with current and lagged values of temperature modeled as bins and seasons.

Our empirical strategy assumes conditional exogeneity. The location of plants in districts across India is exogenous to the temperatures in the districts where they are located. We provide supportive evidence for this assumption in the data section. The temperature effects on output and its determinants are identified using plausibly exogenous variations in the plants' exposure to temperature purged of potential correlation with air pollution and other weather variables. This approach is consistent with those used in previous studies (Deschênes and Greenstone, 2011; Deryugina and Hsiang, 2014; Zhang et al., 2018; Chen and Yang, 2019).

1.4 Data

Our dataset combines a plant-level panel of detailed production data from the formal manufacturing sector in India over 1998-2007 with high-resolution satellite-based estimates for meteorological conditions and air pollution, aggregated to the district-year level. This section describes data sources, cleaning procedures, and reports summary statistics.

1.4.1 Manufacturing Data

We collect detailed micro-level production data from the Annual Survey of Industries (ASI) conducted by the National Statistical Organisation of India.[8] The ASI covers a representative sample of the industrial establishments (called a factory in the case of manufacturing industries) registered under the Factories Act of 1948.[9] Specifically, a factory must register if it employs more than 10 workers and uses electricity, or it employs more than 20 workers and does not use electricity. This means that the ASI surveys only the organized (formal) industrial sector, which, however, produces over 80% of India's manufacturing output (Ghani et al., 2012).[10]

We obtain ASI data for the period covering 1998 through 2007.[11] We restrict our study period to the years 1998-2007 since 2008/09 was the last survey year with available district codes, which are essential for merging production, weather, and pollution datasets.[12] In addition, the Global Financial Crisis of 2008 severely hit India's economy and could potentially disrupt the temperature-output relationship during the post-crisis years (Chatterjee and Subramanian, 2020). Our study period is also the same as those in the related studies on China, allowing for same-period comparison.

We process raw data using the following procedure. First, we create a plant-level panel dataset that allows us to track the same plant over the years. The ASI data are available in two versions: cross-sectional and panel. Cross-sectional ASI data do not provide plant identifiers but determine a particular plant's location at the district level. In contrast, the panel version includes plant identifiers but does not provide district codes. Following Martin et al. (2017), we merge two

[8] National Statistical Organisation (NSO) is a Statistics Wing of the Ministry of Statistics and Programme Implementation (MOSPI, n.d.). NSO consists of the Central Statistical Organisation (CSO) and the National Sample Survey Organisation (NSSO), responsible for ASI compiling. The NSSO's Field Operation Division is responsible for data collection, while CSO's Industrial Statistics Wing conducts data processing and analysis. As a primary investigator, CSO develops ASI design. The ASI is a principal source of industrial statistics in India, which is comparable to manufacturing surveys in the U.S., China, and other countries.

[9] We use the terms "plant" and "factory" interchangeably throughout the study.

[10] In contrast, the unorganized industrial sector accounts for a dominant share of plants and employment (Ghani et al., 2012).

[11] The ASI reports data based on the accounting year, which runs from April 1 to March 31. We refer to the initial year of the accounting period as our year of observations; for example, the year we call 1998 corresponds to the 1998/99 accounting year.

[12] This change in data dissemination procedure was made to hide the identity of a specific plant in accordance with the Collection of Statistics Act, which prohibits disclosure of information related to individual plants.

ASI versions using year-to-year opening and closing stock values of several merging variables.[13] Unique identifiers obtained using this matching algorithm enable us to link plants over time at the district level. High year-to-year rates of matches (around 99%) indicate that the ASI data quality is consistent over time.

Second, we clean our dataset of misclassified observations following standard practices established in prior studies that used ASI data (Allcott et al., 2016; Ghani et al., 2016; Martin et al., 2017). Specifically, we drop closed and non-responsive plants, plants with missing identifiers, and plants-duplicates. We then drop observations with missing or negative values of our key variables – value-added output, total employment, and fixed capital stock.[14] We also drop observations that violate basic accounting principles. To deal with outliers, we restrict our sample to those observations for which our key variables have values within their 0.5 to 99.5 annual percentile range. Additionally, we drop observations if value-added output is larger than the 99th percentile. Finally, we exclude plants with employment of less than 5 because the data on these small units are noisy, or they have unreliable accounting (Sivadasan, 2009). However, we retain plants that have less than 10 employees. Nataraj (2011) argues that even though such plants are not required to register, they can temporally reduce employment or register in advance, expecting growth in the future. Overall, we removed approximately 40% of the initial ASI sample. Most of the deleted observations were attributed to closed plants or had missing values of our key variables.

Third, we reclassify National Industrial Classification (NIC) codes to make them consistent over time. The classification, which has been in operation since 1998, underwent revision in 2004. We convert post-2004 codes to the NIC-1998 scheme using concordances provided by MOSPI, Census of India, and other publicly available sources. Additionally, based on this new classification, we restrict our analysis to plants classified as manufacturing and drop 4,243 observations reporting non-manufacturing NIC codes.

Finally, we deflate monetary values of the resulting variables to constant 2007 Indian rupees (INR) following Martin et al. (2017) and convert them to 2007 international U.S. dollars

[13] These variables include stock of raw materials, fuels, and stores; stock of semi-finished goods; stock of finished goods; inventory; loans; and fixed capital.

[14] Value-added output is computed as the difference between total output and intermediate inputs. Employment is measured by the total number of employees. Fixed capital stock is measured by the total value of fixed assets, which is the depreciated value of land, buildings, plant and machinery, transport equipment, computer equipment, and other fixed assets owned by plants on the closing day of the accounting year.

(USD) at purchasing power parity (PPP) following Ghani et al. (2016). Revenue (gross sales), total output, and value-added output are deflated using commodity-level wholesale price indexes. Wages and material inputs are deflated using the relevant consumer price index. Capital stock values are deflated using the wholesale price index for machinery and equipment. Finally, we use WDI PPP conversion factor to convert monetary values in 2007 INR to monetary values in 2007 USD. In 2007, the PPP conversion factor was 11.763 INR per international USD.

1.4.2 Measuring Plant-Level TFP

To estimate the plant-level TFP, we apply an approach originally suggested by Olley and Pakes (1996). To illustrate this approach, we rewrite the log-linearized production function in Eq. (2) for plant i in district d and year t:

$$\ln Q_{idt} = \sigma_L \ln L_{idt} + \sigma_K \ln K_{idt} + \mu_{idt} \qquad (5)$$

where log output ($\ln Q_{idt}$), log employment ($\ln L_{idt}$), and log fixed capital stock ($\ln K_{idt}$) are constructed using the ASI dataset. TFP is represented by a residual μ_{idt} (Syverson, 2011). Then, the estimated log TFP ($\hat{\mu}_{idt}$) is the difference between observed output and output predicted by the OLS-estimated production function (Yasar et al., 2008):

$$\hat{\mu}_{idt} = \ln Q_{idt} - \hat{\sigma}_L \ln L_{idt} + \hat{\sigma}_K \ln K_{idt} \qquad (6)$$

where $\hat{\sigma}_L, \hat{\sigma}_K$ are estimated output elasticities of labor and capital. However, such OLS estimates may be biased because of simultaneity and sample selection. Simultaneity bias becomes an issue when a firm observes productivity and endogenously chooses inputs. In this case, correlations between L_{idt}, K_{idt} and μ_{idt} give rise to bias. The problem of sample selection arises when lower productivity firms exit, while firms with higher productivity remain in the sample.

Olley and Pakes (1996) propose an estimator that addresses simultaneity bias by using investment to proxy for unobserved productivity shocks and addresses selection bias by using firms' survival probabilities. This estimator is one of the most widely used in the literature (Zhang et al., 2018). To implement the Olley-Pakes approach, we use a Stata command introduced by Yasar et al. (2008).

1.4.3 Weather Data

Our identification strategy requires a rich set of daily weather data with good geographic coverage and a minimum number of missing observations. As the in-situ monitor readings of temperature and other weather variables that satisfy these conditions are not readily available in India (Burgess et al., 2017), we take advantage of publicly accessible reanalysis data products obtained from NASA's MERRA-2.[15,16] MERRA-2 data are the result of atmospheric reanalysis that combines satellite-based measurements, ground-based monitor readings, and other data sources with sophisticated chemical-transport and climate modeling to create global gridded estimates for various atmospheric and aerosol variables with global coverage starting from 1980. MERRA-2 temperature and precipitation data have been successfully validated against the observation-based Indian Meteorological Department data, indicating that MERRA-2 products are reliable substitutes to the observed weather indicators (Ghodichore et al., 2018; Gupta et al., 2020).

We retrieve MERRA-2 estimates for surface temperature, precipitation, humidity, atmospheric pressure, U (east-west) and V (north-south) wind components at 0.5° x 0.625° spatial resolution (50 x 62 km at the equator). We then use wind components to calculate wind speed as suggested by NASA's MERRA-2 technical note (Ostrenga, 2019). Our analysis uses daily averages of temperature, annual sum values of precipitation calculated from daily average estimates, and annual mean values of other weather variables constructed by averaging daily average values. As averaging of wind speed requires a special approach, we strictly follow the steps described in NASA's MERRA-2 technical note (NASA, n.d).

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[15] Gelaro et al. (2017, p. 5419) define reanalysis as "the process whereby an unchanging data assimilation system is used to provide a consistent reprocessing of meteorological observations, typically spanning an extended segment of the historical data record. The process relies on an underlying forecast model to combine disparate observations in a physically consistent manner, enabling the production of gridded datasets for a broad range of variables, including ones that are sparsely or not directly observed".

[16] NASA's MERRA-2 stands for NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2. For more detailed information about MERRA-2, see Gelaro et al. (2017).

1.4.4 Air Pollution Data

To construct our air pollution control variable, we leverage recent advances in satellite technology. Specifically, satellite-based Aerosol Optical Depth (AOD) retrievals make it possible to estimate surface PM2.5 concentrations at granular spatial resolution and with comprehensive geographical and temporal coverage. AOD measures the amount of sunlight absorbed, reflected, and scattered by the particles suspended in the air. AOD-based estimates are shown to be a good proxy for PM2.5 pollution over India (Dey et al., 2012).

We obtain satellite-based estimates of PM2.5 concentrations from the Atmospheric Composition Analysis Group (ACAG) at Dalhousie University, which provides global coverage starting from 1998. This source of air pollution data has been increasingly popular among social scientists (Fowlie, Rubin, and Walker, 2019). The data represent global gridded datasets of annual mean values at 0.01° x 0.01° spatial resolution (1 x 1 km at the equator) estimated by combining AOD retrievals from multiple satellite sources (MODIS, MISR, SeaWIFS) with simulations in a chemical transport model, subsequently calibrated against ground-based monitor readings using geographically weighted regressions (Hammer et al., 2020).

1.4.5 Matching Plant and Weather Data

As the final step, we merge the plant-level ASI data with the grid-level weather and pollution data by year and district, assigning weather and pollution information in a district to all plants operating in that district.[17] Indian districts are periodically reorganized, usually by splitting districts over time. Between 1998 and 2007, the number of the ASI districts increased from 503 to 589[18], leading to inconsistency in plant and district identifiers that we obtained by matching cross-sectional and panel ASI datasets. To account for the districts' changing boundaries and to preserve consistency in plant and district identifiers over time, we construct a concordance table allowing us to match every district in each year to its parent district in 1998. We then use this concordance table to construct a GIS map of consistent district boundaries that we further use to match gridded

[17] A district in India is an administrative unit within a state roughly equivalent to a U.S. county and is the smallest geographical unit available for our analysis.

[18] These numbers exclude districts from Arunachal Pradesh, Lakshadweep, Mizoram, and Sikkim. The ASI does not report information on the plants in these states.

data to the district level. By construction, we obtain a map of 503 consistent districts over the sample period as defined by their 1998 boundaries.

Using the concordance table, the aggregation of the ASI data to the level of the administrative districts as of 1998 is straightforward. To create district-level weather and pollution datasets from the grid, we overlap each gridded weather and pollution dataset with our map of consistent districts and calculate the average across all grid points within each district. We then merge the resulting datasets by year and district.

1.4.6 Summary Statistics

Table 1 reports summary statistics for our merged dataset. We have an unbalanced panel of 113,305 unique plants for 1998-2007, with 263,717 plant-by-year observations across 473 districts and 26 two-digit industries. Fig. 1 disentangles the last two columns of Table 1 by showing percentage distributions of observations (left panel) and the number of plants (right panel) for each of 26 two-digit industries in the sample. Manufacture of foods, non-metallic minerals, textiles, machinery and equipment, and chemicals are the five largest industries in the sample. They together account for 50% of all observations and the number of plants. The joint contribution of these industries to total output constitutes roughly 50%.

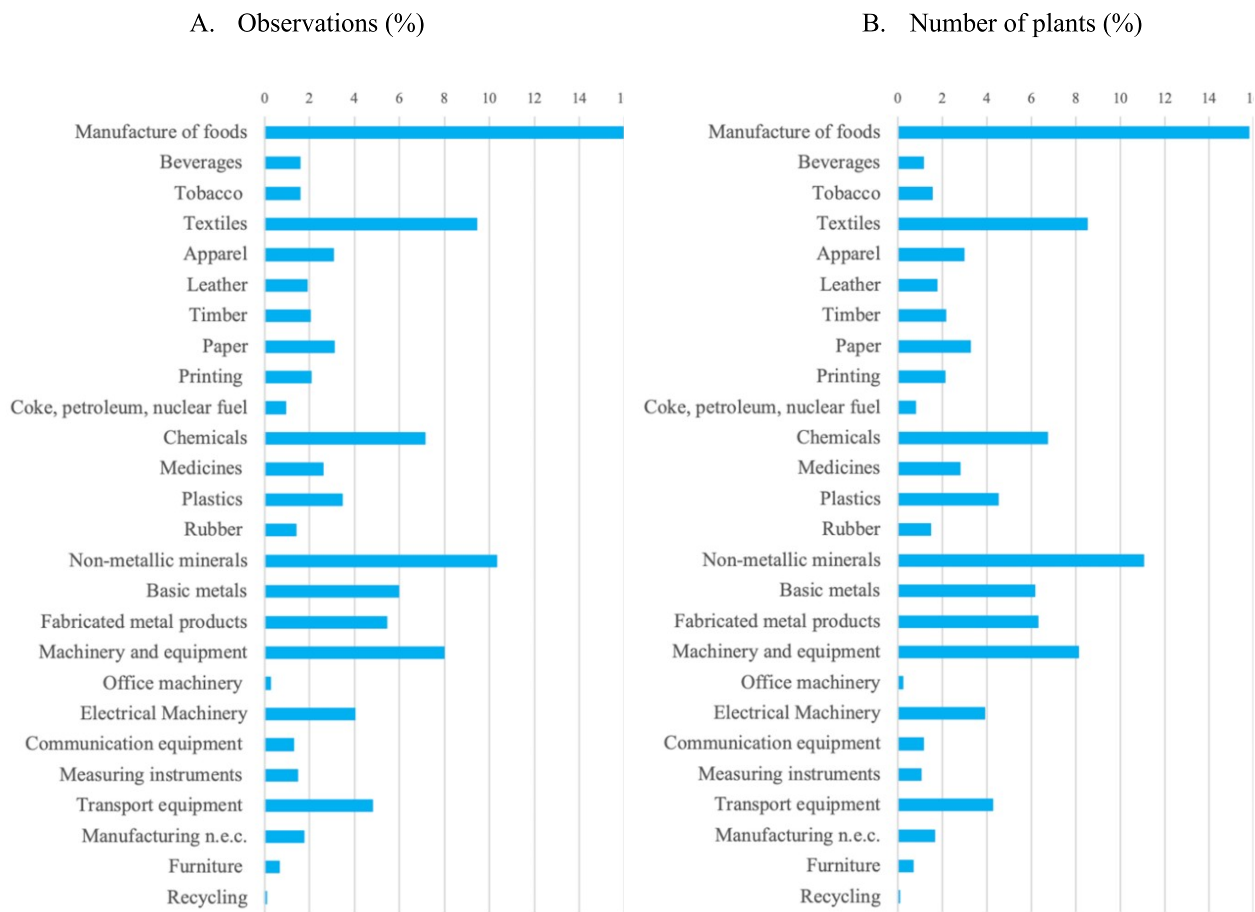
Panel A of Table 1 provides summary statistics on key plant characteristics. The average plant-level value-added output for our study period is USD 3.124 million. The average plant in our dataset operates with a log TFP equal to 2.23, employs 133 workers, and accumulates fixed capital stock of USD 5.653 million. Summary statistics suggest a large degree of dispersion in our key variables across plants.

Table 1 - Summary statistics

	Unit	Mean	Std. Dev.	Min	Max	Obs	Plants
A. Plant Data							
Output	1000 USD	3,124.19	7,862.17	2.82	69,843.70	263,717	113,305
TFP	-	11.53	66.02	1.31	12,935.10	263,717	113,305
Log TFP	-	2.23	0.47	0.27	9.47	263,717	113,305
Labor	persons	133	256	5	4,024	263,717	113,305
Capital	1000 USD	5,653.05	20,022.82	0.06	493,258.90	263,717	113,305
B. Weather and Pollution Data							
Temperature	ºC	25.90	1.51	0.53	28.92	263,717	113,305
Temperature - Winter	ºC	21.01	3.28	-8.82	26.96	263,717	113,305
Temperature - Pre-monsoon	ºC	29.08	2.04	-0.68	33.93	263,717	113,305
Temperature - Monsoon	ºC	27.85	2.84	8.90	35.99	263,717	113,305
Temperature - Post-monsoon	ºC	24.45	1.85	-0.56	29.39	263,717	113,305
Precipitation	mm	1,106.28	574.62	48.17	4,098.84	263,717	113,305
Humidity	kg/kg*100	1.16	0.28	0.30	1.75	263,717	113,305
Wind speed	m/s	5.03	0.74	2.43	6.73	263,717	113,305
Atmospheric pressure	Pa	97,535.78	2,689.76	63,978.79	100,903.30	263,717	113,305
$PM_{2.5}$	$\mu g/m^3$	49.11	24.20	12.59	120.50	263,717	113,305

Notes: The table provides summary statistics of plant-level characteristics, weather, and pollution data. Plant data are from India's Annual Survey of Industries. Weather data are from NASA's MERRA-2. PM2.5 air pollution data are from the Atmospheric Composition Analysis Group at Dalhousie University. Output is measured by value added. TFP is obtained using the Olley-Pakes approach. Labor is measured by the total number of employees. Capital is measured by the total value of fixed assets. All monetary values are in 2007 U.S. dollars. Temperature variables are calculated as the annual or seasonal mean values from daily average estimates. Humidity, wind speed, atmospheric pressure are computed by analogy as the annual mean values. Precipitation is calculated as the annual sum from daily average estimates. PM2.5 concentrations are in annual mean values.

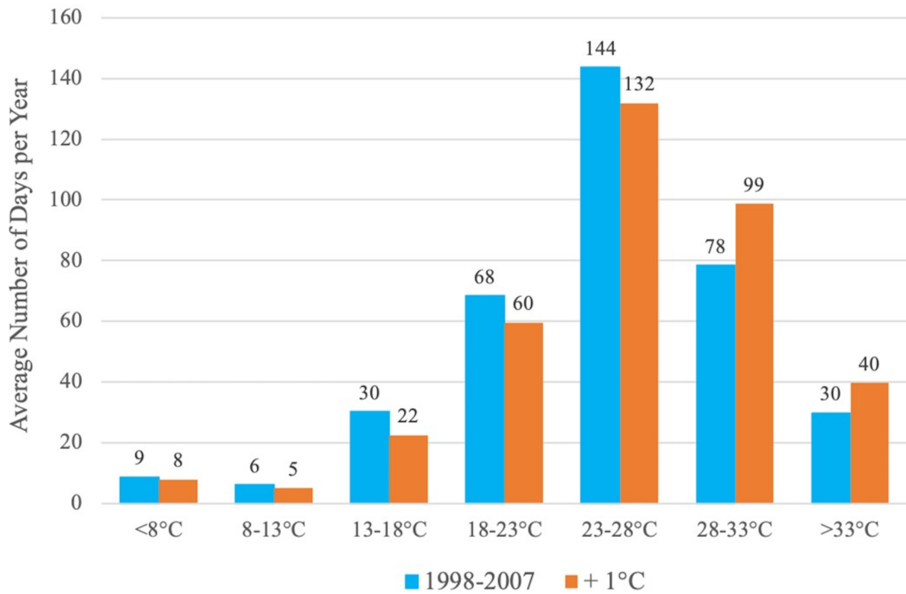
Summary statistics on district-level weather conditions and air pollution are reported in Panel B of Table 1. Each plant in the district is exposed to an average temperature of 25.9ºC throughout our study period. The differences in average temperature across seasons are relatively small, consistent with India's tropical climate. Fig. 2 displays the annual daily temperature distribution averaged across districts for the years 1998-2007. The height of the bars and the numbers along the top of the bars correspond to the average number of days in a year with a daily average temperature that falls into one of seven 5°C-wide temperature bins. Blue bars represent the observed average daily temperature distribution for the years in our sample.



Notes: The figure shows percentage distributions of observations (left panel) and the number of plants (right panel) for each of 26 two-digit industries in the sample. The industries appear in the same order as they are presented in the National Industrial Classification (NIC-1998). We have an unbalanced panel of 113,305 unique plants and 263,717 plant-by-year observations.

Fig. 1. Industry-specific distributions of observations and the number of plants

Climate change is expected to modify the daily temperature distribution by shifting it to the right, replacing cold days with hot. This is demonstrated by the orange-bar distribution. It specifies how the 1998-2007 daily temperature distribution would change if the annual average temperature were to increase by 1°C. We construct the simulated 1998-2007 daily temperature distribution shifted to the right by assuming that each day in each year during our study period becomes warmer by 1°C. Under this assumption, the number of days with daily average temperatures that fall into temperature bins up to (23°C, 28°C) would decline on average by 6 days or 15%, with the largest decline of 26% in (13°C, 18°C) temperature bin. By contrast, the number of days with daily average temperatures that fall into the two highest temperature bins would increase by 20 and 10 days or 26% and 33%, respectively.

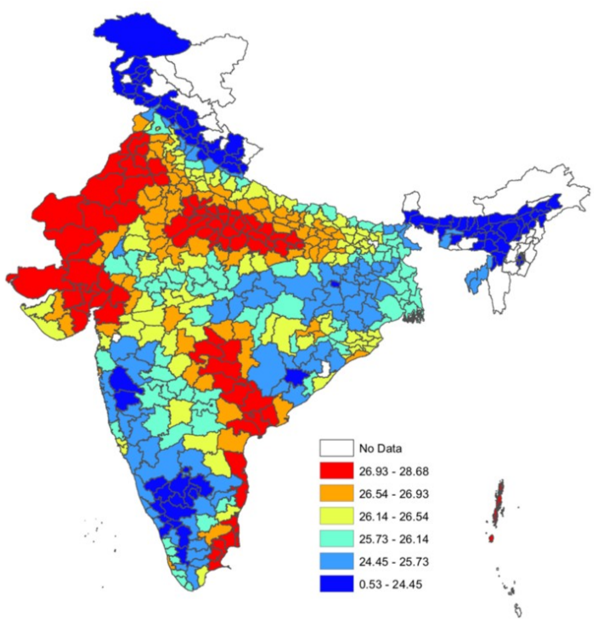


Notes: The figure shows the annual daily temperature distributions for the years 1998-2007 (blue bars) and 1998-2007 shifted to the right by 1°C (orange bars). The orange-bar distribution simulates the impact of climate change assuming that the annual average temperature would increase by 1°C. The height of the bars and the numbers along the top of the bars correspond to the average number of days in a year with a daily average temperature that falls into one of seven 5°C-wide temperature bins.

Fig. 2. Daily temperature distributions: 1998-2007 and 1998-2007 shifted by 1°C

Fig. 3 displays spatial distributions of the annual temperature and value-added output aggregated at the district level and averaged over years 1998-2007. The figure indicates notable spatial heterogeneity and suggests a negative correlation between temperature and value-added output. However, the average temperature and aggregate value-added output mask important characteristics of the plants and temperature, which can shed some light on whether the conditional exogeneity assumption of our empirical strategy holds. Fig. A1-A2 in the Appendix show the spatial distribution of the number of days with daily average temperature across temperature intervals as we use in Eq. (3) and spatial distribution of seasonal temperatures as we use in Eq. (4), while Fig. A3 displays the spatial distribution of value-added shares of two-digit industries as shown in Fig. 1. Based on comparison of spatial distributions of temperature in Fig. A1-A2 and value-added output in Fig. 3 and A3, we do not find any patterns suggesting that the locations of the plants in our sample could be endogenous to the temperatures in the districts where they are located. This suggestive evidence supports the conditional exogeneity assumption of our empirical strategy.

A. Annual temperature B. Value-added output



Notes: The figure shows geographical distribution of the district-level temperature (left panel) and value-added output of manufacturing plants (right panel) averaged across the years in our study period. Colors close to red depict higher levels of temperature and value-added output. The figure suggests a negative correlation between temperature and value-added output.

Fig. 3. Spatial distributions of temperatures and manufacturing output (1998-2007)

1.5 Results

This section begins by examining the relationship between temperature and manufacturing output, TFP, labor and capital inputs using the temperature-bin approach, Eq. (3). We then disentangle the impact of temperature with heterogeneity analyses at a more granular level of disaggregation. We further proceed by exploiting seasonal temperatures to examine within-year variations.

1.5.1 Baseline

Contemporaneous Temperature Effects

Table 2 shows the impact of daily temperatures on manufacturing output, TFP, labor and capital. The coefficients on weather and air pollution controls are shown in Appendix Table A1. Column (1) shows significant adverse effects of extreme high and low temperatures. Relative to the day in the optimal temperature interval, an additional day with a temperature above 33°C decreases annual output by 0.12%, while an additional day with a temperature below 8°C lowers annual output by 0.27%. Notably, the marginal impact of extreme cold days is larger than that of extreme hot days, although the former is estimated less precisely, likely due to fewer observations. These findings can potentially indicate better adaptation to relatively high temperatures in India. The result echoes a recent study by Nath (2020), which, based on a nationally representative firm-level panel from 17 countries, suggests that firms operating in hotter regions can be better adapted to higher temperatures. It can also be the case that in the hotter countries, an extra day with a temperature at a cooler range can be more harmful than an extra day with a temperature at a hotter range because it is more sudden and unexpected (Nath, 2020).[19]

[19] In Nath (2020), cold temperature extreme corresponds to temperatures below 5°C, while hot temperature extreme – to temperatures above 30°C, which are very close to the temperature ranges of the extreme temperature bins used in our study.

Table 2 - Estimated effects of temperature on output and its determinants

	Output		TFP		Capital		Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<8°C	-0.0027**	-0.0026	-0.0007	-0.0003	0.0020	0.0002	0.0000	-0.0010
	(0.0013)	(0.0017)	(0.0005)	(0.0008)	(0.0016)	(0.0014)	(0.0009)	(0.0010)
8-13°C	-0.0014	-0.0016	-0.0006*	-0.0009**	-0.0012	-0.0010	-0.0006	-0.0005
	(0.0010)	(0.0010)	(0.0003)	(0.0004)	(0.0007)	(0.0008)	(0.0007)	(0.0007)
13-18°C	-0.0007**	-0.0009**	-0.0002*	-0.0002*	-0.0001	-0.0000	0.0005**	0.0005**
	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
23-28°C	-0.0005**	-0.0004**	-0.0002**	-0.0002**	-0.0003*	-0.0002	0.0002	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
28-33°C	-0.0008***	-0.0008***	-0.0002***	-0.0002***	-0.0005***	-0.0005**	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
>33°C	-0.0012***	-0.0011***	-0.0004***	-0.0004**	-0.0008***	-0.0008**	0.0001	-0.0000
	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
L1: <8°C		-0.0005		-0.0006		0.0022		0.0010
		(0.0017)		(0.0009)		(0.0015)		(0.0010)
L1: 8-13°C		-0.0005		0.0006		-0.0006		-0.0010*
		(0.0013)		(0.0006)		(0.0008)		(0.0006)
L1: 13-18°C		-0.0004		-0.0001		0.0005		0.0002
		(0.0004)		(0.0001)		(0.0003)		(0.0002)
L1: 23-28°C		-0.0002		-0.0000		-0.0003*		0.0002
		(0.0002)		(0.0001)		(0.0001)		(0.0001)
L1: 28-33°C		-0.0004*		-0.0001		-0.0002		-0.0001
		(0.0002)		(0.0001)		(0.0002)		(0.0001)
L1: >33°C		-0.0002		-0.0000		-0.0000		0.0001
		(0.0003)		(0.0001)		(0.0002)		(0.0002)
R-squared	0.9385	0.9385	0.8320	0.8320	0.9729	0.9729	0.9596	0.9596
Observations	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows coefficient estimates obtained using the binned temperature approach. It documents regression results from estimating Eq. (3) with log values of manufacturing output, TFP, capital, and labor as the outcome variables. Output is measured by value added, labor - by the total number of employees, and capital - by the total value of fixed assets. TFP is obtained using the Olley-Pakes approach. The estimation results are presented separately for specifications with and without lagged temperature variables, odd and even columns for each outcome variable, respectively. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. These estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We only report the coefficients on temperature bins and suppress the coefficients on other weather and air pollution controls. Estimated coefficients on these variables are shown in Table A1 in the Appendix. Standard errors in parentheses are clustered at the plant and district-year levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The temperature impacts are also economically meaningful. The average value-added output of a sample plant was USD 3.124 million in 2007 dollars. Holding all else equal, an additional day with a temperature above 33°C would decrease output by USD 3,749, while an additional day with a temperature below 8°C would decrease output by USD 8,435 for the average plant. At the aggregate level, the average total output of the sample plants during 1998-2007 was

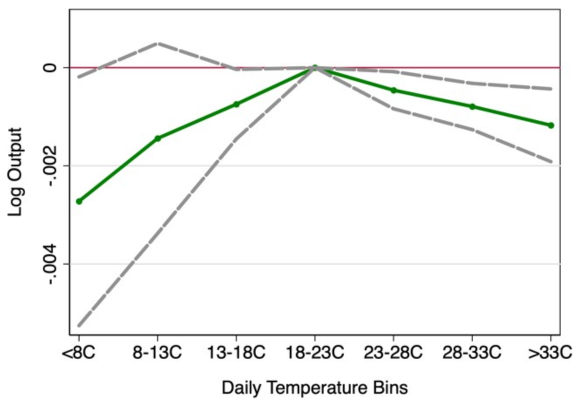
USD 457 billion in 2007 dollars. Thus, if all plants in our sample are jointly exposed to an additional day with temperatures above 33°C or below 8°C, total output would decrease by USD 0.5 billion or USD 1.2 billion, respectively.

Fig. 4 plots the estimates in Table 2 with 95% confidence intervals. The horizontal axes denote temperature bins in degrees Celsius, while the vertical axes show the log values of outcomes. Panel A in Fig. 4 shows that the temperature-output relationship is nonlinear, with an inverted-U shape centered around the (18°C, 23°C) reference interval. Manufacturing output increases with temperature below the reference interval and then declines as temperature further increases above (18°C, 23°C).

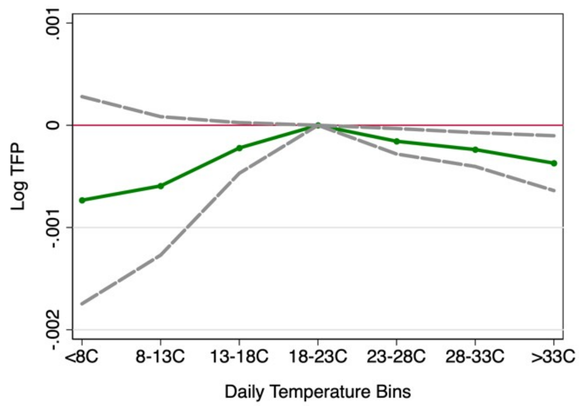
Detected nonlinearity in the temperature-output relationship provides valuable insight into the potential welfare consequences of climate change. There is a possibility that, due to replacing cold days with hot, the reduced negative impact of climate change due to fewer cold days can offset, at least partially, the increased negative impact due to more hot days. To further check this possibility, we compute the net temperature impact on the manufacturing output that would occur if the annual average temperature were to increase by 1°C. We multiply the difference in the number of days in each bin between the observed and +1°C simulated annual daily temperature distributions (Fig. 2) by the relevant estimated coefficients from column (1) of Table 2 and sum the effects of all bins. Our calculations suggest that a 1°C warming would lead to net losses in manufacturing output of 1.3% or USD 0.6 billion, equivalent to a 0.5% reduction in India's 2007 GDP through the manufacturing sector alone.

To shed light on the mechanisms underlying the estimated temperature-output relationship, Table 2 and Fig. 4 further explore the effects of temperature on TFP, labor, and capital. The temperature impact on output seems driven by the joint effects of temperature on TFP and capital. The temperature-TFP relationship in Panel B mirrors the temperature-output relationship in Panel A with smaller magnitudes of impacts. Low temperatures seem only to affect output through TFP, while hot temperatures likely affect output through TFP and capital. An additional day with a temperature above 33°C decreases TFP and capital by 0.04% and 0.08%, relative to a day in the (18°C, 23°C) reference interval. The temperature-TFP effects and temperature-capital effects decompose temperature-driven output losses, contributing roughly 30% and 70%. Interestingly, this finding contrasts with the one from China, where the temperature effects on TFP completely explain the temperature-output relationship (Zhang et al., 2018).

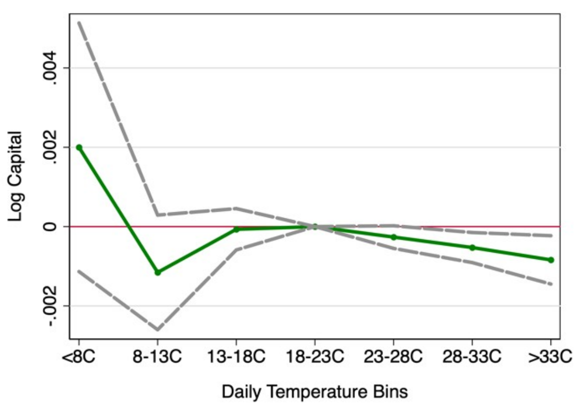
C. Temperature - Log Output



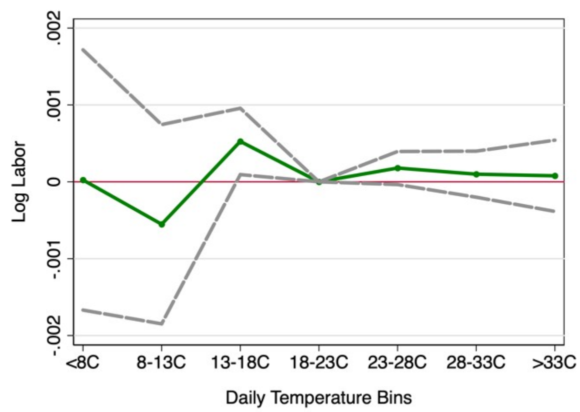
D. Temperature - Log TFP



E. Temperature - Log Capital



F. Temperature - Log Labor



Notes: The figure visualizes the estimated temperature-driven effects on log values of manufacturing output (panel A), TFP (panel B), capital (panel C), and labor (panel D). The horizontal axes denote temperature bins in degrees Celsius, while the vertical axes show the log values of outcome variables. Each panel plots the point estimates of temperature bins (green line) and associated 95% confidence intervals (grey dashed lines) for the coefficients obtained by estimating Eq. (3) with no lags and reported in the odd columns of Table 2. The regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category. Standard errors are clustered at the plant and district-year levels.

Fig. 4. Estimated temperature effects on output, TFP, labor and capital factor inputs.

By contrast, the temperature-labor relationship appears irrelevant for the temperature-driven output losses. The response of labor is flat for the temperatures above the reference interval and has small and statistically insignificant estimates for most temperature bins but one. Panel D documents an increase in labor input for the temperatures within (13°C, 18°C) interval. Given the negative TFP response to an extra day with a temperature within the same temperature interval, this result may suggest that the plants may increase labor supply to offset the productivity losses.

These estimated effects are broadly robust to various specifications. They do not change substantially with the inclusion and exclusion of different sets of fixed effects, measures of temperature, number of temperature bins, and plant-level samples.[20] Important evidence in favor of robustness is shown in Appendix Fig. A4. It visualizes the estimated temperature-driven effects on the plant-level electricity expenditures (panel A) and electricity consumption (panel B), expressed in 1000 USD and kWh, respectively. The figures show that temperature has no statistically significant effects on electricity expenditures and consumption, suggesting that adaptation actions have not been undertaken to reduce the negative impact on output. Our estimates are unlikely biased by the temperature-induced increases in electricity expenditures and consumption to power air conditioning systems or cooling equipment for machinery. Another evidence includes the placebo test that examines the impact of future temperatures on current economic outcomes. We estimate Eq. (3) expanded by adding temperature bins constructed using annual distributions of daily temperatures led by one and two years. Table A2 in the Appendix presents the results of this exercise. When controlling for future temperatures, the response of manufacturing output, TFP, and factor inputs to contemporaneous temperature is similar to our baseline model in Table 2. The coefficients on several temperature bins led by one year are significant, but there does not appear to be a systematic pattern.[21] Furthermore, those coefficients turn insignificant in the specification with the temperature led by two years, while the response of our economic outcomes to contemporaneous temperature remain little changed. This illustrative evidence further confirms the robustness of our baseline findings.

[20] The results of these robustness checks are available upon request.

[21] The significance of the coefficients on several temperature bins led by one year and not two years may be related to the expectation effect.

Lagged Temperature Effects

Table 2 also presents the estimates for the effects of the lagged temperature on the current-year economic outcomes. We consider a specification that expands our baseline model in Eq. (3) by adding temperature bins constructed using annual distributions of daily temperatures lagged by one year. We report coefficients obtained from the estimation of this specification in the even columns of Table 2. For comparison with Fig. 4, Appendix Fig. A5 displays the effects of jointly estimated current and lagged temperatures on output, TFP, and factor inputs (even columns of Table 2).

We find that the response of manufacturing output to contemporaneous temperature is little changed, with the only exception for the negative effect of the temperatures below 8°C, which turned insignificant. Relative to a day with an average temperature within the reference interval, the effects on output of one additional previous-year day with the temperature in other temperature bins are small and statistically insignificant, with the exception of the bin (28°C, 33°C). However, the coefficient estimate on this bin is small, marginally statistically significant, and does not alter the estimate of the contemporaneous temperature effect of this bin. Furthermore, the shape of the contemporaneous temperature-output relationship in panels A of Appendix Fig. A5 is similar to that depicted in our baseline panel A of Fig. 4. Similar to the impact on output, the effects of lagged temperature on TFP, capital and labor are small and statistically insignificant in most of the temperature bins. Taken together, these findings support the hypothesis that only the contemporaneous temperature during the production process drives the output losses. This conclusion is in line with Hsiang (2010), Deryugina and Hsiang (2014), and Zhang et al. (2018), but contrasts with Dell et al. (2012) and Chen and Yang (2019).

1.5.2 Heterogeneity

In this section, we explore the heterogeneity in the temperature effects to further examine the mechanisms and adaptation strategies.

Labor vs Capital Productivity

Our previous analysis demonstrates nonlinear adverse effects of contemporaneous temperature on both output and TFP. Hsiang (2010) argues that such responses are consistent with the decline in labor productivity due to workers' exposure to thermal stress. This argument requires additional evidence, however, given that the TFP is the weighted average of labor and capital productivity ($\ln TFP = \sigma_L \ln A_L + \sigma_K \ln A_K$) and that temperature can also affect capital productivity (Zhang et al., 2018).

We further explore this issue by examining the differential TFP responses across labor- and capital-intensive manufacturing plants. If the economic responses of TFP to temperature propagate primarily through labor productivity (A_L), temperature changes should have a larger negative impact on the TFP of labor-intensive plants, which typically have larger output elasticity of labor (σ_L), while the TFP of capital-intensive plants would be relatively unaffected.

We estimate contemporaneous and lagged specifications of Eq. (3) with TFP as the outcome variable separately for labor- and capital-intensive plants. Plants are classified as labor- or capital-intensive based on labor intensity, which we measure by the plant-level ratio of wage bill over output, both averaged across sample years. We define a plant as labor-intensive if its labor intensity is above the median of all plants in the sample.[22] We report the coefficients obtained from estimation of the contemporaneous specification in Table 3, while Table A4 in the Appendix displays the effects of jointly estimated current and lagged temperatures.

[22] Appendix Table A3 displays detailed descriptive statistics separately for labor-intensive and capital-intensive plants, while Fig. A6 shows the spatial distribution of value added-output shares for both types of plants. The table and figure provide valuable insight into the differences and similarities between labor-intensive and capital-intensive plants, which are equally represented in our sample, for 50% of observations (see Table 3). As expected, the plants differ substantially in the statistics on key plant characteristics. Labor-intensive plants, on average, have substantially lower value-added output, employ fewer workers, accumulate less fixed capital stock, and are less productive. However, the plants are almost identical in the statistics on weather conditions and air pollution in the districts where the plants are located. This again suggests that concern about the endogenous location of plants can be relaxed.

Table 3 – Temperature effects on TFP across labor-intensive and capital-intensive plants

		Labor Intensity =1 if wage bill/output > median	
	Full Sample (1)	Labor-Intensive (2)	Capital-Intensive (3)
<8°C	-0.0007	-0.0005	-0.0011
	(0.0005)	(0.0006)	(0.0008)
8-13°C	-0.0006*	-0.0005	-0.0006
	(0.0003)	(0.0004)	(0.0005)
13-18°C	-0.0002*	-0.0001	-0.0003*
	(0.0001)	(0.0002)	(0.0002)
23-28°C	-0.0002**	-0.0002**	-0.0001
	(0.0001)	(0.0001)	(0.0001)
28-33°C	-0.0002***	-0.0003***	-0.0002
	(0.0001)	(0.0001)	(0.0001)
>33°C	-0.0004***	-0.0007***	-0.0001
	(0.0001)	(0.0002)	(0.0002)
R-squared	0.8320	0.8583	0.7846
Mean Temp (°C)	25.90	25.91	25.89
Shares (%)	100	50.00	50.00
Observations	263,717	131,860	131,857

Notes: The table shows coefficient estimates of the temperature effects on log TFP across labor-intensive and capital-intensive plants obtained using contemporaneous specification of Eq. (3). TFP is measured using the Olley-Pakes (1996) approach. Plant-level labor intensity is measure by the plant-level ratio of wage bill over output, both averaged across sample years. The plant is defined as labor-intensive if its labor intensity is above the median of all plants in the sample. Column (1) shows estimates for the full sample as they are reported in our baseline temperature effects on TFP in column (3) of Table 2. Columns (2) and (3) present estimates for labor-intensive and capital-intensive plants, respectively. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. The estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We suppress the coefficients on weather and air pollution controls. Standard errors in parentheses are clustered at the plant and district-year levels.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

We find persuasive evidence that productivity losses are generally associated with temperature-induced reductions in labor productivity rather than capital productivity. Columns (2)-(3) show that high temperatures have statistically significant negative effects on the TFP of labor-intensive plants and exert no impact on the TFP of capital-intensive plants. Notably, we do not find statistically significant responses of TFP across both labor- and capital-intensive plants to the range of temperatures below 8°C. Additionally, Appendix Table A4 provides evidence that the lagged temperatures have no effects on the contemporaneous TFP of both plant types. These findings are consistent with the evidence from Somanathan et al. (2021), who show that the output of manufacturing workers in India declines on hot days due to the temperature-induced reductions in the output elasticity of labor. Overall, our results support the hypothesis that the workers' exposure to thermal stress is the primary channel through which temperature affects the productivity of manufacturing plants.

Capital Inputs

Table 2 and Fig. 4 show that capital is the only factor input in our setting that responds significantly to high temperatures, suggesting the capital channel can play a role in transmitting adverse temperature shocks to manufacturing output. As capital is a complex factor input that comprises assets with different sensitivity to temperature, we explore which component of capital drives the temperature-capital relationship.

Since we use fixed capital stock as the measure of the plant-level capital, its components represent the depreciated value of fixed assets owned by plants on the closing day of the accounting year. Such assets include land, buildings, plant and machinery, transport equipment, computer equipment, and other fixed assets such as hospitals, schools, etc. Two additional categories include capital work in progress and pollution control equipment, which first appeared as a separate category in the 2001 ASI. We combine these categories with other fixed assets because of the limited number of observations.

We estimate the temperature impact on each capital component using the contemporaneous and lagged specifications of Eq. (3). Results of the estimation are presented in Table 4. Appendix Table A5 displays the effects of jointly estimated current and lagged temperatures.

The estimates in Table 4 show several important margins in the differential effects of temperature on capital components. There is a clear differentiation between fixed assets on those that respond only to lower temperatures, the bins below the reference bin, and those that respond only to higher temperatures, the bins above the reference bin. The only exceptions are plant and machinery and computer equipment, which respond to both lower and higher temperature ranges. Previously, we found statistically significant responses of capital only to the higher temperatures (columns (5)-(6) of Table 2). Importantly, temperature-driven effects associated with lower temperatures are strongly manifested in transport equipment, computer equipment, and plant and machinery, i.e. the fixed assets where climate-related adjustments are the most feasible. The analysis reveals that there are both negative and positive responses of fixed assets to the lower temperatures, with transport equipment responding positively to one additional day in a (18°C, 23°C) bin relative to a day in the reference bin. In addition, we find that capital losses at lower temperatures are disproportionally large and are driven primarily by losses in plant and machinery and computer equipment, respectively 0.22% and 0.31% from an additional day in (8°C, 13°C) temperature bin relative to a day in the reference bin. For comparison, the largest negative impact among all estimated effects at higher temperatures is 0.1%, resulting from the exposure of other fixed assets to one additional day with a temperature higher than 33°C. Effects of similar magnitudes are also revealed for buildings, and plant and machinery. These results are consistent with our previous findings suggesting that more substantial losses in manufacturing output occur at low rather than at high temperatures.

Table 4 - Temperature effects on capital by components

	Capital (1)	Land (2)	Buildings (3)	Plant & Machinery (4)	Transport Equipment (5)	Computer Equipment (6)	Other Fixed Assets (7)
<8°C	0.0020	0.0034	0.0018	0.0009	-0.0004	-0.0001	0.0022
	(0.0016)	(0.0021)	(0.0018)	(0.0018)	(0.0018)	(0.0012)	(0.0016)
8-13°C	-0.0012	0.0007	-0.0010	-0.0022**	-0.0012	-0.0031***	-0.0001
	(0.0007)	(0.0011)	(0.0010)	(0.0009)	(0.0014)	(0.0011)	(0.0011)
13-18°C	-0.0001	0.0003	-0.0003	-0.0004	0.0008*	0.0001	-0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
23-28°C	-0.0003*	-0.0004*	-0.0001	-0.0003*	-0.0000	-0.0004*	-0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
28-33°C	-0.0005***	-0.0003	-0.0005**	-0.0006**	-0.0000	-0.0005	-0.0006**
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
>33°C	-0.0008***	-0.0002	-0.0007*	-0.0009**	0.0001	-0.0003	-0.0010**
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
R-squared	0.9729	0.9271	0.9532	0.9629	0.8838	0.8718	0.9288
Observations	263,717	263,717	263,717	263,717	263,717	263,717	263,717

Notes: The table shows coefficient estimates of the temperature effects on capital by component obtained using contemporaneous specification of Eq. (3). Dependent variables are log values of the overall capital, land, buildings, plant and machinery, transport equipment, computer equipment, and other fixed assets. Capital components are defined according to the ASI documentation and represent the depreciated value of fixed assets owned by plants on the closing day of the accounting year. Column (1) reports our baseline temperature effects on the overall capital from column (5) of Table 2. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. The estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We suppress the coefficients on weather and air pollution controls. Standard errors in parentheses are clustered at the plant and district-year levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Furthermore, the estimates in Appendix Table A5 suggest that the significant effects of lower temperatures on plant and machinery, transport equipment, and computer equipment may persist over time for both higher and lower temperatures, columns (4)-(6). This is in stark contrast to the responses of land, buildings, and other fixed assets to temperature, which are entirely contemporaneous, columns (2), (3), (7). Finally, estimates in columns (1) and (4) show that the responses of the plant and machinery to the extreme high temperatures are the most similar to the responses of overall capital to the same range of temperatures.

Taken together with the fact that plant and machinery responds to both lower and higher temperatures, it makes this category of fixed assets potentially the most suitable for adjustments aimed at more effective adaptation to climate change. This is consistent with engineering studies (Zhang et al., 2018) but is documented for the first time in our study.

1.5.3 Seasonal Temperature

In this section, we explore the heterogeneity in the temperature effects to further examine the mechanisms and adaptation strategies.

We exploit seasonal average temperatures to examine temperature-driven effects on manufacturing output and its determinants at a more granular below-year level. Table 5 summarizes the results and reports coefficients on seasonal average temperatures estimated simultaneously by fitting Eq. (4) without temperature lag (odd columns) and jointly with a one-year temperature lag (even columns). Estimated coefficients on weather and air pollution controls are presented in Appendix Table A6.

The central finding is that the largest output losses are associated with temperature increases during the hottest pre-monsoon season. This season lasts from March to May and has an average temperature of 29.08°C. The coefficient estimate of $Temp^{Pre-monsoon}$ is negative and statistically significant, indicating that a 1°C increase in this season's average temperature can reduce contemporaneous manufacturing output by 2.2%. The effects on output of temperatures during other seasons are relatively small and not statistically significant. Furthermore, the magnitudes of the seasonal responses correspond well with the seasonal average temperatures in Table 1. The season-to-season output effects increase steeply from the coldest winter season to the hottest pre-monsoon season and then gradually decrease during the less hot monsoon and cooler post-monsoon seasons. Such seasonal dynamics are consistent with nonlinear responses of manufacturing output to temperature, with the most substantial reduction in output occurring during the hottest season.

Table 5 - Estimated effects of seasonal temperature on output and its determinants

	Output		TFP		Capital		Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Temp^{Winter}$	0.0034	0.0067	0.0012	0.0024	-0.0097**	-0.0120**	-0.0078**	-0.0067*
	(0.0058)	(0.0060)	(0.0019)	(0.0020)	(0.0046)	(0.0048)	(0.0035)	(0.0037)
$Temp^{Pre\text{-}Monsoon}$	-0.0221***	-0.0258***	-0.0078***	-0.0095***	0.0048	0.0075	-0.0014	-0.0023
	(0.0079)	(0.0079)	(0.0029)	(0.0029)	(0.0061)	(0.0061)	(0.0049)	(0.0050)
$Temp^{Monsoon}$	-0.0056	-0.0081	0.0045	0.0036	-0.0050	-0.0030	-0.0070	-0.0065
	(0.0100)	(0.0101)	(0.0035)	(0.0035)	(0.0073)	(0.0073)	(0.0062)	(0.0062)
$Temp^{Post\text{-}Monsoon}$	0.0009	-0.0003	-0.0000	-0.0005	-0.0101*	-0.0092*	0.0112**	0.0099**
	(0.0074)	(0.0074)	(0.0025)	(0.0025)	(0.0054)	(0.0054)	(0.0047)	(0.0048)
L1: $Temp^{Winter}$		0.0077		0.0035*		-0.0068*		-0.0002
		(0.0050)		(0.0018)		(0.0041)		(0.0034)
L1: $Temp^{Pre\text{-}Monsoon}$		0.0051		0.0018		-0.0027		0.0047
		(0.0045)		(0.0016)		(0.0035)		(0.0030)
L1: $Temp^{Monsoon}$		-0.0038		-0.0029		0.0049		-0.0065*
		(0.0056)		(0.0019)		(0.0042)		(0.0037)
L1: $Temp^{Post\text{-}Monsoon}$		-0.0035		-0.0011		0.0029		-0.0009
		(0.0043)		(0.0014)		(0.0032)		(0.0027)
R-squared	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717
Observations	0.9385	0.9385	0.8320	0.8320	0.9729	0.9729	0.9596	0.9596
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows coefficient estimates obtained using seasonal temperature approach. It documents regression results from estimating Eq. (4) with log values of manufacturing output, TFP, capital, and labor as the outcome variables. Output is measured by value added, labor - by the total number of employees, and capital - by the total value of fixed assets. TFP is obtained using the Olley-Pakes (1996) approach. The estimation results are presented separately for specifications with and without lagged temperature variables, odd and even columns for each outcome variable, respectively. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. These estimated temperature effects can be interpreted as the percentage changes in the outcomes caused by an increase in average temperature in a particular season by 1 °C. We only report the coefficients on seasonal temperatures and suppress the coefficients on other weather and air pollution controls. Estimated coefficients on these variables are shown in Table A6 in the Appendix. Standard errors in parentheses are clustered at the plant and district-year levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As a point of comparison with prior studies, the pattern and the magnitude of the estimated seasonal temperature effects on output are consistent with the evidence for a very similar setting.

Examining a sample of 28 Caribbean-basin countries, Hsiang (2010) finds that a 1°C increase in temperature during the hottest season decreases output in the non-agricultural sector by 2.4%. Recent studies by Somanathan et al. (2021) and Colmer (2021) report output losses of a similar magnitude for India.

Analysis of the mechanisms reveals that seasonal temperature effects on TFP and factor inputs are inherently different. Whereas productivity losses are most strongly associated with the hottest pre-monsoon season, economic responses of capital and labor are driven primarily by the increases in temperature during the two coldest seasons, winter and post-monsoon.

The seasonal contribution of the temperature effects on TFP is structurally similar to that of output. It is nonlinear in temperature and is dominated by temperatures experienced by manufacturing plants during the hottest season. The effect on TFP of temperatures during that season is relatively large, negative, and statistically significant. The temperature-driven TFP losses increase by 0.78% with a 1°C increase in the average temperature during the pre-monsoon season, contributing about 35% to the overall output losses. Our findings and prior studies suggest that such productivity losses are most probably caused by the decline in labor productivity associated with the exposure of workers to thermal stress during the hottest season (Hsiang 2010; Adhvaryu, Kala, and Nyshadham, 2020; Somanathan et al., 2021).

In contrast to output and TFP, the economic effects of seasonal temperatures on capital and labor are most strongly exhibited during the coldest winter and post-monsoon seasons. Combined, these seasons span five months from October to February and have comparable seasonal average temperatures of 21.01°C and 24.45°C for winter and post-monsoon seasons, respectively. Despite being the coldest seasons, temperature averages during these seasons are relatively high.[23]

For capital, the coefficient estimates on both $Temp^{Winter}$ and $Temp^{Post-monsoon}$ are negative and statistically significant, suggesting that capital declines with temperature increases during winter and post-monsoon seasons. Furthermore, the magnitudes of the estimates are comparable, reflecting a small difference between winter and post-monsoon temperature averages. A 1°C increase in these seasons' average temperature is associated with a 0.97-1.01% reduction in capital,

[23] For comparison, $Temp^{Winter}$ in India is about 5°C higher/lower than the average spring/summer temperature in China, whereas $Temp^{Post-monsoon}$ in India is less than 2°C lower than the average summer temperature in China (Chen and Yang, 2019). The seasonal temperature effects on capital and labor during the other seasons are not statistically significant.

with the larger reduction occurring during a hotter post-monsoon season. The negative response of capital to the temperature increases during the coldest seasons is likely due to the already high average temperatures. Our finding is consistent with engineering studies, reporting that high temperatures can lower the ability of lubricants to reduce surface frictions between mechanical components and increase machines' failure rates by expanding the volume of input materials (Collins, 1963; Mortier et al., 2010; Zhang et al., 2018).

For labor, manufacturing employment responds negatively to increases in winter temperatures and positively to increases in post-monsoon temperatures. A 1°C increase in average $Temp^{Winter}$ reduces employment by 0.78%, while a 1°C increase in average $Temp^{Post-monsoon}$ increases employment by 1.12%. This finding can potentially be explained by the temperature effects on the seasonal fluctuations in employment both across seasonal manufacturing industries and across economic sectors.

Agarwal and Varshney (1969) show that between-industry seasonal fluctuations exist in at least 14 Indian manufacturing industries.[24] The majority of the seasonal industries release a substantial share of their labor force during the monsoon season and have a peak or larger employment during the post-monsoon because they can produce only during a specific period of the year.[25] Industries that depend on seasonal demand have a slack period during both monsoon and post-monsoon seasons, releasing a large share of employed workers.[26] Only a few seasonal industries employ more workers during the monsoon season.[27] Thus, it seems unlikely that these industries can wholly absorb workers released by other seasonal industries during their slack season, leading to the net loss in employment among seasonal manufacturing workers during the monsoon.

[24] These industries exhibit a seasonal character because their production is not possible in certain seasons, depends on the perishable or raw materials available only in certain seasons, or their products are subject to seasonal demand.

[25] Such industries include production of sugar in mills, production of indigenous sugar, production of coffee, and cotton ginning and baling, which use perishable raw materials; production of jerda and other chewing tobacco, which depends on raw materials that are available only in certain seasons; production of salt and bricks and tiles, which can be produced only at a certain period of the year.

[26] Examples of such industries include the production of aerated or mineral water. Production of cigarette and cigarette tobacco also has a similar pattern of seasonal employment.

[27] Such industries are limited to the processing and baling of jute and wool, and the production of cigars and cheroots.

Increases in seasonal temperatures can amplify between-industry seasonal fluctuations, affecting the output and productivity of seasonal manufacturing industries because their production depends on the weather. For example, the higher post-monsoon temperatures can increase demand for labor and, in turn, the employment of workers in industries depending on seasonal demand. Moreover, such temperature-driven impact can be substantial as seasonal industries employ 15-20% of the workers engaged in manufacturing (Agarwal and Varshney, 1969).

The higher seasonal temperatures can also affect the seasonal reallocation of the labor force between economic sectors, first of all between manufacturing and agriculture. These sectors are not only subject to seasonal fluctuations in employment but also experience an opposite seasonal movement of labor because they have peak and slack periods at different seasons. Normally, employment in agriculture increases during monsoon and decreases during post-monsoon, while employment in manufacturing takes place in the opposite direction, with manufacturing industries hiring more workers during the off-season of agriculture (Agarwal and Varshney, 1969). Consistent with existing evidence, increases in post-monsoon temperatures can further modify this pattern of seasonal labor movement. Colmer (2021) shows that temperature-driven changes in agriculture productivity in India force workers to move across economic sectors, increasing employment in the formal manufacturing sector.[28]

Overall, the estimated effects of the increases in $Temp^{Monsoon}$ and $Temp^{Post-monsoon}$ are consistent with both channels. Although insignificant, the large and negative coefficient on $Temp^{Monsoon}$ may indicate a decline in employment, probably due to the release of labor by the seasonal manufacturing industries or perhaps due to labor reallocation from manufacturing to agriculture sectors during the monsoon season, which is favorable to agriculture (Chakraborty and Shukla, 2020). Then, the positive and statistically significant coefficient on $Temp^{Post-monsoon}$ may suggest a reverse reallocation of workers from agriculture to manufacturing, consistent with Colmer (2021).

The even columns in Table 5 show that the lagged seasonal temperatures have limited effects on the contemporaneous output and its determinants, except for capital. Estimates in column (6) suggest that fixed capital assets can wear and tear 0.68% faster if they are exposed to a 1°C increase in temperature during the winter season in the previous year. Importantly, the effect

[28] Importantly, such labor reallocation occurs across sectors within a district, which represents a local labor market, rather than across districts.

may propagate into the following years and reduce the current-year value of capital. Specifically, it causes the coefficient estimate on the current-year $Temp^{Winter}$ to increase by 24%, from 0.97% to 1.2%. Neither of the other lagged seasonal temperatures have a significant effect on current capital.

The coefficients on the lagged seasonal temperatures indicate a statistically significant impact during the winter season for TFP and during the monsoon season for labor. However, the corresponding contemporaneous temperature effects remain insignificant. Notably, the temperature-induced decline in employment during the monsoon season in the prior year seems consistent with seasonal employment fluctuations both across seasonal manufacturing industries and across economic sectors.

1.6 Discussion and Conclusion

This chapter examines the effects of temperature on the output of manufacturing plants in India and the mechanisms underlying the temperature-output relationship to support policymaking.

Applying a uniform empirical framework to the nationally representative sample of plants from the formal manufacturing sector for 1998-2007, we find that the relationship between temperature and manufacturing output is nonlinear. Using binned temperatures, we discover that the temperature-output relationship exhibits an inverted U-shape with a clearly defined optimum that falls into the (18°C, 23°C) interval. The output losses are especially large for extreme temperature intervals. Using seasonal temperatures, we confirm the nonlinear relationship and show that the most substantial losses occur during the hottest pre-monsoon season. The estimated impact on the output of a 1°C increase in the average temperature during the pre-monsoon season is consistent with that found in most literature.

Analysis of the mechanisms shows that the negative responses of manufacturing output to temperature are driven primarily by the adverse effects of temperature on TFP and capital, contributing roughly 30% and 70%, respectively. The response of TFP to temperature closely follows the response of output, while the response of capital mirrors the response of output only to higher temperatures. Further disentangling these primary mechanisms using heterogeneity analysis, we find that TFP losses propagate through the adverse temperature effects on labor productivity and that the responses of machinery to extreme high temperatures are the most similar to the responses of overall capital. We also find suggestive evidence of labor reallocation across seasonal manufacturing industries and across economic sectors. These results imply that in the context of India, reducing the sensitivity of productivity to temperature and lowering the cost of factor adjustments are two important margins for adaptation. Finally, we find that the lagged temperatures have a significant impact only on the current-year stock of capital.

Our findings have several implications for the climate change adaptation strategies of manufacturing plants in India. First, productivity-related adjustments can be considered a universal adaptation channel since the shape of the TFP response to temperature closely follows the shape of the output response. At higher temperatures, however, India's manufacturing sector should prioritize capital-related adjustments when possible because of the larger contribution of the temperature-capital effects to the overall temperature-driven output losses.

Second, the evidence that high temperatures negatively affect TFP through labor productivity suggests that India's manufacturing sector could adapt to climate change by either focusing on reducing the sensitivity of labor productivity to high temperatures or by associated labor-related adjustments. The former strategy could focus on optimization of working hours or regular breaks to avoid the hottest parts of the day during the year, while the latter strategy could involve the reallocation of labor between labor-intensive and capital-intensive industries or optimization in the number of employed workers (Day et al., 2019). When developing the productivity-related adjustments, it is important to consider that TFP is most sensitive to the temperatures during the hottest pre-monsoon season and that such adjustments could have contemporaneous effects.

Third, manufacturing plants can make capital-related compensatory investments to either offset direct productivity losses or adjust capital input. In the former case, strategies range from investments in air cooling systems to improvements in building design. In the latter case, strategies can include investments in new machinery that is better adapted to temperature extremes (Day et al., 2019). Although our estimates indicate that climate change adaptation policy should focus on prioritizing investments in machinery, given that the lagged temperatures in the prior year exert a large and significant impact on the current-year stock of machinery, such investments could have a delayed effect.

Other categories of capital that respond to temperature changes significantly, such as buildings, transport and computer equipment, can also be considered for investment. In either case, manufacturing plants should also take into account the pattern of the seasonal responses of the specific category of capital to ensure effectiveness.

Another reason manufacturing plants may want to prioritize adjustments in capital input instead of offsetting direct productivity losses is the limited and environmentally harmful impact of air cooling systems. On the one hand, there is potential for expansion because the adoption of industrial air-cooling systems in the manufacturing sector remains very limited (Somanathan et al., 2021). On the other hand, a number of labor-intensive manufacturing industries, which the decision-makers should target for lowering labor productivity losses, carry out their economic activity outdoors. Further, the adoption of air-cooling systems may be prohibitively costly or of limited use because of insufficient energy infrastructure capacity, which may fail precisely when the air conditioning is needed most (Heal and Park, 2015). In addition, wider adoption of air-cooling systems may trigger a vicious cycle as it could lead to an increase in electricity demand, which would need to be balanced by the increase in electricity supply coming at the expense of higher GHG emissions, reinforcing climate change in the long run.

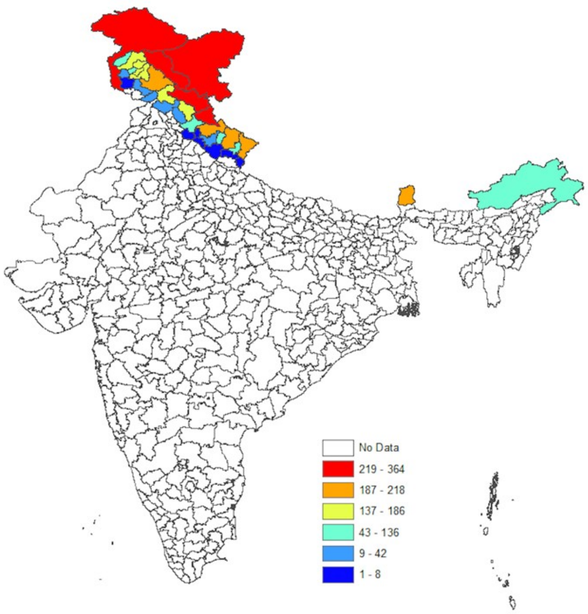
Finally, we also find suggestive evidence favoring labor-related adjustments apart from those associated with offsetting labor productivity losses. Such adjustments can contribute to the mitigation of the economic consequences of temperature shocks by absorbing the excessive temperature-driven supply of workers moving from one seasonal industry to another or moving out of agriculture to manufacturing. In both cases, the ability of the manufacturing sector to absorb the surplus workforce would play a crucial role. Given the potentially large scale of the required labor-related adjustments, incentives from central and state-level governments may be needed.

The implications of our findings would allow India to achieve climate change policy goals without compromising the country's growth and development prospects.

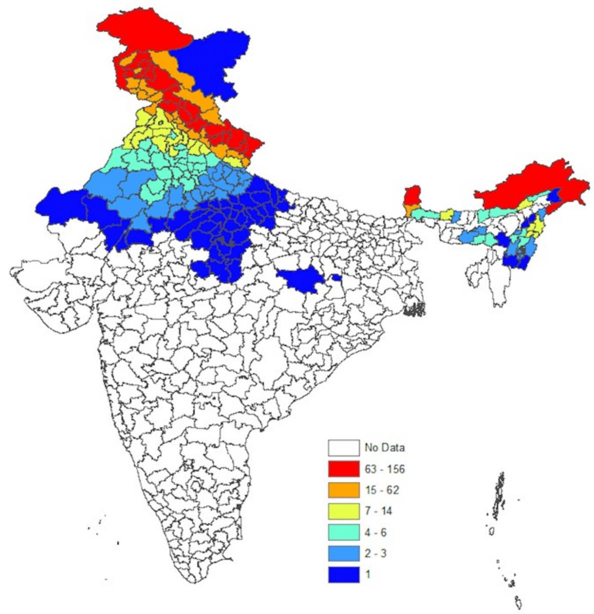
1.7 Appendix

Fig. A1. Spatial distribution of the number of days with daily average temperatures across temperature bins (1998-2007)

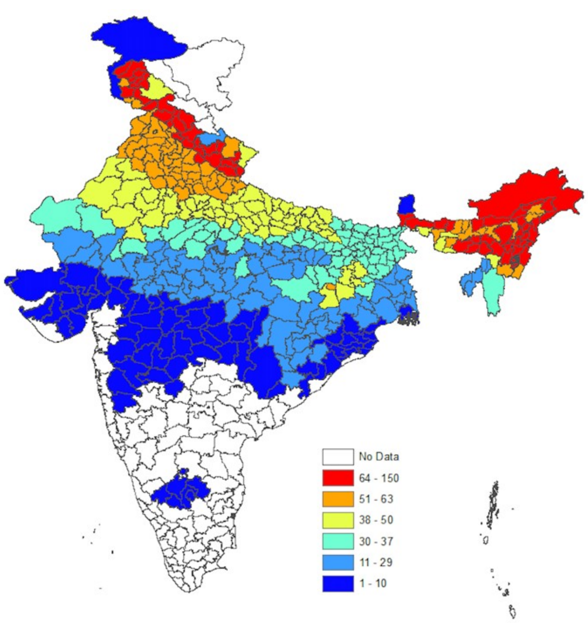
A. Temperature interval: <8°C



B. Temperature interval: 8-13°C



C. Temperature interval: 13-18°C



D. Temperature interval: 18-23°C

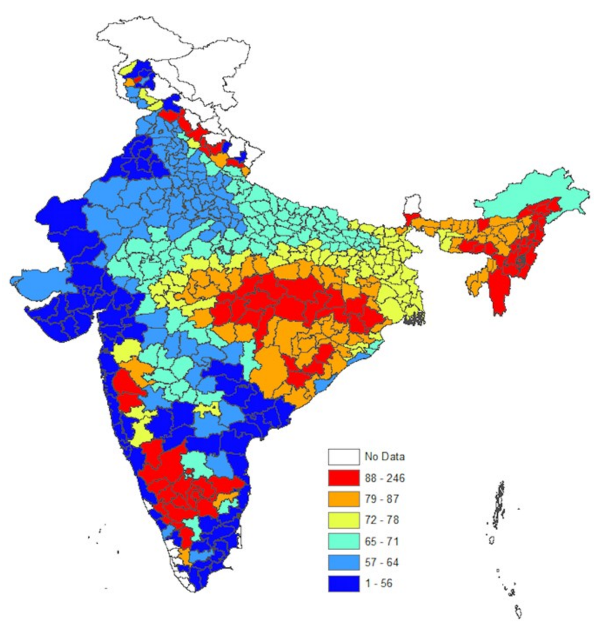
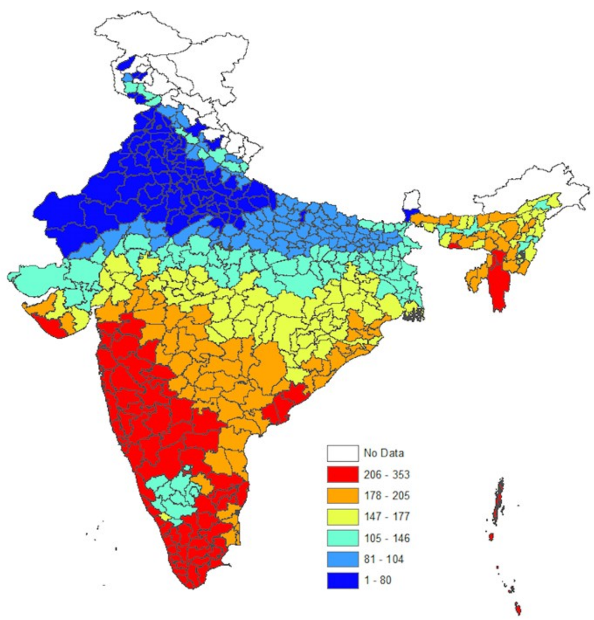
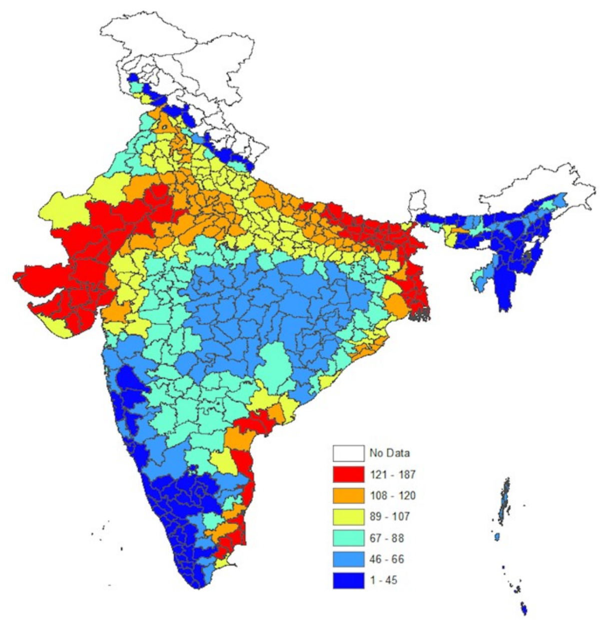


Fig. A1. Spatial distribution of the number of days with daily average temperatures across temperature bins (1998-2007) (continued)

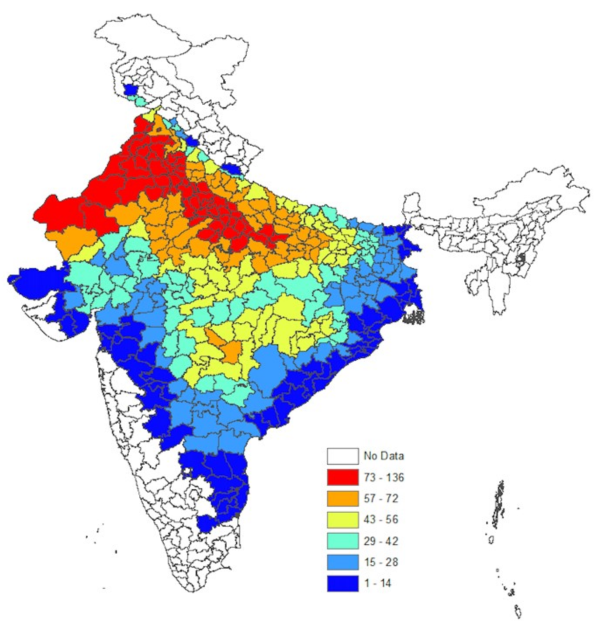
E. Temperature interval: 23-28°C



F. Temperature interval: 28-33°C



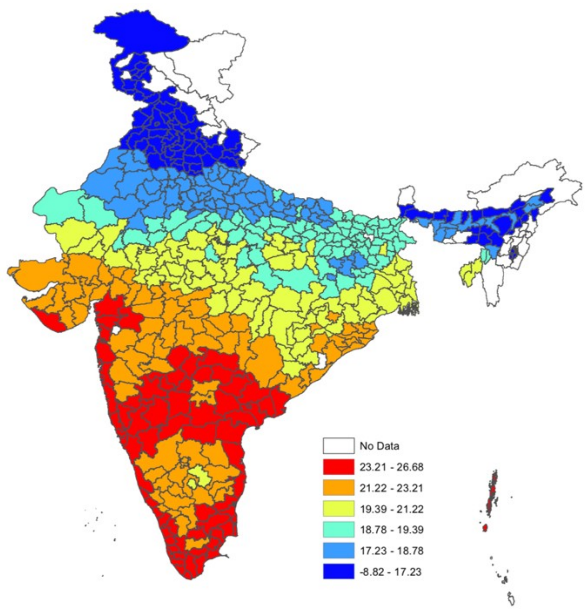
G. Temperature interval: >33°C



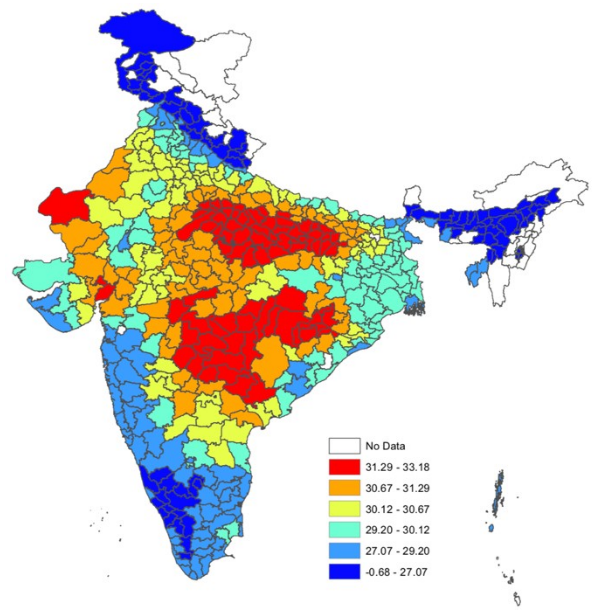
Notes: The figure shows spatial distribution of the average number of days in a year with daily average temperature that falls into one of seven 5°C-wide temperature bins (intervals). The maps display district-level numbers averaged across the years in our study period. Colors close to red depict higher number of days with a specific temperature in a particular interval. The figure indicates notable spatial heterogeneity in temperature across districts and temperature intervals.

Fig. A2. Spatial distribution of seasonal temperatures (1998-2007)

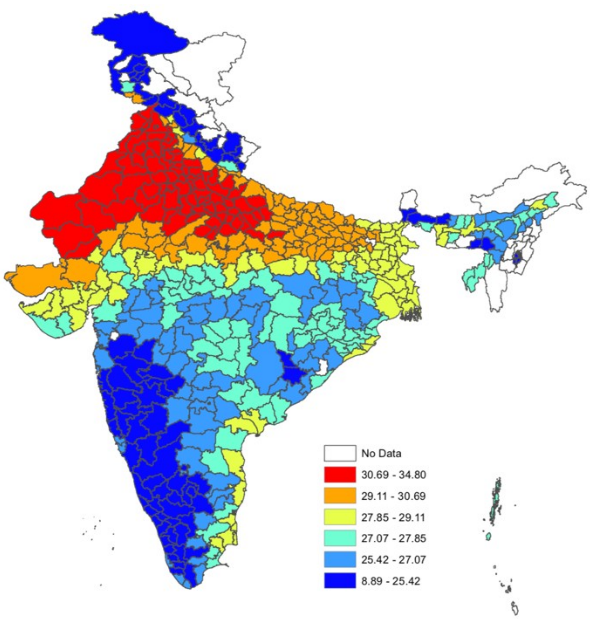
A. Winter temperature



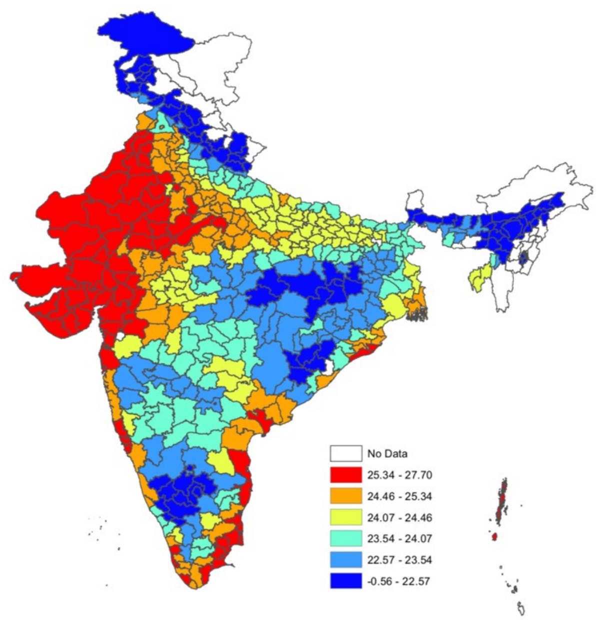
B. Pre-monsoon temperature



C. Monsoon temperature



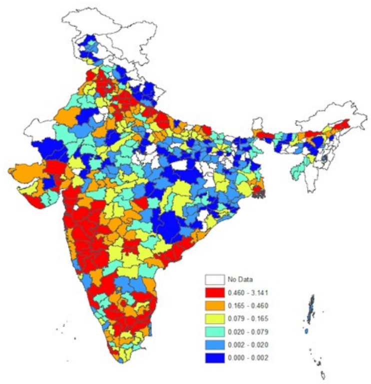
D. Post-monsoon temperature



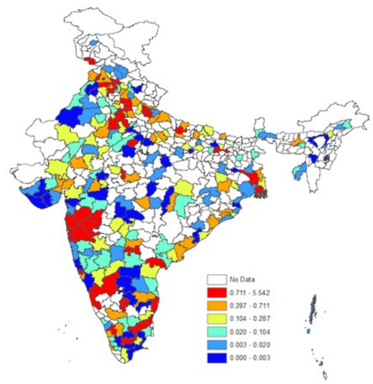
Notes: The figure shows spatial distribution of district-level seasonal temperatures: winter, pre-monsoon, monsoon, and post-monsoon, averaged across the years in our study period. Colors close to red depict higher levels of temperature. The figure indicates notable spatial heterogeneity in temperature across districts and seasons.

Fig. A3. Spatial distribution of industry-wise shares in value-added output (1998-2007)

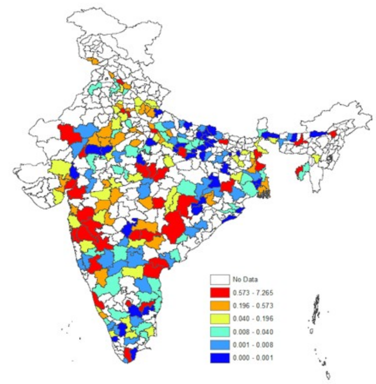
A. Manufacture of foods
430 districts



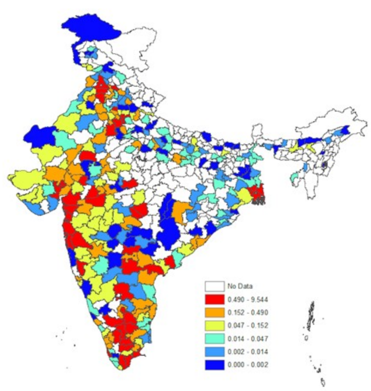
B. Beverages
254 districts



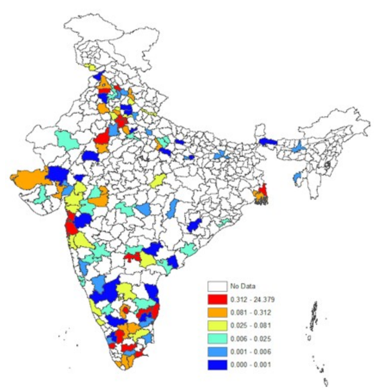
C. Tobacco
227 districts



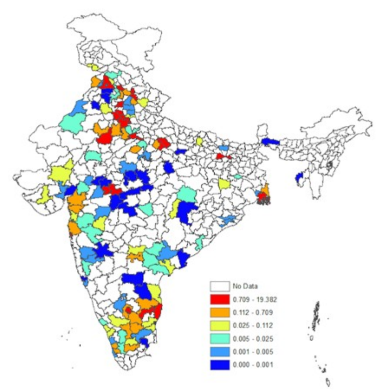
D. Textiles
297 districts



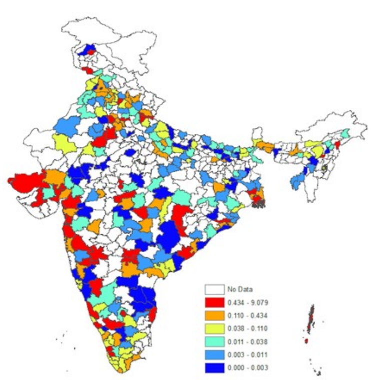
E. Apparel
121 districts



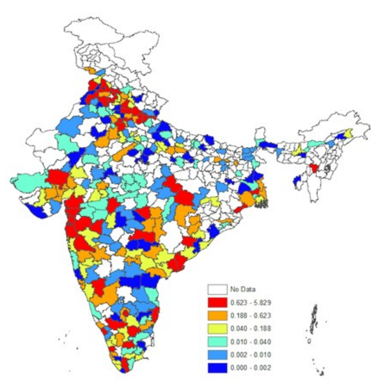
F. Leather
139 districts



G. Timber
264 districts



H. Paper
281 districts



I. Printing
204 districts

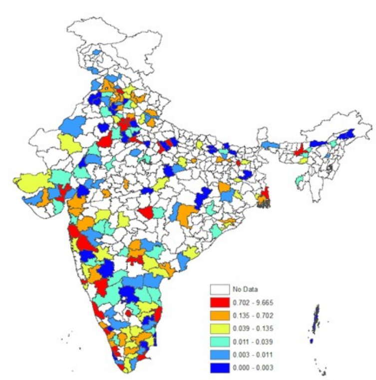
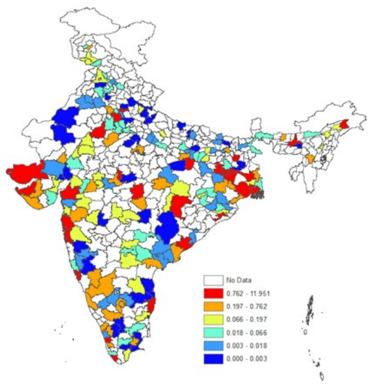


Fig. A3. Spatial distribution of industry-wise shares in value-added output (continued)

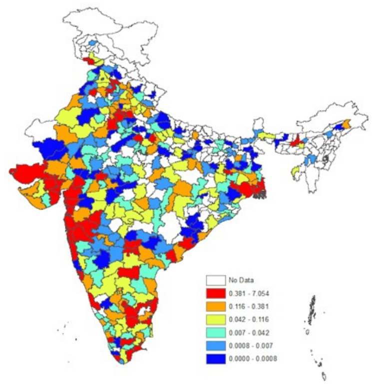
J. Coke, petroleum, nuclear fuel

200 districts



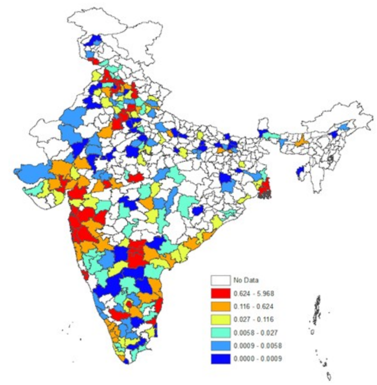
K. Chemicals

341 districts



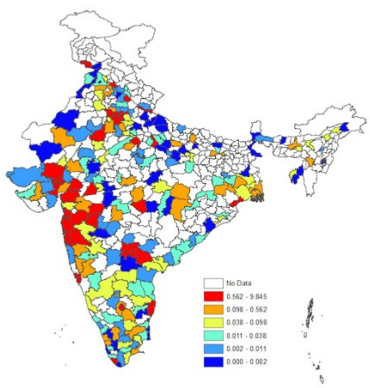
L. Medicines

232 districts



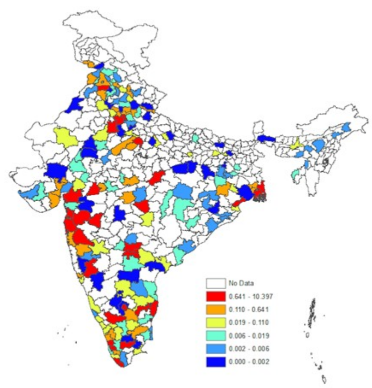
M. Plastics

237 districts



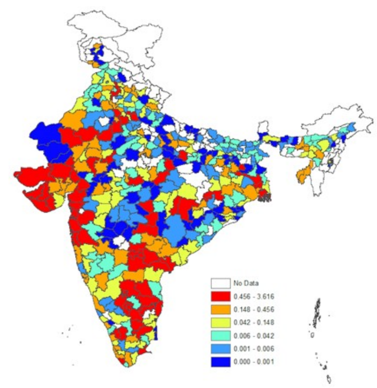
N. Rubber

199 districts



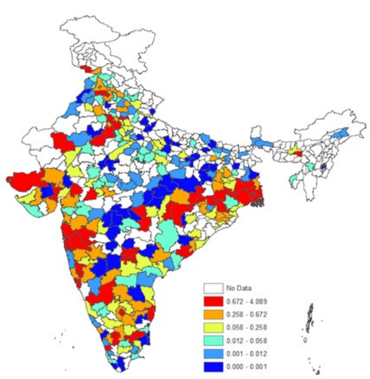
O. Non-metallic minerals

412 districts



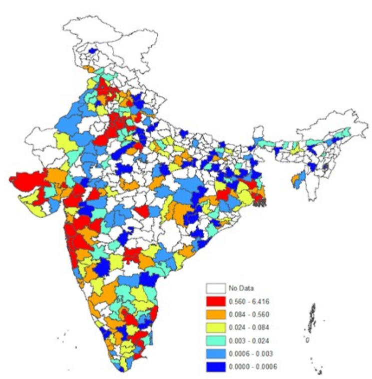
P. Basic metals

289 districts



Q. Fabricated metal products

285 districts



R. Machinery and equipment

263 districts

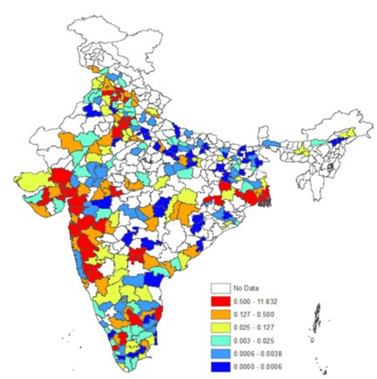
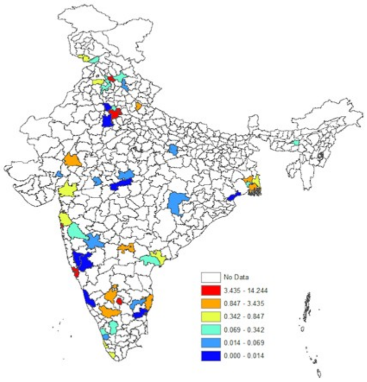


Fig. A3. Spatial distribution of industry-wise shares in value-added output (continued)

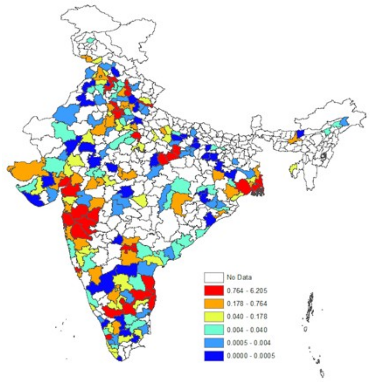
S. Office machinery

57 districts



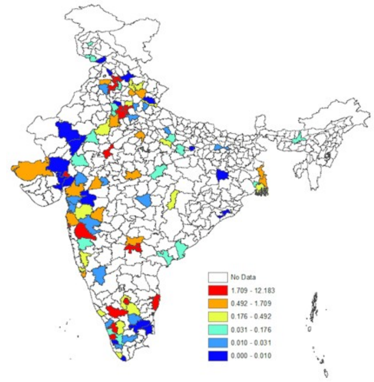
T. Electrical Machinery

226 districts



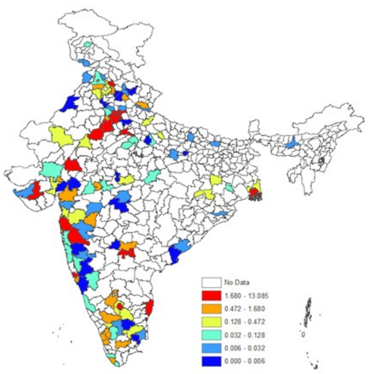
U. Communication equipment

107 districts



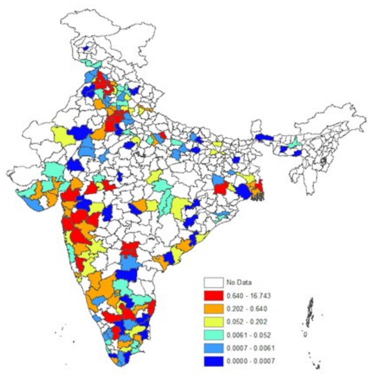
V. Measuring instruments

122 districts



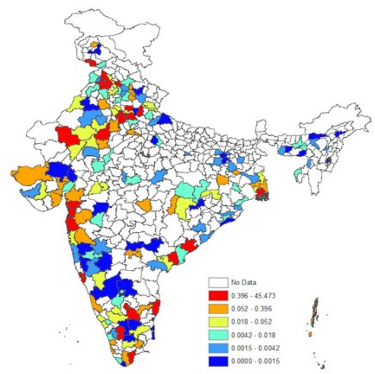
W. Transport equipment

181 districts



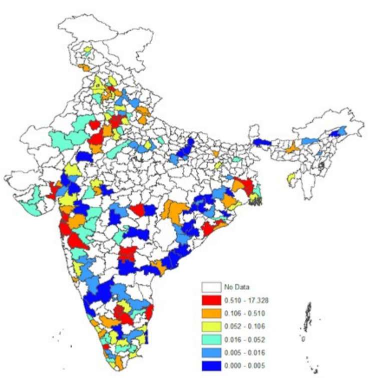
X. Manufacturing n.e.c.

181 districts



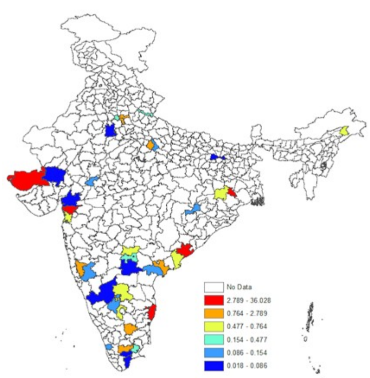
Y. Furniture

171 districts



Z. Recycling

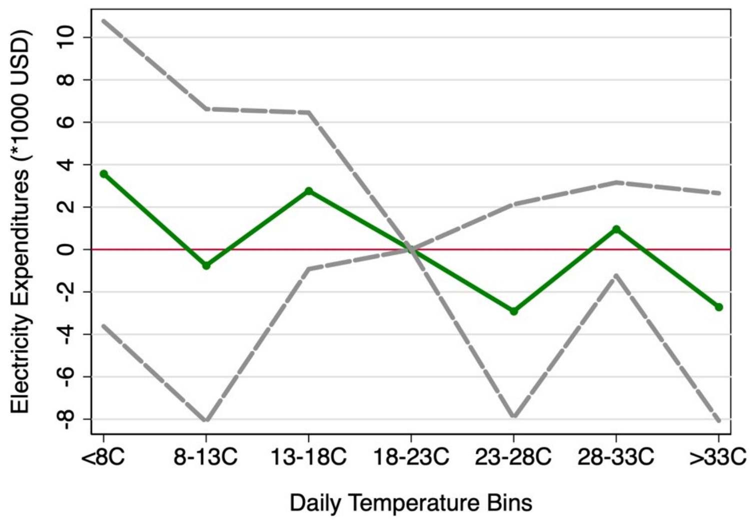
43 districts



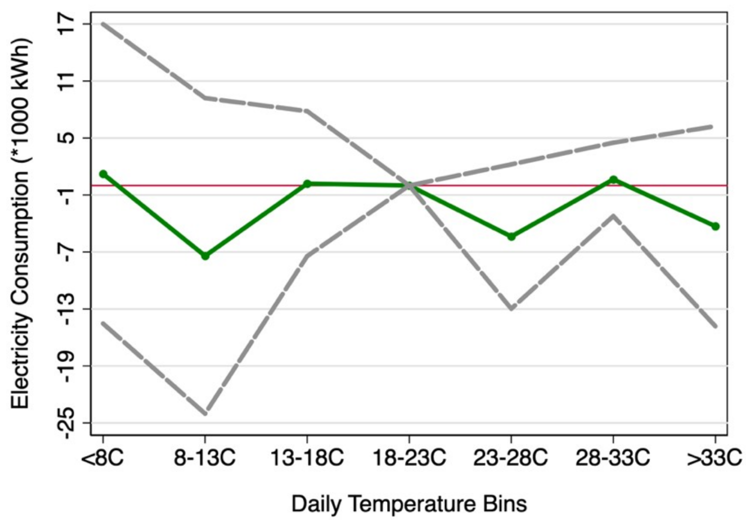
Notes: The figure shows spatial distribution of the district-level value-added output of manufacturing plants across two-digit industries and averaged across the years in our study period. Colors close to red depict higher levels of value-added output. The figure indicates notable spatial heterogeneity in value-added output across districts and industries.

Fig. A4. Estimated responses of electricity expenditures and consumption to temperature

A. Temperature - Electricity Expenditures (*1000 USD)



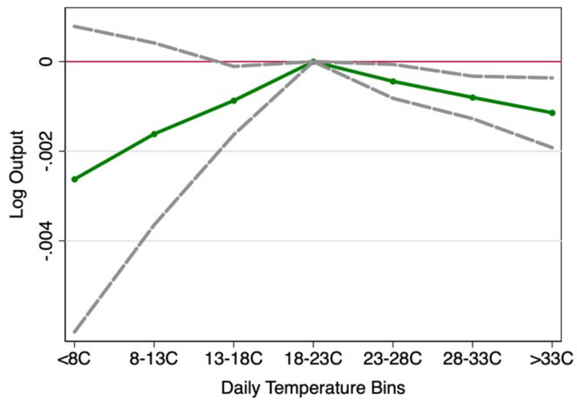
B. Temperature - Electricity Consumption (*1000 kWh)



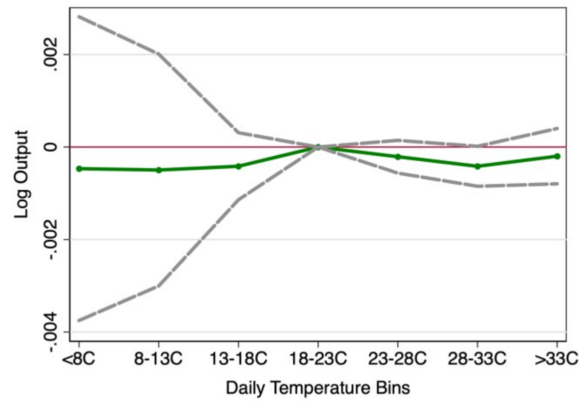
Notes: The figures visualize the estimated temperature-driven effects on the plant-level electricity expenditures (panel A) and electricity consumption (panel B), expressed in 1000 USD and kWh, respectively. The horizontal axes denote temperature bins in degrees Celsius, while the vertical axes show the values of outcome variables. Each panel plots the point estimates of temperature bins (green line) and associated 95% confidence intervals (grey dashed lines) for the coefficients obtained by estimating Eq. (3) with no lags. The outcome variables data come from India's Annual Survey of Industries. The estimates of daily average temperatures are retrieved from NASA's MERRA-2. The regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category. Standard errors are clustered at the plant and district-year levels. The figures generally show that temperature has no statistically significant effects on electricity expenditures and consumption, suggesting that adaptation actions have not been undertaken to reduce the negative impact on output.

Fig. A5. Joint effects of current and lagged temperatures on output and its determinants

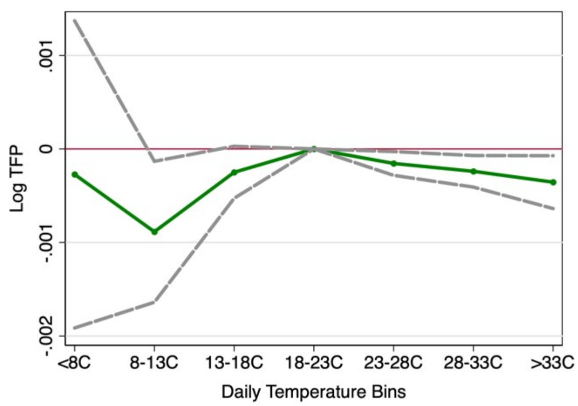
A. Current Temperature - Log Output



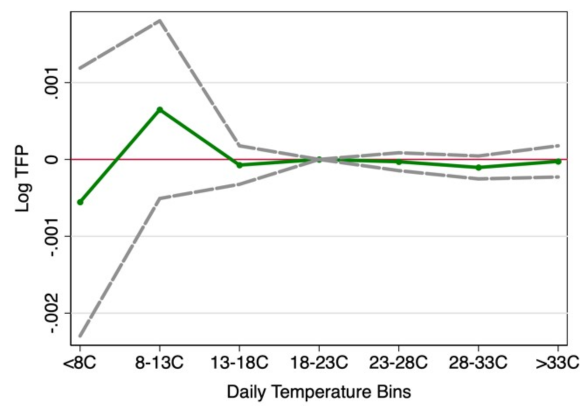
B. Lagged Temperature - Log Output



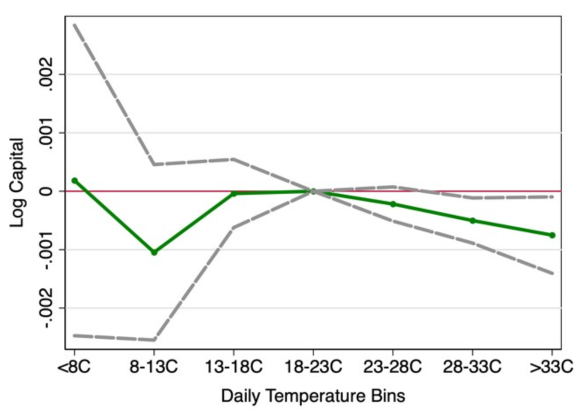
C. Current Temperature - Log TFP



D. Lagged Temperature - Log TFP



E. Current Temperature - Log Capital



F. Lagged Temperature - Log Capital

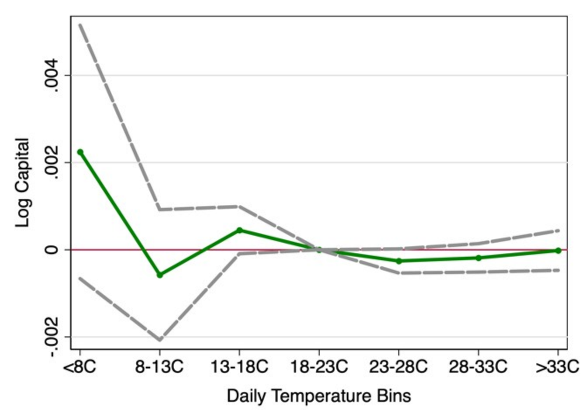
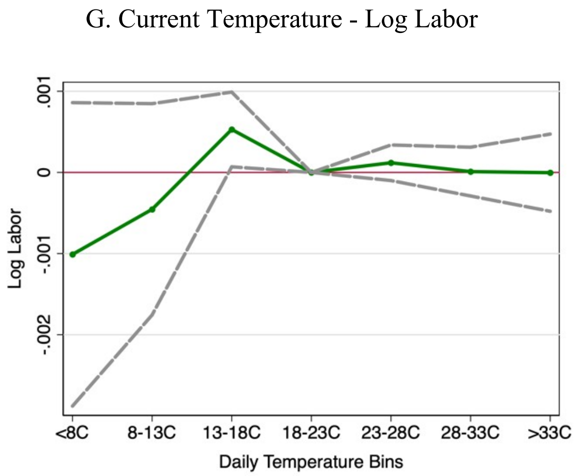
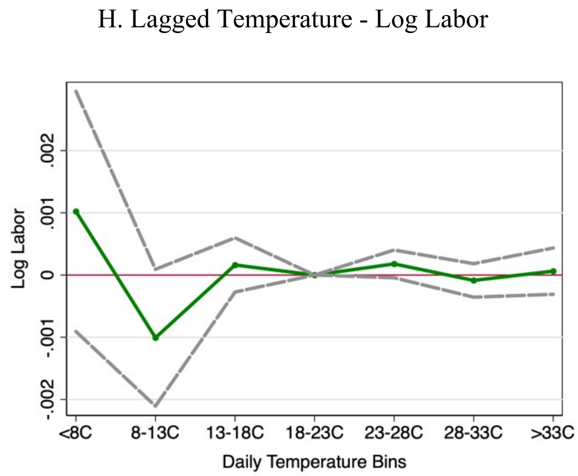


Fig. A5. Joint effects of current and lagged temperatures on output and its determinants (continued)

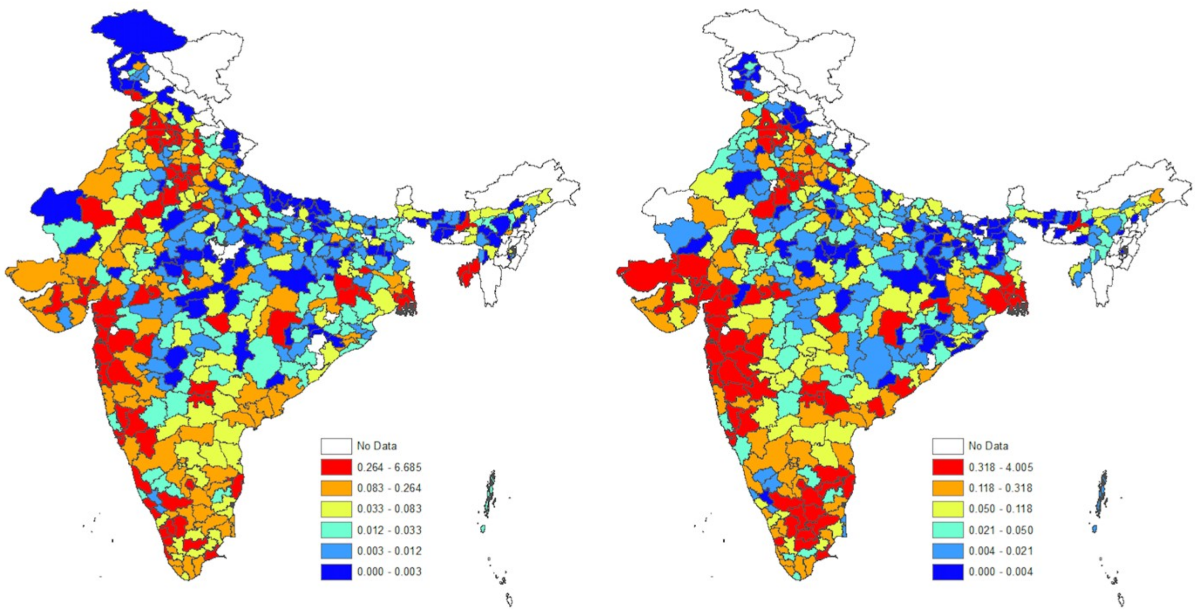




Notes: The figure provides a pairwise comparison between the effects of jointly estimated current and lagged temperatures on log values of manufacturing output (panels A and B), TFP (panels C and D), capital (panels E and F), and labor (panels G and H). The horizontal axes denote temperature bins in degrees Celsius, while the vertical axes show the log values of outcome variables. Each panel plots the point estimates of temperature bins (green line) and associated 95% confidence intervals (grey dashed lines) for the coefficients obtained by estimating Eq. (3) with lagged temperatures and reported in the even columns of Table 2. The regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category. Standard errors are clustered at the plant and district-year levels.

Fig. A6. Spatial distribution of value added-output shares for labor-intensive and capital- intensive plants (1998-2007)

A. Labor-intensive plants B. Capital-intensive plants



Notes: The figure shows spatial distribution of the district-level value-added output shares separately for labor-intensive and capital-intensive manufacturing plants. Plant is defined as labor-intensive if its labor intensity is above the median of all plants in the sample. We define a plant as capital-intensive if its labor intensity is below the median of all plants in the sample. Plant-level labor intensity is measured by the plant-level ratio of wage bill over output, both averaged across sample years. The shares of value-added output are averaged across the years in our study period. Colors close to red depict higher levels of value-added output. The figure indicates notable spatial heterogeneity in value-added output across districts but similar patterns between both types of plants.

Table A1 - Estimated coefficients on weather and air pollution controls: binned temperature

	Output		TFP		Capital		Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0001**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Precipitation squared	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Humidity	-0.7675***	-0.7447***	-0.2101**	-0.2163**	-0.4155*	-0.4452*	0.0534	-0.0345
	(0.2653)	(0.2771)	(0.0954)	(0.0984)	(0.2256)	(0.2400)	(0.1866)	(0.1905)
Humidity squared	0.3505***	0.3300***	0.0757*	0.0735*	0.2118**	0.2336**	-0.0262	-0.0010
	(0.1138)	(0.1168)	(0.0405)	(0.0412)	(0.0936)	(0.0978)	(0.0790)	(0.0804)
Atmospheric pressure	-0.0002**	-0.0002**	-0.0001**	-0.0001**	0.0000	0.0001	-0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Atmospheric pressure squared	0.0000**	0.0000**	0.0000**	0.0000**	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wind speed	-0.0929	-0.1012	0.0223	0.0239	-0.0258	-0.0233	0.0320	0.0197
	(0.1010)	(0.1011)	(0.0362)	(0.0358)	(0.0858)	(0.0855)	(0.0681)	(0.0680)
Wind speed squared	0.0106	0.0118	-0.0022	-0.0021	0.0031	0.0033	-0.0023	-0.0010
	(0.0100)	(0.0100)	(0.0036)	(0.0035)	(0.0084)	(0.0084)	(0.0068)	(0.0068)
PM 2.5	0.0024	0.0025	0.0008*	0.0008*	0.0013	0.0013	-0.0003	-0.0002
	(0.0015)	(0.0015)	(0.0005)	(0.0005)	(0.0011)	(0.0011)	(0.0009)	(0.0009)
PM 2.5 squared	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	0.9385	0.9385	0.8320	0.8320	0.9729	0.9729	0.9596	0.9596
Observations	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged Temperature	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table shows coefficients on weather and air pollution controls estimated using the binned temperature approach (Eq. (3)) and omitted from Table 2. These controls include linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution. Outcome variables are log values of manufacturing output, TFP, capital, and labor. Output is measured by value added, labor - by the total number of employees, and capital - by the total value of fixed assets. TFP is obtained using the Olley-Pakes (1996) approach. The results are presented separately for specifications with and without lagged temperature variables, odd and even columns, respectively. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. All regressions include plant fixed effects and year-by-two-digit-industry fixed effects. Standard errors in parentheses are clustered at the plant and district-year levels.

$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$.

Table A2 - Effects of jointly estimated current and led temperatures on output and its determinants

	Output			TFP			Capital			Labor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<8°C	-0.0027**	-0.0011	-0.0035*	-0.0007	0.0005	-0.0012	0.0020	0.0018	0.0025	0.0000	-0.0005	-0.0003
	(0.0013)	(0.0020)	(0.0018)	(0.0005)	(0.0008)	(0.0008)	(0.0016)	(0.0016)	(0.0017)	(0.0009)	(0.0010)	(0.0009)
8-13°C	-0.0014	-0.0008	-0.0017	-0.0006*	-0.0004	-0.0006*	-0.0012	-0.0010	-0.0011	-0.0006	-0.0003	-0.0006
	(0.0010)	(0.0010)	(0.0011)	(0.0003)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
13-18°C	-0.0007**	-0.0007*	-0.0007*	-0.0002*	-0.0002	-0.0002*	-0.0001	-0.0001	-0.0001	0.0005**	0.0006***	0.0006**
	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
23-28°C	-0.0005**	-0.0005**	-0.0005**	-0.0002**	-0.0002**	-0.0002***	-0.0003*	-0.0003*	-0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
28-33°C	-0.0008***	-0.0008***	-0.0008***	-0.0002***	-0.0002***	-0.0003***	-0.0005***	-0.0005***	-0.0005**	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
>33°C	-0.0012***	-0.0008**	-0.0012***	-0.0004***	-0.0002	-0.0004***	-0.0008***	-0.0009***	-0.0009***	0.0001	0.0000	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Lead 1: <8°C		-0.0027			-0.0017			0.0001			0.0002	
		(0.0023)			(0.0011)			(0.0014)			(0.0010)	
Lead 1: 8-13°C		-0.0032***			-0.0008**			-0.0008			-0.0019***	
		(0.0010)			(0.0004)			(0.0007)			(0.0006)	
Lead 1: 13-18°C		-0.0007**			-0.0003***			-0.0001			0.0001	
		(0.0004)			(0.0001)			(0.0003)			(0.0002)	
Lead 1: 23-28°C		-0.0001			-0.0001			-0.0001			-0.0001	
		(0.0002)			(0.0001)			(0.0002)			(0.0001)	
Lead 1: 28-33°C		-0.0004*			-0.0002**			0.0001			-0.0003*	
		(0.0002)			(0.0001)			(0.0002)			(0.0001)	
Lead 1: >33°C		-0.0002			-0.0000			0.0000			-0.0006***	
		(0.0003)			(0.0001)			(0.0003)			(0.0002)	
Lead 2: <8°C			0.0011			0.0007			-0.0006			0.0005
			(0.0017)			(0.0008)			(0.0016)			(0.0008)
Lead 2: 8-13°C			-0.0002			-0.0003			0.0000			-0.0005
			(0.0008)			(0.0003)			(0.0007)			(0.0006)
Lead 2: 13-18°C			0.0003			0.0001			-0.0003			0.0002
			(0.0004)			(0.0001)			(0.0003)			(0.0002)
Lead 2: 23-28°C			-0.0001			0.0000			-0.0003*			-0.0000
			(0.0002)			(0.0001)			(0.0002)			(0.0001)
Lead 2: 28-33°C			0.0001			0.0001			-0.0000			0.0000
			(0.0002)			(0.0001)			(0.0002)			(0.0002)
Lead 2: >33°C			-0.0003			-0.0000			-0.0000			-0.0002
			(0.0004)			(0.0001)			(0.0003)			(0.0002)
R-squared	0.9385	0.9385	0.9385	0.8320	0.8320	0.8320	0.9729	0.9729	0.9729	0.9596	0.9596	0.9596
Observations	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table shows coefficient estimates of the jointly estimated current and led temperatures on log values of manufacturing output, TFP, capital, and labor. Output is measured by value added, labor - by the total number of employees, and capital - by the total value of fixed assets. TFP is obtained using the Olley-Pakes approach. The coefficients are from the specification that expands our baseline model in Eq. (3) by adding temperature bins constructed using annual distributions of daily temperatures led by one and two years. The estimation results are for specifications without and with led temperature variables. Columns (1), (4), (7), and (10) show coefficients for output, TFP, capital, and labor, respectively obtained from the estimation of our baseline specification and are the same as those in the odd columns of Table 2. Columns (2)-(3), (5)-(6), (8)-(9), and (11)-(12) report coefficients for output, TFP, capital, and labor, respectively estimated by including temperature variables led by one year (odd columns) and two years (even columns). All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. The estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We suppress the coefficients on weather and air pollution controls. Standard errors in parentheses are clustered at the plant and district-year levels.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3 – Summary statistics for labor-intensive and capital-intensive plants

		Unit	Mean	Std. Dev.	Min	Max	Obs	Plants
A. Plant Data								
Output		1000 USD	3,124.19	7,862.17	2.82	69,843.70	263,717	113,305
	Labor-Intensive	1000 USD	287.51	546.38	2.82	28,453.16	131,860	69,042
	Capital-Intensive	1000 USD	5,960.94	10,355.50	4.33	69,843.70	131,857	44,263
TFP		-	11.53	66.02	1.31	12,935.10	263,717	113,305
	Labor-Intensive	-	9.64	15.32	1.31	2,065.33	131,860	69,042
	Capital-Intensive	-	13.43	92.07	2.11	12,935.10	131,857	44,263
Log TFP		-	2.23	0.47	0.27	9.47	263,717	113,305
	Labor-Intensive	-	2.11	0.45	0.27	7.63	131,860	69,042
	Capital-Intensive	-	2.35	0.45	0.75	9.47	131,857	44,263
Labor		persons	133	256	5	4,024	263,717	113,305
	Labor-Intensive	persons	30	41	5	2,029	131,860	69,042
	Capital-Intensive	persons	236	328	5	4,024	131,857	44,263
Capital		1000 USD	5,653.05	20,022.82	0.06	493,258.90	263,717	113,305
	Labor-Intensive	1000 USD	433.48	1,665.46	0.06	148,049.00	131,860	69,042
	Capital-Intensive	1000 USD	10,872.74	27,286.90	0.09	493,258.90	131,857	44,263
B. Weather and Pollution Data								
Temperature		°C	25.90	1.51	0.53	28.92	263,717	113,305
	Labor-Intensive	°C	25.91	1.55	0.53	28.92	131,860	69,042
	Capital-Intensive	°C	25.89	1.47	6.28	28.92	131,857	44,263
Temperature - Winter		°C	21.01	3.28	-8.82	26.96	263,717	113,305
	Labor-Intensive	°C	20.90	3.35	-8.82	26.96	131,860	69,042
	Capital-Intensive	°C	21.12	3.21	-3.25	26.96	131,857	44,263
Temperature - Pre-monsoon		°C	29.08	2.04	-0.68	33.93	263,717	113,305
	Labor-Intensive	°C	29.08	2.06	-0.68	33.93	131,860	69,042
	Capital-Intensive	°C	29.08	2.02	5.20	33.93	131,857	44,263
Temperature - Monsoon		°C	27.85	2.84	8.90	35.99	263,717	113,305
	Labor-Intensive	°C	27.95	2.89	8.90	36.00	131,860	69,042
	Capital-Intensive	°C	27.75	2.80	12.71	36.00	131,857	44,263
Temperature - Post-monsoon		°C	24.45	1.85	-0.56	29.39	263,717	113,305
	Labor-Intensive	°C	24.45	1.88	-0.56	29.39	131,860	69,042
	Capital-Intensive	°C	24.44	1.82	4.82	29.39	131,857	44,263
Precipitation		mm	1,106.28	574.62	48.17	4,098.84	263,717	113,305
	Labor-Intensive	mm	1,108.39	591.90	48.17	4,098.84	131,860	69,042
	Capital-Intensive	mm	1,104.18	556.80	55.07	4,098.84	131,857	44,263
Humidity		kg/kg*100	1.16	0.28	0.30	1.75	263,717	113,305
	Labor-Intensive	kg/kg*100	1.15	0.28	0.30	1.75	131,860	69,042
	Capital-Intensive	kg/kg*100	1.17	0.27	0.42	1.75	131,857	44,263
Wind speed		m/s	5.03	0.74	2.43	6.73	263,717	113,305
	Labor-Intensive	m/s	5.01	0.73	2.43	6.73	131,860	69,042
	Capital-Intensive	m/s	5.05	0.74	2.43	6.73	131,857	44,263
Atmospheric pressure		Pa	97,535.78	2,689.76	63,978.79	100,903.30	263,717	113,305
	Labor-Intensive	Pa	97,581.65	2,740.72	63,978.79	100,903.30	131,860	69,042
	Capital-Intensive	Pa	97,489.90	2,637.04	67,783.47	100,903.30	131,857	44,263
$PM_{2.5}$		$\mu g/m^3$	49.11	24.20	12.59	120.50	263,717	113,305
	Labor-Intensive	$\mu g/m^3$	49.66	24.19	12.59	120.50	131,860	69,042
	Capital-Intensive	$\mu g/m^3$	48.55	24.18	12.59	120.50	131,857	44,263

Notes: The table summarizes statistics of plant-level characteristics, weather, and pollution data separately for labor- and capital-intensive plants. Plant data are from the Annual Survey of Industries. Weather data are from NASA's MERRA-2. PM2.5 air pollution data are from the Atmospheric Composition Analysis Group at Dalhousie University, Canada. Output is measured by value added. TFP is obtained using the Olley-Pakes approach. Labor is measured by the total number of employees. Capital is measured by the total value of fixed assets. All monetary values are in 2007 U.S. dollars. Temperature variables are calculated as the annual or seasonal mean values from daily average estimates. Humidity, wind speed, atmospheric pressure are the annual mean values. Precipitation is calculated as the annual sum from daily average estimates. PM2.5 concentrations are in annual mean values.

Table A4 - Effects of jointly estimated current and lagged temperatures on TFP across labor-intensive and capital-intensive plants

		Labor Intensity =1 if wage bill/output > median	
	Full Sample (1)	Labor-Intensive (2)	Capital-Intensive (3)
<8°C	-0.0003	-0.0004	0.0001
	(0.0008)	(0.0011)	(0.0012)
8-13°C	-0.0009**	-0.0008*	-0.0009*
	(0.0004)	(0.0005)	(0.0005)
13-18°C	-0.0002*	-0.0002	-0.0003*
	(0.0001)	(0.0002)	(0.0002)
23-28°C	-0.0002**	-0.0002**	-0.0001
	(0.0001)	(0.0001)	(0.0001)
28-33°C	-0.0002***	-0.0003***	-0.0002
	(0.0001)	(0.0001)	(0.0001)
>33°C	-0.0004**	-0.0007***	-0.0001
	(0.0001)	(0.0002)	(0.0002)
L1: <8°C	-0.0006	0.0000	-0.0016
	(0.0009)	(0.0011)	(0.0013)
L1: 8-13°C	0.0006	0.0006	0.0008
	(0.0006)	(0.0007)	(0.0007)
L1: 13-18°C	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0002)	(0.0002)
L1: 23-28°C	-0.0000	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)
L1: 28-33°C	-0.0001	-0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)
L1: >33°C	-0.0000	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
R-squared	0.8320	0.8583	0.7846
Mean Temp (°C)	25.90	25.91	25.89
Shares (%)	100	50.00	50.00
Observations	263,717	131,860	131,857

Notes: The table shows coefficient estimates of the temperature effects on log TFP across labor-intensive and capital-intensive plants obtained using lagged specification of Eq. (3). TFP is measured using the Olley-Pakes (1996) approach. Plant-level labor intensity is measure by the plant-level ratio of wage bill over output both averaged across sample years. The plant is defined as labor-intensive if its labor intensity is above the median of all plants in the sample. Column (1) shows estimates for the full sample as they are reported in our baseline temperature effects on TFP in column (4) of Table 2. Columns (2) and (3) present estimates for labor-intensive and capital-intensive plants, respectively. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. The estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We suppress the coefficients on weather and air pollution controls. Standard errors in parentheses are clustered at the plant and district-year levels.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 - Effects of jointly estimated current and lagged temperatures on capital by components

	Capital	Land	Buildings	Plant & Machinery	Transport Equipment	Computer Equipment	Other Fixed Assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<8°C	0.0002	0.0041**	-0.0001	-0.0009	-0.0025	-0.0010	0.0002
	(0.0014)	(0.0020)	(0.0016)	(0.0017)	(0.0021)	(0.0018)	(0.0017)
8-13°C	-0.0010	0.0007	-0.0009	-0.0021**	-0.0019	-0.0033***	-0.0002
	(0.0008)	(0.0011)	(0.0010)	(0.0010)	(0.0014)	(0.0011)	(0.0012)
13-18°C	0.0000	0.0003	-0.0002	-0.0004	0.0010**	0.0004	-0.0005
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
23-28°C	-0.0002	-0.0003	-0.0001	-0.0003*	-0.0001	-0.0003	-0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
28-33°C	-0.0005**	-0.0003	-0.0005**	-0.0006**	-0.0001	-0.0004	-0.0007**
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
>33°C	-0.0008**	-0.0001	-0.0007	-0.0008**	-0.0001	-0.0003	-0.0009*
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
L1: <8°C	0.0022	-0.0006	0.0026	0.0017	0.0025	0.0015	0.0026
	(0.0015)	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0014)	(0.0019)
L1: 8-13°C	-0.0006	0.0011	-0.0004	-0.0016*	0.0006	0.0010	-0.0000
	(0.0008)	(0.0011)	(0.0009)	(0.0009)	(0.0012)	(0.0009)	(0.0011)
L1: 13-18°C	0.0005	0.0001	0.0005	0.0002	0.0009*	0.0007*	0.0002
	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0005)
L1: 23-28°C	-0.0003*	-0.0001	-0.0002	-0.0004**	-0.0001	-0.0004*	-0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
L1: 28-33°C	-0.0002	0.0002	-0.0001	-0.0005**	-0.0006**	-0.0002	-0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
L1: >33°C	-0.0000	0.0001	-0.0000	-0.0003	-0.0004	-0.0005	0.0005
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
R-squared	0.9729	0.9271	0.9533	0.9629	0.8838	0.8718	0.9288
Observations	263,717	263,717	263,717	263,717	263,717	263,717	263,717

Notes: The table shows coefficient estimates of the temperature effects on capital by component obtained using lagged specification of Eq. (3). Dependent variables are log values of the overall capital, land, buildings, plant and machinery, transport equipment, computer equipment, and other fixed assets. Capital components are defined according to the ASI documentation and represent the depreciated value of fixed assets owned by plants on the closing day of the accounting year. Column (1) reports our baseline temperature effects on the overall capital from column (5) of Table 2. All regressions control for linear and quadratic forms of precipitation, humidity, atmospheric pressure, wind speed, fine particulate air pollution and include plant fixed effects and year-by-two-digit-industry fixed effects. The temperature bin (18°C, 23°C) is set as an omitted, reference category to avoid collinearity. The estimated temperature effects can be interpreted as the marginal effects of an extra day in the mth temperature bin relative to a day in the (18°C, 23°C) bin. We suppress the coefficients on weather and air pollution controls. Standard errors in parentheses are clustered at the plant and district-year levels.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6 - Estimated coefficients on weather and air pollution controls: seasonal temperature

	Output		TFP		Capital		Labor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation^{Winter}	-0.0001	-0.0001	-0.0000	-0.0000	-0.0001	-0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Precipitation$^{Pre\text{-}Monsoon}$	0.0001**	0.0001*	0.0000	-0.0000	-0.0000	-0.0000	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Precipitation^{Monsoon}	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000***	-0.0000***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Precipitation$^{Post\text{-}Monsoon}$	0.0000	0.0000	0.0000	0.0000*	0.0000	0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Humidity^{Winter}	0.0898	0.1117	-0.0129	-0.0037	0.0157	0.0016	0.0831*	0.0896*
	(0.0691)	(0.0713)	(0.0237)	(0.0245)	(0.0522)	(0.0533)	(0.0459)	(0.0464)
Humidity$^{Pre\text{-}Monsoon}$	-0.0274	-0.0451	-0.0434**	-0.0537**	0.0953**	0.1123**	0.0085	-0.0004
	(0.0595)	(0.0597)	(0.0214)	(0.0217)	(0.0462)	(0.0467)	(0.0390)	(0.0395)
Humidity^{Monsoon}	-0.1100	-0.1312	0.0286	0.0228	-0.0206	-0.0078	-0.0005	0.0064
	(0.0810)	(0.0833)	(0.0284)	(0.0295)	(0.0635)	(0.0658)	(0.0517)	(0.0538)
Humidity$^{Post\text{-}Monsoon}$	0.0096	0.0074	-0.0012	-0.0039	-0.0474	-0.0423	0.0611**	0.0554**
	(0.0397)	(0.0400)	(0.0143)	(0.0146)	(0.0313)	(0.0314)	(0.0269)	(0.0270)
Pressure^{Winter}	0.0000	0.0001	-0.0000	-0.0000	-0.0001	-0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Pressure$^{Pre\text{-}Monsoon}$	-0.0005***	-0.0006***	-0.0001***	-0.0002***	-0.0001	-0.0000	-0.0001	-0.0001*
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Pressure^{Monsoon}	0.0001	0.0002*	0.0001*	0.0001**	0.0000	-0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Pressure$^{Post\text{-}Monsoon}$	0.0003***	0.0003***	0.0001***	0.0001***	0.0002**	0.0002*	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wind speed^{Winter}	0.0112	0.0143	0.0010	0.0024	0.0086	0.0057	-0.0028	-0.0030
	(0.0112)	(0.0113)	(0.0039)	(0.0039)	(0.0085)	(0.0086)	(0.0075)	(0.0075)
Wind speed$^{Pre\text{-}Monsoon}$	-0.0108	-0.0139	-0.0017	-0.0031	-0.0037	-0.0010	0.0048	0.0040
	(0.0105)	(0.0105)	(0.0035)	(0.0036)	(0.0081)	(0.0082)	(0.0068)	(0.0068)
Wind speed^{Monsoon}	-0.0077	-0.0113	0.0033	0.0013	-0.0020	0.0021	-0.0067	-0.0085
	(0.0088)	(0.0089)	(0.0030)	(0.0031)	(0.0070)	(0.0070)	(0.0059)	(0.0060)
Wind speed$^{Post\text{-}Monsoon}$	0.0131*	0.0159**	-0.0016	-0.0000	0.0020	-0.0010	0.0119**	0.0149***
	(0.0073)	(0.0076)	(0.0027)	(0.0028)	(0.0055)	(0.0058)	(0.0052)	(0.0054)
PM 2.5	0.0031**	0.0033**	0.0009*	0.0010*	0.0021*	0.0020*	0.0003	0.0004
	(0.0015)	(0.0015)	(0.0005)	(0.0005)	(0.0012)	(0.0012)	(0.0009)	(0.0009)
PM 2.5 squared	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	263,717	263,717	263,717	263,717	263,717	263,717	263,717	263,717
Observations	0.9385	0.9385	0.8320	0.8320	0.9729	0.9729	0.9596	0.9596
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-by-Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Lagged Temperature	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table shows coefficients on weather and air pollution controls estimated using the seasonal temperature approach (Eq. (4)) and omitted from Table 3. These controls include seasonal precipitation, humidity, atmospheric pressure, wind speed, and linear and quadratic forms of fine particulate air pollution. Outcome variables are log values of manufacturing output, TFP, capital, and labor. Output is measured by value added, labor - by the total number of employees, and capital - by the total value of fixed assets. TFP is obtained using the Olley-Pakes approach. The estimation results are presented separately for specifications with and without lagged temperature variables, odd and even columns for each outcome variable, respectively. All regressions include plant fixed effects and year-by-two-digit-industry fixed effects. Standard errors in parentheses are clustered at the plant and district-year levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2 Environmental Regulations, Air Pollution, and Infant Mortality in India: A Reexamination

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2.1 Introduction

Substantial health and economic costs of air pollution have forced countries around the world to enact increasingly stringent environmental regulations (Botta and Koźluk, 2014). Whether such regulations have been effective remains an important policy question, particularly in developing countries that suffer from weak institutions, severe air pollution, and limited data availability.

An American Economic Review paper by Michael Greenstone and Rema Hanna (2014) – henceforth, GH – is an important piece of empirical evidence for this line of research. It examines the impact of air pollution control policies in India on two integral dimensions of effectiveness: policy-induced changes in air pollution and associated changes in infant mortality.[29,30] Interestingly, GH report somewhat counterintuitively that the policies have been effective in improving air quality but have had a modest and statistically insignificant effect on infant mortality.[31] A likely explanation for GH's findings might stem from the scarcity of reliable air pollution measures and the effects of unaccounted confounding factors. I show that GH's dataset, which was constructed using readings from a spatially sparse network of public air pollution monitors, suffers from high interannual variability in sample size, relatively inaccurate measures of

[29] GH also assess the effects of water pollution regulations, but I focus exclusively on the part of GH's paper that analyzes the effectiveness of air pollution regulations.

[30] Matus et al. (2012) show that health costs account for 71.4% of total air pollution-induced welfare losses in China and that mortality captures around 86% of those losses. Others have shown that mortality impacts associated with air pollution are strongest for infants (Ebenstein et al.; 2015, Tanaka, 2015). Compared to adults, infants' deaths lead to larger losses in life expectancy.

[31] GH's findings contradict the conclusions of others in the literature. There is a substantial body of causal evidence that the regulation-induced improvements in air quality in developing countries lead to a decline in infant mortality. For example, see Foster, Gutierrez, and Kumar (2009), Ebenstein et al. (2015), Tanaka (2015), He, Fan, and Zhou (2016), Cesur, Tekin, and Ulker (2016).

air pollution, and the absence of critical meteorological confounders. I argue that ignoring these limitations could potentially lead to misleading conclusions about the effectiveness of air pollution mitigation efforts. Coupled with the prominence of GH's study, this conclusion motivates a reexamination of GH's findings using alternative data sources.

This chapter reexamines the link between environmental regulations, air pollution, and infant mortality using new data that were unavailable to GH. I take advantage of satellite-based data to revise air pollution measures and to extract meteorological conditions that proved to be important confounders. Maintaining GH's methodology, I test the sensitivity of their findings to the revised air pollution outcomes, extended number of observations, and meteorological controls. Thus, comparing results using satellite-based to ground-based data used by GH, I present complementing empirical evidence on the effectiveness of air pollution control policies in India.

Based on a careful account of similarities and disparities in the results generated by two data sources, it seems reasonable to confirm GH's findings and interpret air pollution control policies in India as effective, although with substantially weaker effects on air pollution. Further research exploring the prospects for using satellite-based data will be particularly valuable, especially for developing countries. Such research will be critical in uncovering the effects of environmental regulations and recommending sensible interventions to mitigate the environmental burden of air pollution and to protect population health.

2.2 Review of Greenstone and Hanna (2014)

Using a panel of 140 Indian cities for the years 1987-2007, GH assess the impact of the Supreme Court Action Plans (SCAP) and the Mandated Catalytic Converters (CAT) on air pollution and infant mortality. Both policies belong to the command-and-control instruments and were at the forefront of India's environmental regulation since the 1970s. SCAP are a suite of policy actions aimed at reducing pollution in the cities identified by the Supreme Court of India as critically polluted. SCAP typically vary across cities and can take different forms depending on the type of targeted air pollutant.[32] CAT requires new cars to be equipped with a catalytic converter –

[32] Action plans for vehicular pollution include an odd-even program for private cars, compulsory retirement of old vehicles, or restrictions on the use of heavy vehicles, while plans that regulate industrial pollution include the mandated reallocation of heavily polluting industries, installation of specific abatement technologies, or bans on production processes.

an exhaust emission control device aimed at reducing toxic gases and pollutants in the exhaust gas by converting them into less harmful pollutants using catalyzing reaction. There are two distinctive features of this regulation. First, its enforcement is stringent as vehicle registrations are tied to the installation of catalytic converters. Second, its impact obviously increases over time with the increase in the share of newer vehicles (Greenstone, Harish, Pande, and Sudarshan, 2017).

SCAP and CAT policies can plausibly affect air pollutants analyzed in GH: nitrogen dioxide (NO2), sulfur dioxide (SO2), and suspended particulate matter (SPM). NO2 and SO2 are gaseous air pollutants composed of oxygen and nitrogen or sulfur, respectively. The primary sources of NO2 emissions are vehicles, power plants, and off-road equipment. SO2 emissions are primarily from the combustion of sulfur-containing fossil fuels for thermal power generation and industrial facilities. NO2 and SO2 convert in the atmosphere to nitrates and sulfates, respectively, and contribute to the formation of particulate matter. Particulate air pollution is a complex mixture of solid and liquid particles of various chemicals and sizes. SPM consists of particles of less than 100 micrometers (μm) in diameter and is a general indicator of air pollution. All three pollutants are widely considered to cause serious health and economic costs (U.S. EPA, 2022a).

GH's empirical strategy combines event study and difference-in-differences designs in a two-step econometric approach. At the first step, the approach measures average annual levels of air pollutants and infant mortality in the pre and post policies' adoption periods, while in the second step, it tests for the policies' impact. Equations (1) and (2) correspond to the first and second-step specifications. Together, these equations represent GH's preferred specification that controls for city fixed effects, year fixed effects, preexisting differential trends in the outcomes, and allows for a mean shift and trend break after the policies' implementation. Identifying variation comes from the variation in the timing of the policies' enactment across cities.

$$Y_{ct} = \alpha + \sum_{\tau} \sigma_{\tau} D_{\tau,ct} + \beta X_{ct} + \mu_t + \gamma_c + \epsilon_{ct} \tag{1}$$

where Y_{ct} is an outcome variable measuring either concentrations of air pollutants or infant mortality rate in city c in year t. $D_{\tau,ct}$ is a vector of indicator variables for each year before and after a policy is in force. τ is normalized so that it is equal to zero in the year the policy was enacted; it ranges from −17 (for 17 years before a policy's adoption in a city) to 12 (for 12 years after its adoption). For the nonadopting cities, τs are equal to zero. $X_{ct}$is a set of additional control variables (consumption per capita and literacy rates). μ_t – year fixed effects to control for year-specific common shocks for all cities; γ_c – time-invariant city fixed effects to control for the permanent unobserved determinants of the outcome variable across cities. Equation (1) is weighted by the district-urban population in air pollution estimations and by the number of births in infant mortality estimations. The coefficients of interest σ_τ measure the levels of average annual outcomes in the pre- and postadoption periods. The estimated coefficients $\widehat{\sigma_\tau}$ are then fit into equation (2) that corresponds to the equation (2C) in GH.

$$\widehat{\sigma_\tau} = \pi_0 + \pi_1 1(Policy)_\tau + \pi_2 \tau + \pi_3 (1(Policy)_\tau \cdot \tau) + \epsilon_\tau \qquad (2)$$

where $1(Policy)_\tau$ is a dummy variable that takes on the value 1 to indicate that the policy is in force; τ is a linear time trend to control for the differential preexisting trends in adopting cities. $1(Policy)_\tau \cdot \tau$ allows for the policies' effects to evolve over time; ϵ_τ – heteroskedasticity-consistent standard errors. GH weight equation (2) by the inverse of the standard errors for the relevant σ_τ to account for differences in precision in the σ_τ's estimation. The specification tests for a policy impact after adjustment for the trend in outcome variable (π_2), and allows for both a mean shift (π_1) and trend break (π_3). From this equation, GH also report the policies' effects five years after implementation, $\pi_1 + 5\pi_3$. They then complement a two-step approach by its numerically identical one-step version.[33]

[33] The specification below represents a one-step version of the two-step approach. GH include both policies into the one-step approach and limit the policies' dummies to the observed event years to preserve the comparability with the two-stage approach, specifically 20 city years for CAT and 15 city years for SCAP.

$$\begin{gathered} Y_{ct} = \alpha + \theta_1 1(SCAP\ Range)_\tau + \theta_2 1(SCAP)_\tau * (SCAP\ Range)_\tau + \theta_3 1(SCAP\ Range)_\tau * \tau \\ + \theta_4 1(SCAP)_\tau * \tau * (SCAP\ Range)_\tau + \theta_5 1(\tau Left)_\tau + \theta_6 1(\tau Right)_\tau + \rho_1 1(CAT\ Range)_\phi \\ + \rho_2 1(CAT)_\phi * (CAT\ Range)_\phi + \rho_3 1(CAT\ Range)_\phi * \phi + \rho_4 1(CAT)_\phi * \phi * (CAT\ Range)_\phi \\ + \rho_5 1(\phi Left)_\phi + \rho_6 1(\phi Right)_\phi + \beta X_{ct} + \mu_t + \gamma_c + \epsilon_{ct} \end{gathered}$$

$1(SCAP\ Range)_\tau$ is a dummy variable for $-7 \leq \tau \leq 3$ and $1(CAT\ Range)_\phi$ is a dummy variable for $-7 \leq \phi \leq 9$; $1(SCAP)_\tau$ and $1(CAT)_\phi$ are the policy dummies that indicate whether $SCAP$ or CAT policies are in force and that take on the value 1 for the adopting cities with $\tau \geq 0$ and/or $\phi \geq 0$; $1(\tau Left)_\tau$ and $1(\tau Right)_\tau$ are dummies indicating

GH's central result is that the Mandated Catalytic Converters policy was strongly associated with air pollution reduction. Specifically, five years after the policy was in force, SPM and SO2 concentrations declined by 48.6 μg/m3 and 13.5 μg/m3, or 19% and 69% of the 1987–1990 nationwide mean concentrations. The impact of the CAT policy on NO2 was a statistically insignificant decline by 4.4 μg/m3 or 19% of the 1987–1990 nationwide mean concentrations. In contrast, the Supreme Court Action Plans resulted in a marginally statistically significant decline in NO2 concentrations without any evidence of an impact on SPM and SO2. GH then proceed with the CAT policy, i.e. the one that was found to be the most strongly related to improvements in air quality, to show that the policy resulted in a modest and statistically insignificant decline in infant mortality.

2.3 Data

I reexamine the effectiveness of air pollution control policies combining GH's original datasets with new and improved data. GH undertook an extensive data-collecting exercise and made resulting datasets and Stata do-files publicly available.[34] I use GH's data on environmental regulations, infant mortality, and sociodemographic characteristics without modification. Instead, I revise data on air pollution outcomes and add key meteorological confounders absent in GH's paper.

2.3.1 GH's Data Limitations

Air Pollution Data

GH's air pollution data came from India's Central Pollution Control Board (CPCB), which operates a national network of ground-based monitoring stations. GH obtained monthly city-by-

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that $\tau < -7$ or $\tau > 3$, respectively; by analogy, $1(\phi Left)_\phi$ and $1(\phi Right)_\phi$ indicate that $\phi <$¿-7 or $\phi >$¿9, respectively; $1(SCAP\ Range)_\tau * \tau$ and $1(CAT\ Range)_\phi * \phi$ are a linear time trend variables interacted with a policy range dummies; $1(SCAP)_\tau * \tau * (SCAP\ Range)_\tau$ and $1(CAT)_\phi * \phi * (CAT\ Range)_\phi + \rho_5$ are policy*time-trend*policy-range interaction terms; ϵ_{ct} – standard errors clustered at the city-level (Bertrand, Duflo, and Mullainathan, 2004).

[34] I downloaded GH's data and Stata code from the *AER* website.

state monitor readings for NO2, SO2, and SPM concentrations from a spatially sparse network of 572 monitors in 140 cities.[35] To calculate the annual average concentrations for each city, GH took a simple average of the monthly average concentrations for the monitors within the city.

GH's final air pollution dataset has two major issues. First, the sample size is substantially restricted and highly variable. Column 1 of Table 1 tabulates the number of cities in GH's sample with at least one monitor reading in a particular year. Thus, the city counts in this column represent the maximum possible number of the cities available for the analysis in a given year. This number varies substantially because CPCB's monitor readings are not available for all years for most of the cities. Only 20 of 140 cities were covered by the monitoring network in 1987, while 115 cities were monitored by 2007. Another concern is that some of the monitors were not operating for a whole sample of cities, were not functioning appropriately, or were moved and reclassified over the years. These reasons may explain the substantial variability in GH's sample size over time. As column 1 indicates, the number of cities was steadily increasing until 1993 when it reached 65. Then, the sample size declined sharply to 42 cities in 1995, rapidly increased to 73 in 1997, dropped again to 54 in 2001, and continued growing until it peaked in 2007 with 115 cities. The variability appears high, although GH do not discuss this issue in detail. GH further restricted the sample of cities based on the availability of air pollution data. Policy-adopting cities were included in the analysis if they had at least one observation three or more years before the policy's implementation and at least one observation four or more years after. Non-adopting cities and adopting cites without post-policy pollution data were included if they had at least two air pollution readings.

[35] For comparison, the U.S. network of ground-based monitors that measure ambient PM concentrations consists of around 1200 monitors. This network covers 63% of the U.S. population in less than 20% of U.S. counties and is still considered spatially sparse by researchers (Sullivan and Krupnick, 2018; Fowlie, Rubin, and Walker, 2019).

Table 1 – Number of cities and prevalence of air pollution control policies

	Cities		Policies	
	GH sample	Full sample	SCAP	CAT
Year	1	2	3	4
1987	20	140	0	0
1988	25	140	0	0
1989	31	140	0	0
1990	44	140	0	0
1991	47	140	0	0
1992	58	140	0	0
1993	65	140	0	0
1994	57	140	0	0
1995	42	140	0	2
1996	68	140	0	4
1997	73	140	1	4
1998	65	140	1	22
1999	74	140	1	26
2000	66	140	1	24
2001	54	140	1	19
2002	63	140	1	22
2003	72	140	11	25
2004	78	140	15	24
2005	93	140	16	24
2006	112	140	16	24
2007	115	140	16	24

Notes: The table corresponds to GH's Table 1. SCAP and CAT stand for the Supreme Court Action Plans and the Mandated Catalytic Converters. Column 1 shows the number of the cities that have at least one air pollution reading in the particular year. Those numbers represent maximums out of 140 cities (column 2) used in GH. Columns 3 and 4 show the number of cities where the specified policy was implemented.

Second, measures of the city-level concentrations might be relatively inaccurate. Several problems can emerge when using a sparse network of monitors to infer air pollution levels. First, there can be significant discrepancies between the monitor's readings and surface concentrations because of air pollution's physical properties. The fundamental issue is that air pollution can both vary sharply over short distances with higher concentrations downwind of the source of emission and travel long distances from its source being dispersed by wind or washed away by rain. Therefore, the further a particular location is from a monitor, the less accurate is the measure of concentration inferred from this monitor for this location (Sullivan, 2016; Sullivan and Krupnick, 2018). Second, evidence shows that local officials can manipulate ground-based pollution readings, particularly in developing countries (Andrews, 2008; Chen, Jin, Kumar, and Shi, 2012;

Ghanem and Zhang, 2014). Such manipulations can take the form of strategically placing monitors in less polluted parts of the cities, relocating monitors from locations downwind of polluters to locations upwind, or even spraying water over monitors to decrease local pollution concentrations (Fan and Grainger, 2019). Third, the aggregation method used in GH can also cast doubt on the accuracy of measurements. A monitor measures concentration from a single point in space to represent a concentration over a city, in which neighborhoods can have a varying landscape, wind pattern, population density, and emission sources. However, in 2007, 18% of sample cities did not have a SPM monitor, 21% had one monitor, 31% had two monitors, and 16% had three. Thus, an aggregation by a simple averaging can be highly misleading. Ideally, the computation of air pollution levels that relies on data obtained from ground-based monitors should include the interpolation of monitor-level data into the surface.[36] The outcomes of this procedure, i.e. average concentrations at every grid point, can then be temporally and spatially aggregated by averaging concentrations at all grid points that fall within the cities' administrative boundaries. Following these steps, one can accurately measure the city-level pollution concentrations over time.

Meteorological Data

Additionally, GH's dataset does not include meteorological conditions. Not controlling for these conditions can potentially confound GH's findings because of the significant impact of meteorological conditions on air pollution and infant mortality. Apart from anthropogenic emissions, meteorological forces are the primary factors that shape air pollution trends over cities around the world.[37] They play a critical role in dispersion, transformation, transport, removal of air pollutants in the atmosphere and can exacerbate or mitigate their concentrations (Zhong et al., 2018; Li et al., 2019; He at al., 2019; Zhou et al., 2020). Rain can wash air pollutants away and high wind speeds disperse them, lowering concentrations. Low wind speeds coupled with low winter temperatures and thermal inversions tend to worsen air quality, increasing concentrations. In turn, these processes also affect infant mortality, indirectly through the impact on air pollution or directly (Goyal, 2002). Many studies find statistically significant effects of extreme air

[36] This can be usually achieved using spatial interpolation methods such as inverse distance weighting or Kriging.

[37] For example, variation in meteorological conditions explains more than 70% of daily variations in five air pollutants in major Chinese cities during the 2014-2015 period (He et al., 2017) and up to 50% of daily PM2.5 variation in the U.S. during the 1998-2008 period (Tai, Mickley, and Jacob, 2010).

temperature, rainfall, and humidity on infant mortality in developed and developing countries (Deschênes and Greenstone, 2011; Kudamatsu, Persson, and Strömberg, 2012; Gasparrini et al., 2015; Barreca, 2016; Heutel, Miller, and Molitor, 2017; Burgess et al., 2017; Geruso and Spears, 2018). Thus, ignoring considerable fluctuations in meteorological conditions can lead to misleading conclusions about the effectiveness of air pollution mitigation efforts. In line with this argument, Sullivan (2016) formally shows that economic studies underestimate the effects of changes in air pollution exposure, including those induced by exogenous shock, because of the bias that arises when researchers do not account for meteorological confounders, specifically for wind speed. It has been shown that at the time of writing GH, publicly available in-situ monitor readings of meteorological conditions in India were highly sparse and erratic (Burgess et al., 2017). That likely explains the absence of these data in GH's dataset, despite an extensive data collection exercise.

Nevertheless, high variability in the interannual sample size, relatively accurate measures of air pollution concentrations, and the absence of important meteorological confounders motivate a reexamination of GH's findings using alternative data sources.

2.3.2 New and Revised Data

Revised Air Pollution Outcomes

To address the issues with GH's air pollution data, I leverage recent advances in satellite technology. I construct air pollution outcomes, i.e. annual city-level averages of fine particulate matter (PM2.5) and sulfur dioxide (SO2), from the satellite-based Aerosol Optical Depth (AOD) retrievals.[38] AOD measures the amount of sunlight absorbed, reflected, and scattered by particles suspended in the air. Satellite observations of AOD make it possible to estimate surface PM2.5 and SO2 concentrations at granular spatial resolution and with comprehensive geographical and temporal coverage. AOD-based estimates are a good proxy of air pollution over India (Dey et al., 2012).

[38] Data on NO2 concentrations are not readily available for the temporal and geographic scope required for GH's reexamination.

I replace GH's SPM with the satellite-based estimates for PM2.5, a fraction of SPM with a much smaller diameter: less than 2.5 μm compared to less than 100 μm. Size is an important indicator of the particles' penetrating ability that highlights the most probable site of the respiratory tract where they can be trapped being inhaled. Smaller PM2.5 particles penetrate deeper into the lungs, pass through them, and get into the bloodstream, thus causing more severe adverse health effects than GH's SPM (Schwartz, Dockery, & Neas, 1996; U.S. EPA, 2004; WHO, 2006a). Substantial scientific evidence across disciplines shows that PM2.5 exposure can result in various health impacts, including respiratory, cardiovascular, and nervous system effects, cancer, and mortality (for more details, see U.S. EPA, 2022b). SMP and PM2.5 are originated from the same primary sources, which can be anthropogenic or natural. The former sources include manufacturing processes, vehicular exhaust, power generation, household heating, cooking, and fuel combustion, while the latter adds sea salt, dust, volcanic and fire ash. Secondary sources, like sulfates and nitrates formed in the atmosphere through chemical reactions, also contribute to the formation of secondary SPM and PM2.5. More toxic components of particulate matter are generally contained in the fine fraction (Larssen & Hagen, 1997), which makes PM2.5 a more sophisticated air pollution exposure indicator. An increasing number of social scientists focus on PM2.5 to study the effectiveness of environmental regulations, health effects, and the economic impacts of pollution exposure (Voorheis, 2016; Chen, Oliva, & Zhang, 2017; Fu, Viard, & Zhang, 2017; Sullivan & Krupnick, 2018; Fowlie, Rubin, & Walker, 2019). PM2.5 data were unavailable to GH as PM2.5 monitoring in India started only in 2009 after the second revision of the national air quality standards.

I obtained satellite-based estimates for PM2.5 and SO2 concentrations from NASA's Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2; GMAO, 2015).[39] MERRA-2 data result from atmospheric reanalysis that combines satellite-based measurements of AOD, ground-based monitor readings, and other sources with sophisticated chemical-transport and climate modeling to create gridded estimates for surface air pollution variables. MERRA-2 reanalysis data are widely used in various studies due to their high quality, granular spatial and temporal resolutions, and diverse atmospheric variables (Chen et al., 2017; Fu et al., 2017; He et al., 2019). MERRA-2 is the only alternative that provides estimates for PM2.5 and SO2 concentrations for GH's sample years, 1987-2007. For comparison, another source of air

[39] M2TMNXAER product, version 5.12.4.

pollution data popular among social scientists, van Donkelaar et al. (2019), provides estimates for PM2.5 concentrations starting only from 1998. Therefore, MERRA-2 is my preferred source of data for air pollution outcomes.

MERRA-2 provides global gridded data of monthly means at 0.5º x 0.625º spatial resolution (approximately 56km x 69km at the equator). Estimates for SO2 concentrations are readily available, while PM2.5 concentrations need to be calculated using estimates for PM2.5 components: dust (DUST2.5), sea salt (SS2.5), black carbon (BC), organic carbon (OC) and sulfate particulate (SO4).[40] I follow the literature from atmospheric science, Buchard et al. (2016), and apply equation (3) to calculate PM2.5 concentrations at every grid point.

$$PM_{2.5} = DUST_{2.5} + SS_{2.5} + BC + 1.4 * OC + 1.375 * SO_4 \quad (3)$$

Fig. 1 maps the resulting spatial distribution of MERRA-2 PM2.5 and SO2 pollution in India. Panels A and B show long-run average PM2.5 and SO2 concentrations in µg/m3 for 1987-2007. The figure depicts higher levels of air pollution with the shades of red color. For PM2.5, broad areas in North-West India, Gangetic Plains, and northern regions of Central India are well above national and WHO air quality guidelines, which are annual averages of 40 µg/m3 and 10 µg/m3, respectively. Even though there are observable SO2 hot spots, most of India is in rough compliance with the national standard, which is 50 µg/m3.

To map MERRA-2 air pollution concentrations to the city level, I construct urban extent polygons that correspond to the cities' administrative boundaries using 2011 ML InfoMap's digital maps.[41] The definition of what to consider a city is a major challenge as GH do not provide any information about this. I rely on the operational definition of an urban area (town) adopted by the Office of the Registrar General and Census Commissioner of India as, I believe, GH also did by default.[42] They retrieved data from the official administrative sources, and I assume that Indian

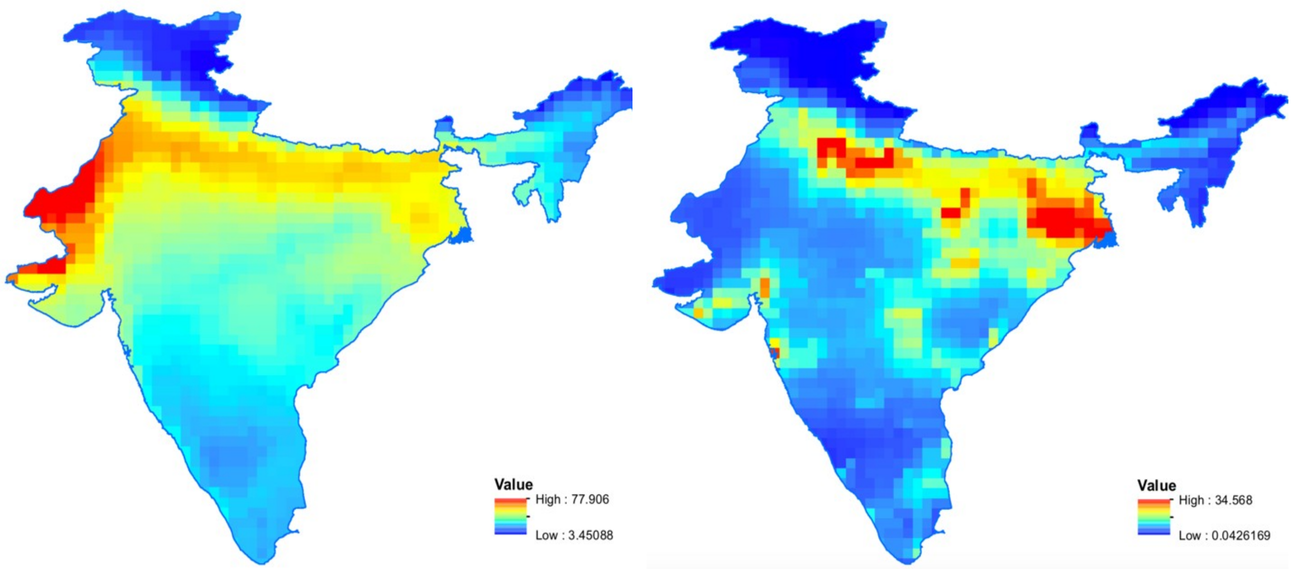
[40] Sources of SO4 (sulfate), BC and OC (carbonaceous) are emissions from power plants, vehicle exhaust, and biomass burning. DUST2.5 comes from local arid sources or transported from abroad by dust storms. SS2.5 penetrates the land from the seas and oceans.

[41] State-wise ML InfoMap village (and town) boundary polygons represent a digital map that provides socio-demographic and economic census data in GIS file format. I downloaded ML InfoMap's shapefiles from the Princeton University Digital Maps and Geospatial Data Library during my research visit.

[42] The Office of the Registrar General and Census Commissioner of India is the central authority in charge of the population (Census) and vital statistics. The Census statistics for urban areas (towns) comprises two types of towns,

government agencies, including CPCB, define administrative units uniformly. The list of the cities was obtained from GH's Stata do-files and Vital Statistics of India, while the cities' geometry from the maps in the India District Census Handbooks 2011.[43]

A. Average PM2.5, 1987-2007 B. Average SO2, 1987-2007



Notes: The figure maps spatial distributions of PM2.5 and SO2 concentrations constructed using MERRA-2 reanalysis products. Panels A and B show long-run average PM2.5 and SO2 concentrations in μg/m3 for 1987-2007, respectively. Shades of red color depict higher concentrations of the specific air pollutants.

Fig. 1. Spatial distribution of air pollution concentrations in India, 1987-2007

ML InfoMap's digital maps depict cities' administrative boundaries as of 2011, a year that is outside of GH's study period of 1987-2007. Whenever possible, I adjust the resulting polygons so that they correspond to the cities' administrative boundaries as they were at the time of the 2001Census. Most of the District Census Handbooks contain Table 3 that provides a list of new towns, denotified, declassified, and merged during the decade of 2001-2011. Exploiting this

namely Statutory towns and Census towns. Statutory towns are all places with a municipality, corporation, cantonment board or notified town area committee. Census towns are defined as a place satisfying three criteria simultaneously: (i) a minimum population of 5000; (ii) at least 75% of the male working population engaged in non-agricultural activities; (iii) a density of population of at least 400 persons per km^2 (Census of India 2011).

[43] Princeton University also granted access to the annual issues of the Vital Statistics of India. India District Census Handbooks depicting district-wise village and town administrative boundaries as of 2011 were downloaded from the website of the Census of India.

information, I retrieve ML InfoMap's administrative boundaries polygons net of 2001-2011 changes. In rare cases in which the ML InfoMap's digital maps do not contain cities' boundaries, I geo-reference and digitize them using maps from the District Census Handbooks. For some of the larger cities, their administrative boundaries consist of several ML InfoMap polygons, which I merge to obtain a single polygon for each city.

Overall, I selected the final sample of 140 polygons from about 619,000 across 28 Indian states. Appendix Fig. A1 through A5 highlight the construction of the resulting cities' administrative boundaries. Finally, I average monthly MERRA-2 PM2.5 and SO2 concentrations to annual levels and then take an average of annual average concentrations at all MERRA-2 grid points that fall within the cities' administrative boundaries. The final dataset represents city-by-year annual PM2.5 and SO2 average concentrations for the years 1987-2007.

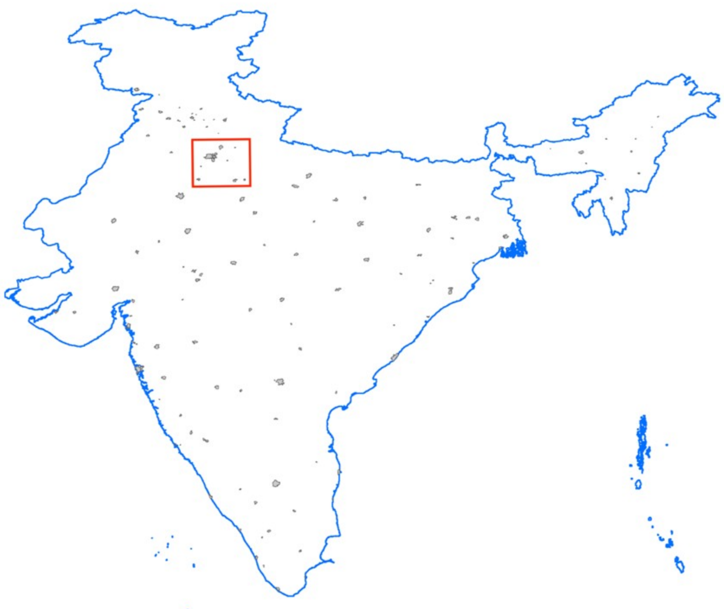
Fig. 2 shows the exact geometry and location of the constructed urban extent polygons and examples of cities with already assigned concentrations of PM2.5 and SO2 air pollution.

Concerns About Revised Air Pollution Outcomes

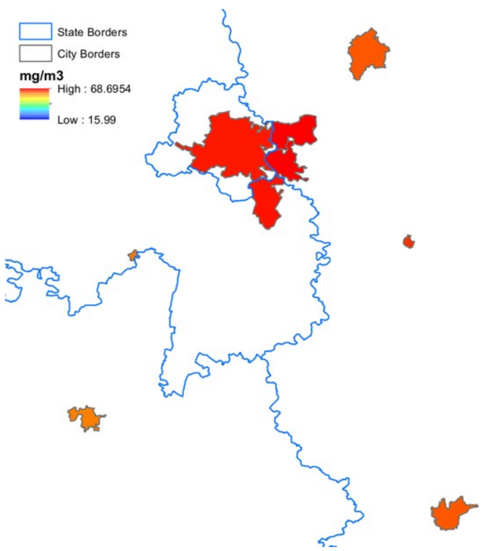
Resulting estimates of the city-level average concentrations of air pollution are not immune to plausible concerns. The first two pertain to MERRA-2 data and the approach I use to construct the cities' administrative boundaries, while the last one is common to all satellite-based estimates.

MERRA-2 PM2.5 data lack nitrate particulate matter, an important PM2.5 component and precursor, primarily emitted by vehicle exhaust and industrial activities (Buchard et al., 2016; He et al., 2019). Thus, resulting from the equation (3), estimates of PM2.5 concentrations can underestimate ground-based PM2.5 measurements. As a sensitivity test, I construct estimates for PM2.5 concentrations for the years 1998-2007 using van Donkelaar et al. (2019) and compare them with MERRA-2 PM2.5 concentrations. Previous studies point on a good match between van Donkelaar's PM2.5 estimates and ground-based PM2.5 observations (van Donkelaar et al., 2013; He et al., 2019). Therefore, a high correlation coefficient between MERRA-2 and van Donkelaar's PM2.5 estimates (91%) provides evidence for high consistency between them and relaxes the MERRA-specific concern.

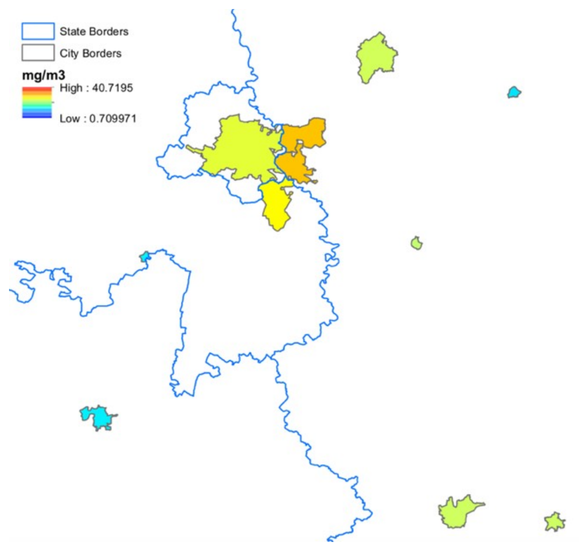
A. City-level administrative boundaries



B. Average PM2.5, a closer look



C. Average SO2, a closer look



Notes: The figure denotes all cities from the full sample with the resulting administrative boundaries. Panel A depicts the cities preserving their exact geometry and location across India. Panels B and C show examples of the cities with already assigned levels of PM2.5 and SO2 pollution in µg/m3 for randomly selected year 2004. Shades of red color depict higher concentrations of the specific air pollutants. The cluster of four cities at the center represents the capital city of Delhi (National Capital Territory), Ghaziabad and Noida (Uttar Pradesh), and Faridabad (Haryana). Despite the spatial proximity of these cities, the approach that I use to construct their exact urban extent polygons allows me to assign air pollution to each of these cities and to analyze them as separate administrative units. PM2.5 and SO2 pollution measures are constructed using the MERRA-2 reanalysis product and represent annual average concentrations at the city's level.

Fig. 2. Cities' administrative boundaries with assigned air pollution levels

The approach I use to construct the cities' administrative boundaries might also be subject to concern. As I use ML InfoMap's digital maps with administrative boundaries as they were at a single year, the resulting urban extent polygons do not trace the cities' spatial expansion at different points in time. However, Seto et al. (2011) show that Indian cities were expanding at an average annual rate of 4.84% between 1970 and 2000. This evidence raises the possibility that the approach I adopt in this study can potentially lead to measurement error. Generally, too narrowly or too broadly defined boundaries of urban footprints may affect an assignment of air pollution. Nevertheless, I believe that this is not a major concern, and my approach is preferable to other available alternatives. I pursued the goal of constructing urban extent polygons separately for each city in GH's sample and preserving consistency with GH's default definition of a city. However, the most commonly used alternative approach for the delineation of urban areas, night-time lights satellite imagery, fell short in achieving this goal. Appendix Fig. A6 provides an illustration. The figure compares urban extent polygons defined by the cities' administrative boundaries in this study with those defined by the combination of the night-time lights and buffered settlement centroids in the Global Rural-Urban Mapping Project (GRUMP).[44]

Two apparent observations arise. First, urban areas retrieved from the night-time lights dataset do not correspond to their Census counterparts, making it impossible to obtain a single polygon for each city. For example, the cluster of four cities at the center of the figure includes the capital city of Delhi, Ghaziabad, Noida, and Faridabad. Despite spatial proximity, the approach I use allows me to analyze these cities as separate administrative units. In contrast, GRUMP's output is a single polygon, a multi-city agglomeration that extends beyond the administrative boundaries of these four cities and additionally includes the city of Meerut 70 kilometers away from Delhi to the North-East.[45]

Second, even if both approaches result in a single polygon for each city, the polygons retrieved from the night-time lights are larger than the polygons represented by the cities' administrative boundaries. This observation suggests that GRUMP polygons overestimate the extent of the cities. The GRUMP relies on the 1994/1995 stable city night-time lights dataset, meaning that the resulting output exhibits boundaries of urban areas as of 1995. However, given

[44] More information about the GRUMP can be found at https://sedac.ciesin.columbia.edu/data/collection/grump-v1/about-us.

[45] This is because the approach based on the night-time lights satellite imagery delineates urban areas by considering spatially contiguous lighted pixels surrounding a city's coordinates, with luminosity above a pre-defined threshold.

the evidence above of Seto et al. (2011), it is highly unlikely that the ML InfoMap polygons of the adjusted cities' administrative boundaries as of 2001 were smaller than the corresponding GRUMP polygons as of 1995. Thus, I believe that the approach used in this study performs well and matches the goal better.

Finally, a limitation common to all satellite-based estimates is that such estimates are just a reflection of the actual air pollution concentrations and are prone to prediction and forecast errors. Fowlie et al. (2019) highlight the importance of accounting for these errors. In this study, however, it is difficult to perform such a check because of the limited availability of reliable ground-based air pollution measurements for India. In general, a comprehensive analysis of this issue is yet to be discussed in the literature and is beyond the scope of this study.

New Meteorological Data

To control for the effects of the meteorological conditions on air pollution and infant mortality, I collect data on air temperature, precipitation, and wind speed.[46] Specifically, I obtain raw data on these covariates from various MERRA-2 reanalysis products and process them the same way as air pollution data to construct variables at the city-by-year level.[47] MERRA-2 temperature and precipitation data have been successfully validated against the observation-based Indian Meteorological Department data, indicating that MERRA-2 products are reliable substitutes to the observed weather indicators (Ghodichore et al., 2018; Gupta et al., 2020).

I control flexibly for meteorological confounders by including $f(W_{ct})$ into equation (1) and a one-step version of GH's two-step approach. W_{ct} is a set of meteorological covariates that includes a count of the number of days each year in which the average daily temperature falls into 10 temperature bins, precipitation calculated as the annual sum from daily observations and its quadratic, and a count of the number of days each year in which the average daily wind speed falls into 12 wind speed bins.

[46] Most of the relevant studies in economic literature control at least for air temperature and precipitation. However, Sullivan (2016) and Zhang, Zhang, and Chen (2017) demonstrate the importance of additional meteorological covariates, especially humidity and wind speed.

[47] M2I1NXLFO product for air temperature and wind speed; M2T1NXLND product for precipitation

In particular, to estimate the effects of daily temperatures on annual outcomes, I follow a widely-used method that transforms an annual distribution of daily temperatures into a set of temperature bins (Deschênes and Greenstone, 2011; Deryugina and Hsiang, 2014; Cheng and Yang, 2017; Zhang et al., 2018). This approach allows flexible estimation of nonlinear temperature effects across daily temperature values. In practice, a vector of temperature bins, $Temp_{ct}^{m}$, denotes the number of days in year t with daily average temperatures in city c that fall into the mth temperature bin, m = 1,2,…,10. Following Burgess et al. (2017), I divide daily average temperatures, measured in °C, into ten bins, each of which is 3 °C wide. For example, $Temp_{ct}^{1}$ is the number of days in city c during year t with daily temperature below 12 °C. Then, $Temp_{ct}^{10}$ is the number of days with temperature above 35 °C. To avoid collinearity, the temperature bin (21°C, 23 °C) is set as an omitted, reference category.

A vector of wind speed bins, $Wind_{ct}^{m}$, is constructed similarly, but bins are defined as a Beaufort wind scale. I distributed daily average wind speeds, measured in knots, between 12 categories that characterize wind force from calm to hurricane.

2.3.3 Comparison of Trends

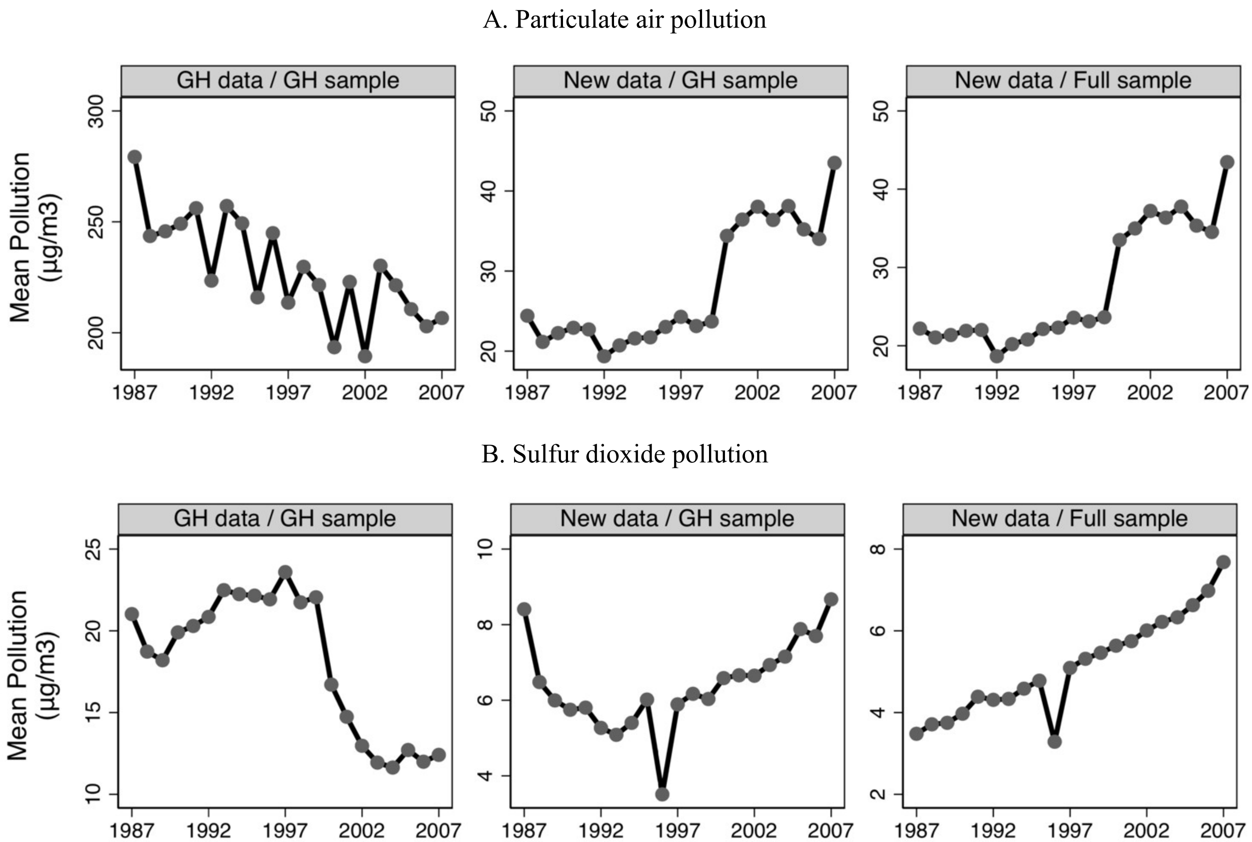
Fig. 3 compares trends in air pollution outcomes constructed using CPCB data exploited by GH and the data obtained from MERRA-2 products. Panels A and B plot the city-level average concentrations of particulate matter and SO2 for the years 1987-2007. Left-hand graphs in both panels show SPM and SO2 trends in GH's data for the restricted sample of cities used in GH.[48] Right-hand graphs show trends in MERRA-2 PM2.5 and SO2 for the full sample of 140 cities, while the middle graphs plot the trends for the same pollutants across GH's sample of cities. Compared to GH's data, revised air pollution outcomes yield substantially more city-by-year observations: 2,940 against 1,370 and 1,344 for GH's particulate matter and SO2, respectively. I refer to these observations as the GH sample and the full sample. Table 2 provides the corresponding sample statistics for both ground-based and satellite-based data. The table reports the city-level averages, the number of observations, the tenth and ninetieth percentiles of air

[48] These graphs correspond to the first two graphs in panel A of GH's Fig. 4.

pollution outcomes, meteorological variables, and infant mortality rate, broken down by the whole of GH's study period, early (1987-1990), and later (2004-2007) periods of the sample.

The striking finding that immediately emerges from Figure 3 is the opposite air pollution trends in GH's data relative to MERRA-2 data. While SPM and SO2 levels were falling in GH, concentrations of the revised air pollution outcomes are continuously increasing. As Table 2 indicates, concentrations of GH's SPM fall steadily from 252.13 μg/m3 during 1987-1990 to 209.42 μg/m3 during 2004-2007, or a 17% reduction. SO2 concentrations are quite stable until the late 1990s but then decline sharply from the 1987-1990 levels, overall, by 37% during 2004-2007, from 19.36 to 12.19 μg/m3. In contrast, the concentrations of MERRA-2 PM2.5 increase by 68% in 2004-2007 compared to 1987-1990, from 22.63 to 37.92 μg/m3 for GH's sample of cities. Similarly, MERRA-2 SO2 concentrations increase by 24%, from 6.36 to 7.89 μg/m3. The increase in the revised air pollution outcomes is even more pronounced for the full sample of cities, 75% and 85% for PM2.5 and SO2, respectively.

Appendix Fig. A7 provides additional evidence on the opposite trends. It compares kernel density estimates of GH's and revised air pollutant distributions across Indian cities for two periods, 1987-1990 and 2004-2007. While GH's entire SPM and SO2 distributions shifted to the left, the opposite shift is apparent for the pollutants derived using MERRA-2 reanalysis data. The shift to the right is particularly substantial for MERRA-2 PM2.5. As Table 2 reports, the tenth and the ninetieth percentiles of GH's SMP and SO2 concentrations demonstrate a decline between two periods: about 10% in the tenth percentiles for both pollutants, 5% in the ninetieth percentile for SPM and 40% in the ninetieth percentile for SO2. In contrast, the distributions of MERRA-2 PM2.5 and SO2 concentrations worsened substantially, with striking increases in the tenth percentiles by about 50% and in the ninetieth percentiles by 100% for the full sample.



Notes: The figure plots annual city-level average concentrations of particulate air pollution (Panel A) and SO_2 (Panel B). Left-hand graphs show SPM and SO2 trends in GH's data for their restricted sample of cities. Right-hand graphs in Fig. 3 show trends in PM2.5 and SO2 estimates for the full sample of 140 cities, while the middle graphs plot the trends for the same pollutants across GH's sample of cities. GH's air pollution data were drawn from the CPCB ground-based monitoring network, while the revised air pollution data - from the MERRA-2 satellite-derived estimates.

Fig 3. Trends in air pollution, 1987-2007

The difference in trends between GH's SPM and MERRA-2 PM2.5 cannot be explained by the fact that SPM and PM2.5 are not directly comparable pollutants. I convert GH's SPM concentrations into PM2.5 concentrations applying SPM/PM10 and PM10/PM2.5 ratios used in Nilekani (2014) and Greenstone et al. (2015).[49] Column 2 of Table 2 demonstrates the summary statistics for GH's PM2.5 air pollution. The results are qualitatively similar in terms of the difference in trends between GH's SPM/PM2.5 and MERRA-2 PM2.5.

[49] PM10 is a fraction of SPM; PM10 is particulate matter with a diameter less than 10 µm. PM10 = 0.5053SPM, PM2.5=0.438PM10

Table 2 – Comparison of Summary Statistics

	Air Pollution							Meteorological Variables			Infant Mortality
	GH data GH sample			New data GH sample		New data Full sample		New data Full sample			GH data GH sample
	SPM	PM2.5	SO2	PM2.5	SO2	PM2.5	SO2	Temp-ture	Precip-tion	Wind speed	IM Rate
Period	1	2	3	4	5	6	7	8	9	10	11
Full Period											
Mean	223.23	49.41	17.26	29.89	6.49	27.44	5.13	25.57	1152.02	4.86	23.46
Standard deviation	113.99	25.23	15.17	13.16	7.35	12.14	5.67	1.85	562.64	0.79	22.09
Observations	1370	1370	1344	1370	1344	2940	2940	2940	2940	2940	1247
Tenth percentile	90.51	20.03	4.00	16.47	1.63	14.93	1.34	23.40	547.81	3.84	3.36
Ninetieth percentile	378.44	83.76	35.37	50.15	13.23	45.17	10.39	27.28	1947.70	5.86	46.23
1987-1990											
Mean	252.13	55.8	19.36	22.63	6.36	21.64	3.73	25.60	1078.50	4.94	29.60
Standard deviation	126.35	27.96	13.28	5.52	8.46	5.91	4.54	2.24	541.13	0.80	31.44
Observations	120	120	116	120	116	560	560	560	560	560	358
Tenth percentile	101.55	22.48	4.40	14.01	1.17	13.77	1.10	23.34	460.77	3.90	4.79
Ninetieth percentile	384.30	85.05	38.23	29.21	29.41	29.16	7.10	27.47	1888.23	5.87	56.20
2004-2007											
Mean	209.42	46.35	12.19	37.92	7.89	37.78	6.90	25.59	1315.35	4.79	16.70
Standard deviation	97.13	21.5	8.09	14.66	7.52	14.18	6.76	1.54	681.19	0.76	14.09
Observations	420	420	381	420	381	560	560	560	560	560	216
Tenth percentile	92.01	20.36	4.00	21.17	2.10	21.22	1.69	23.41	625.60	3.75	2.73
Ninetieth percentile	366.59	81.13	22.95	59.83	15.84	58.83	14.41	27.12	2328.06	5.74	36.15

Notes: This table provides summary statistics on air pollution, meteorological variables, and infant mortality. GH's air pollution data are the annual city-level average SPM and SO2 concentrations constructed using CPCB ground-based monitoring network, and PM2.5 converted from SPM using SPM-PM10-PM2.5 ratios. New air pollution data are the revised PM2.5 and SO2 air pollution outcomes derived using MERRA-2 satellite-based estimates. GH's sample corresponds to the number of cities used in GH. The number is restricted by the availability of the ground-based air pollution monitor readings. The full sample contains a panel of 140 cities used in the GH reexamination. Columns with meteorological variables provide summary statistics on city-level air temperature, precipitation, and wind speed constructed using various MERRA-2 products. Construction of GH and revised air pollution outcomes, as well as meteorological covariates, is described in detail in the text. Infant mortality data are taken from GH without modification. The sources of infant mortality data include the Vital Statistics of India from various years and some offices of the state registrar.

Several potential explanations for such a dramatic difference in the observed air pollution trends relate to the arguments summarizing issues with GH's data and highlighting the advantages of the satellite-derived estimates relative to ground-based measures. Specifically, the limited availability of air pollution data and the problems with using a sparse ground-based monitoring network can explain an unusual year-to-year spike-and-drop pattern in GH's SPM/PM2.5 concentrations (left-hand graph in panel A of Fig. 3). MERRA-2 reanalysis products have been compiled consistently during GH's study period and potentially provide a more reliable air pollution measure. Indeed, the trends in the revised air pollution outcomes correspond well with the similar trends documented in other recent studies and perfectly reflect numerous concerns about increasingly deteriorating air quality in China and India over the past decades (Greenstone et al., 2015; Ebenstein et al., 2015; Chen et al., 2017). A similar trend in particulate air pollution is also indicated by PM2.5 estimates constructed for the period 1998-2007 using van Donkelaar et al. (2019).

However, sharp increases in the trend of MERRA-2 PM2.5 in 2000 and 2007 look suspicious. Appendix Fig. A8 shows the trends in the components of this pollutant that shed some light on the developments in PM2.5 air pollution. The left-hand graph of panel B shows that the first episode of the substantial increase in PM2.5 concentrations in 2000 can be explained by the spike in DUST2.5 that was likely caused by dust storms (Prasad and Singh, 2007). The second episode in 2007 is likely attributable to the mutually magnifying effects of the simultaneous increase in concentrations of SO4, Organic and Black Carbons. With the peak in PM2.5 air pollution in 2008, the worsening of air quality in 2007 could be associated with the accelerating economic growth during the pre-crisis wave of globalization accompanied by the increasing trends in industrialization, fast-growing population and deterioration of the natural environment (CPCB, 2014). During other years, a continuously rising trend in MERRA-2 PM2.5 was predetermined by Black and Organic Carbons, the products of the anthropogenic emissions.

The comparisons in Fig. 3 and Table 2 indicate that the trends in particulate and SO2 air pollution outcomes constructed using GH and MERRA-2 data differ substantially. This conclusion suggests that the reexamination of the empirical evidence on the effectiveness of environmental policies using revised air pollution outcomes, extended number of observations, and meteorological controls may lead to different results than those estimated by GH.

2.4 Effects of Revised Air Pollution Outcomes

In this section, I maintain GH's methodology to test the sensitivity of their findings to the revised air pollution outcomes and the extended number of observations. Table 3 demonstrates the effects of these revisions by reporting the estimated impacts of the SCAP and CAT policies on PM2.5 and SO2 air pollution. For each policy-pollutant and data-sample combination, the table reports estimates from fitting equation (2) and its one-step analog. Exactly following GH's methodology ensures that the differences in the results stem only from the differences in air pollution data.

Columns 1-2 replicate GH's results using their data. The outcome variables in these columns are the city-level annual average PM2.5 and SO2 concentrations. PM2.5 here is an indicator of particulate air pollution converted from GH's SPM using SPM-PM10-PM2.5 ratios. I use GH's PM2.5 for consistency as I focus on MERRA-2 PM2.5 in the following reexamination. Appendix Table A1 compares replication results using GH's SPM and PM2.5 as the outcome variables. The results are qualitatively similar in terms of the sign and statistical significance of the coefficients. Relying on this comparison, I use GH's PM2.5 in the rest of the analysis. I successfully reproduce GH's results, confirming that the CAT policy is strongly associated with the reduction in PM2.5 and SO2 concentrations five years after the policy implementation by 10.75 μg/m3 and 13.45 μg/m3, or 19.3% and 69.5% of the 1987–1990 nationwide mean concentrations. The coefficients on policy dummy are not statistically significant and suggest a decline only in the case of SO2 pollution. However, panels C and D point to a negative and statistically significant break in PM2.5 and SO2 trends caused by the CAT policy.

Columns 3-4 use the same sample of cities as in GH but replace original air pollution outcomes by MERRA-2 PM2.5 and SO2. The effects of this substitution are quantitively captured by the column-wise differences between the coefficients in columns 1-2 and 3-4 (i.e., column 1 - column 3, column 2 - column 4). Revised air pollution outcomes yield remarkable changes in the estimated effects of the SCAP and CAT policies. In contrast to GH, the significance of the CAT policy's effects on PM2.5 and SO2 five years after its implementation vanish. Not only that, but also the magnitude of the estimated effects is substantially smaller. Although not significant, the results in panels C and D, based on our estimation of equation (2), suggest a relative decline of 2.48 $\mu g/m^3$ and 0.22 $\mu g/m^3$, or 11% and 3.5% of the 1987–1990 nationwide average PM2.5 and SO2 concentrations. For PM2.5, another notable change in the CAT policy's effects includes the significance of the positive coefficients on a policy dummy in panel C.[50]

[50] One possible reason for the positive sign of the coefficients is that the binary variable that captures the effects of the CAT policy enactment might fail to account for some of the policy's features. Specifically, for the fact that the impact of the CAT policy evolves in line with the higher proportion of newer vehicles subject to the mandatory installation of catalytic converters (Greenstone et al., 2017). Negative coefficient on the policy's effects five years after its implementation seems to support this hypothesis.

Table 3 – Effectiveness of air quality policies: Effects of MERRA-2 air pollution data

	Replication GH data / GH sample		Reexamination New data / GH sample		Reexamination New data / Full sample	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6
			Supreme Court Action Plans			
			Panel A. PM2.5			
π1: 1(Policy)	1.66	0.07	-0.69	-1.70	-1.41	-1.85
	(4.56)	(4.76)	(2.79)	(1.90)	(2.18)	(1.74)
π2 : time trend	-0.80	-0.63	0.67	0.58	0.55	0.54
	(0.61)	(0.95)	(0.38)	(0.54)	(0.29)	(0.50)
π3: 1(Policy)*time trend	-0.34	0.03	1.83	2.28*	2.11**	2.21*
	(1.58)	(1.32)	(0.97)	(1.33)	(0.76)	(1.26)
5-year effect: π1+5π3	-.05	.20	8.46*	9.68**	9.12**	9.19*
p-value	[.99]	[.98]	[.07]	[.05]	[.02]	[.06]
Observations	11	1,165	11	1165	11	2720
1987–1990 mean	55.8		22.63		21.64	
			Panel B. SO2			
π1: 1(Policy)	-1.44	-1.25	-0.27	-0.12	-0.34	-0.14
	(0.88)	(2.13)	(0.30)	(0.44)	(0.33)	(0.45)
π2: time trend	0.20	0.09	0.12**	0.09	0.07	0.05
	(0.12)	(0.55)	(0.04)	(0.14)	(0.04)	(0.12)
π3: 1(Policy)*time trend	-0.06	0.10	-0.03	-0.03	0.07	0.04
	(0.31)	(0.98)	(0.10)	(0.12)	(0.11)	(0.10)
5-year effect: π1+5π3	-1.74	-.78	-.4	-.28	-.01	.04
p-value	[.21]	[.87]	[.37]	[.71]	[.98]	[.94]
Observations	11	1158	11	1158	11	2720
1987–1990 mean	19.36		6.36		3.73	
			Mandated Catalytic Converters			
			Panel C. PM2.5			
π1: 1(Policy)	1.23	1.69	2.26*	1.96*	2.15**	1.95**
	(2.82)	(2.71)	(1.24)	(1.15)	(0.84)	(0.97)
π2 : time trend	1.72***	1.73**	0.32	0.23	0.19	0.15
	(0.55)	(0.73)	(0.24)	(0.25)	(0.17)	(0.11)
π3: 1(Policy)*time trend	-2.40***	-2.48**	-0.95***	-0.79**	-0.82***	-0.73***
	(0.64)	(1.01)	(0.28)	(0.39)	(0.19)	(0.27)
5-year effect: π1+5π3	-10.75**	-10.71*	-2.48	-1.99	-1.93	-1.71
p-value	[.04]	[.06]	[.25]	[.19]	[.19]	[.15]
Observations	17	1,165	17	1165	17	2720
1987–1990 mean	55.8		22.63		21.64	
			Panel D. SO2			
π1: 1(Policy)	-0.53	-0.76	-0.75	-0.88***	-0.89**	-0.86***
	(1.52)	(2.56)	(0.49)	(0.22)	(0.38)	(0.19)
π2: time trend	2.02***	1.91***	-0.03	-0.03	0.06	0.06
	(0.29)	(0.70)	(0.09)	(0.07)	(0.07)	(0.04)
π3: 1(Policy)*time trend	-2.58***	-2.39**	0.11	0.12	0.03	0.02
	(0.34)	(0.98)	(0.11)	(0.10)	(0.09)	(0.07)
5-year effect: π1+5π3	-13.45***	-12.69**	-.22	-.28	-.73	-.75*
p-value	[.00]	[.02]	[.79]	[.62]	[.27]	[.07]
Observations	17	1158	17	1158	17	2720
1987–1990 mean	19.36		6.36		3.73	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to the revised air pollution outcomes and the extended number of observations. It reports estimates from fitting the second-step equation (2), odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) levels. Columns 1-2 use GH's original data to replicate their results. I substitute GH's SPM by GH's PM2.5 converted from GH's SPM using SPM-PM10-PM2.5 ratios for comparability with the policies' effects on MERRA-2 PM2.5. Columns 3-4 exploit the same sample of cities as in GH and revised PM2.5 and SO2 air pollution outcomes to reexamine GH findings. Columns 5-6 reexamine GH results by taking full advantage of the revised outcome variables and fitting equation (2) and its one-step version to all available city-by-year observations. Standard errors are reported in parentheses. Liner combination of the coefficients $\pi_1+5\pi_3$ is an estimate of the policies' effect 5 years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

For SO2, the revised air pollution data indicate a higher magnitude of the policy dummy coefficient, which remains negative but, in contrast to GH, turns statistically significant in the one-step specification. The coefficient in column 4, panel D, suggests that SO2 concentrations decrease by 0.88 μg/m3 or 13.8% of the 1987–1990 nationwide mean concentrations. Another change is that the coefficients on the break in SO2 trend turn positive, small, and statistically insignificant. The effects of the SCAP policies on PM2.5 are also substantially different from those found in GH. In contrast to GH, the effects of the SCAP policies five years after implementation enter positively, large, and significantly. Thus, the SCAP policies do not appear to have helped reduce PM2.5 concentrations but are rather associated with their increase.[51] The policy dummy coefficients in panel A turn negative but remain statistically insignificant. Column 4, panel A, based on estimating the one-step version of equation (2), shows a positive and statistically significant break in PM2.5 trend. The general pattern of the SCAP policies' effects on SO2 is similar to those in GH. However, their magnitudes are much smaller than those estimated using GH's data.

Finally, columns 5-6 take full advantage of MERRA-2 air pollution data and report coefficients estimated from fitting GH's specifications to the revised air pollution outcomes and the extended number of observations. The column-wise differences between the estimates in columns 3-4 and 5-6 capture the effects of the full sample (i.e., column 3 - column 5, column 4 - column 6). Of all the changes attributable to the extended number of observations, the most prominent change occurs with the impact of the CAT policy on SO2. Alongside the negative and statistically significant coefficient on the policy dummy already observed in column 4, panel D, the results from the one-step specification in column 6, panel D, show that the policy is associated with a statistically significant decline in SO2 concentrations five years after its implementation. Although substantially larger than in columns 3-4, -0.75 μg/m3 against -0.28 μg/m3, the effect remains considerably smaller than that obtained by GH, 20% against 69.5% of the 1987–1990 nationwide mean concentrations. The effects of the SCAP policies on SO2, panel B, also change

[51] It may well be that the coefficients on the SCAP policies' effects five years after implementation capture some other changes. Some blame lies with the energy generation by power plants, on which GH focus to a lesser degree than on vehicular pollution. Energy generation is the major contributor to air pollution in many developing countries and is certainly the driving force behind the rapid economic growth in China and India. At the city level, Goyal (2002) refers to the fossil fuel burning power plants in Delhi as the primary source of SO2 and SPM air pollution, with the respective shares of 56.8% and 60.4%. For comparison, vehicular emissions contribute a modest 4.8% and 6.7% to SO2 and SPM air pollution in Delhi. Thus, any increase in the power plant emissions increases levels of particulate air pollution. This can happen directly through the SPM channel and indirectly because of the conversion of SO2 to sulfate particulates (SO4), a PM2.5 component.

considerably compared to those in columns 3-4. The coefficients on the break in SO2 trend enter with the opposite sign, while the policies' effects five years after implementation become almost indistinguishable from zero and change the sign in the one-step specification. The SCAP and CAT policies' effects on PM2.5 change moderately compared to those in columns 3-4. The general pattern of these impacts in terms of the sign and significance of the coefficients does not change. Notably, the size of the column-wise coefficients based on the numerically identical equation (2) and its one-step version in columns 5 and 6 becomes more similar compared to the size of the coefficients in other columns, perhaps due to the increase in the sample size and less noise in MERRA-2 data. These reasons are also behind the decrease in standard errors.

2.5 Effects of Meteorological Controls

2.5.1 Air Pollution

This subsection explores the effects of meteorological conditions on the robustness of GH's findings by estimating a two-step approach and its one-step version with air temperature, precipitation, and wind speed as control variables.[52] Table 4 summarizes the regression results. For brevity, it reports only estimates from the regressions that are based on the most complete data-sample combination, the same as in columns 5-6 of Table 3, and control for a complete set of the meteorological variables. Paralleling analysis in section 4, Appendix Table A2 shows the results for other data-sample combinations from Table 3. Appendix Tables A3-A5 document a detailed, data-sample combination-specific breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed.

Columns in Table 4 report results from the regressions that incorporate all changes in the data, particularly revised air pollution outcomes, extended number of observations, and a full set of the meteorological controls. Altogether, these changes yield the most striking result of reexamination. Negative coefficients on the CAT policy's effects on PM2.5 five years after implementation turn statistically significant (panel C). However, the magnitudes of the effects are smaller compared to the policy's five-year effects on GH's PM2.5 and correspond to a decline of

[52] I control for a set of meteorological covariates by including $f(W_{ct})$ into Equation (1) of a two-step econometric approach.

2.28 μg/m3 to 2.53 μg/m3 against 10.75 μg/m3, or 11.7% against 19.3% of the 1987–1990 nationwide mean concentrations. Further, the pattern of the estimates in column 6 of panel C, based on estimating the one-step version of equation (2), is the most similar to that in GH.

Table 4 – Effectiveness of air quality policies: Effects of meteorological controls

	Reexamination: *Full set of meteorological controls* New data / Full sample							
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans				*Mandated Catalytic Converters*			
	Panel A. PM2.5		*Panel B. SO2*		*Panel C. PM2.5*		*Panel D. SO2*	
π1: 1(Policy)	-1.41	-1.63	-0.71**	-0.43	1.58**	1.52	-1.07**	-0.98***
	(2.35)	(1.65)	(0.29)	(0.38)	(0.72)	(0.93)	(0.38)	(0.17)
π2 : time trend	0.50	0.48	0.07	0.05	0.30*	0.25**	0.08	0.07*
	(0.32)	(0.47)	(0.04)	(0.11)	(0.14)	(0.12)	(0.08)	(0.04)
π3: 1(Policy)*time trend	1.57*	1.64*	0.08	0.01	-0.82***	-0.76***	0.02	0.01
	(0.81)	(0.91)	(0.10)	(0.09)	(0.16)	(0.23)	(0.09)	(0.07)
5-year effect: π1+5π3	6.42*	6.55*	-.32	-.36	-2.53**	-2.28*	-.96	-.95**
p-value	[.09]	[.06]	[.47]	[.49]	[.05]	[.09]	[.15]	[.03]
Observations	11	2720	11	2720	17	2720	17	2720
1987–1990 mean	21.64		3.73		21.64		3.73	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to additional controlling for meteorological confounders. It reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) concentrations. Both specifications include a full set of meteorological controls, specifically air temperature, precipitation, its quadratic, and wind speed. The table reports only estimates from the regressions that are based on the most complete data-sample combination, the same as in columns 5-6 of Table 3. Specifically, the columns use new air pollution outcome variables and fit equation (2) and its one-step version to full sample of cities. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effect five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Do meteorological controls matter? The column-wise differences between the estimates in columns 5-6 in Tables 3 and 4 (i.e., column 5 in Table 3 - column 5 in Table 4) isolate the impacts of the meteorological confounders on the policies' effects net of the impacts of the extended number of observations (i.e., column 3 - column 5 in Table 3).[53] Substantially larger impacts of the

[53] I illustrate this point on the example of the effects of the CAT policy on PM2.5 estimated using a two-step approach. The difference between the coefficients on policy dummy that captures the combined effect of the sample extension and inclusion of the meteorological controls is equal to 0.68 μg/m3 (2.26 - 1.58 or column 3 in Table 3 - column 5 in Table 4, panel C). The difference that captures the effect of the sample extension alone is equal to 0.11 μg/m3 (2.26 - 2.15 or column 3 - column 5 in Table 3, panel C). Then, the effect of the inclusion of the meteorological controls is equal to 0.57 μg/m3 (0.68 - 0.11). This is exactly the difference between the policy dummy coefficients that captures the effect of meteorological covariates described above, i.e., column 5 in Table 3 - column 5 in Table 4, panel C, or 2.15 - 1.58 = 0.57 μg/m3.

meteorological confounders compared to the impacts of the extended number of observations indicate that the changes in the CAT policy's effects on PM2.5 are driven by controlling for meteorological conditions. Wind speed makes a major contribution to improvements in air quality, while the size and significance of the policy's effects are mostly unchanged after controlling for air temperature and precipitation (Appendix Table A5, panel C).

Likewise, meteorological conditions are important factors behind the changes in the SCAP policies' effects on SO2. Panel B of Table 4 indicates that meteorological controls alter the magnitude and significance of the policies' impacts. The policy dummy coefficient from estimating the two-step approach doubled compared to that in Table 3 to statistically significant -0.71 μg/m3 (19% of the 1987–1990 nationwide mean concentrations), while the five-year policies' effects increase from -0.01 μg/m3 and 0.04 μg/m3 to -0.32 μg/m3 and -0.36 μg/m3 (10% of the 1987–1990 nationwide mean concentrations) and remain insignificant. Although substantially different from those in columns 5-6 of Table 3, these effects are similar to those reported in columns 3-4 of Appendix Table 2. Panel B of Appendix Table A5 indicates that wind speed plays a major role in magnifying the effects of SCAP policies on SO2 and improving air quality.

For the remaining policy-pollutant pairs, the impact of the meteorological controls is weaker. Although the magnitude of the CAT policy's effects on SO2 increases (panel D), the general pattern of the estimates is comparable to those in columns 5-6 of Table 3. In this case, the effect of the inclusion of meteorological covariates is equivalent to the effect of the extended number of observations. However, the significance of the CAT policy's impact five years after implementation is attributed to the increase in the sample size as the policy's impact first becomes significant in Table 3. Appendix Table A5, panel D, documents that all three meteorological covariates are beneficial for the effects of the CAT policy on SO2. Air temperature and precipitation alter mainly the magnitude of the policy' effects five years after implementation, while wind speed also changes the coefficients on the policy dummy. In the case of the SCAP policies' effects on PM2.5 (panel A), the effects of the inclusion of meteorological controls substantially reduces the positive and significant effects of the SCAP policies on PM2.5 five years after implementation. Appendix Table A5, panel A, suggests that all meteorological conditions are beneficial for the five-year policies' effects. In contrast, meteorological controls change the coefficients on policy dummy minimally. Air temperature and precipitation are harmful to the policies' effects, while wind speed is beneficial. However, meteorological controls do not change the significance of the policy dummy coefficients, which remain statistically insignificant.

2.5.2 Infant Mortality

This subsection reexamines the effects of the CAT policy on infant mortality. Following GH, I apply a two-step econometric approach with infant mortality rate as the outcome variable. As air pollution concentrations do not enter this equation directly, I test the sensitivity of GH's findings solely to the inclusion of the meteorological controls. Table 5 reports the resulting estimates.

Table 5 – Effectiveness of air quality policies: Infant mortality

	Replication	Reexamination		
		GH data / GH sample		
	No Meteo Vars	Air temperature	Add precipitation	Add wind speed
	Eq. 2	Eq. 2	Eq. 2	Eq. 2
	1	2	3	4
	Mandated Catalytic Converters			
	Infant Mortality Rate			
π1: 1(Policy)	3.57**	3.19**	3.30**	3.81**
	(1.49)	(1.43)	(1.43)	(1.59)
π2 : time trend	-0.26	-0.26*	-0.27*	-0.28
	(0.15)	(0.14)	(0.14)	(0.16)
π3: 1(Policy)*time trend	-0.84**	-0.71*	-0.72*	-0.64
	(0.36)	(0.34)	(0.34)	(0.38)
5-year effect: π1+5π3	-.64	-.36	-.29	.59
p-value	[.71]	[.83]	[.86]	[.74]
Observations	16	16	16	16
1987–1990 mean		29.60		

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach that tests for the effects of the CAT policy on infant mortality rate. Column 1 uses GH's original data to replicate their results. Columns 2-4 reexamine GH's findings by reporting a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation and its quadratic, and wind speed. Standard errors are reported in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policy's effect five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

I begin by successfully reproducing GH estimates of the CAT policy's effects on infant mortality rate using GH's original data. Column 1 of Table 5 indicates that the policy is associated with a modest and statistically insignificant decline in the infant mortality rate of 0.64 per 1000 live births five years after implementation. This result corresponds to that reported by GH in column 3 of Table 6. However, the policy dummy coefficient is positive and statistically significant at the 5 percent level. GH do not report the significance of this coefficient. The estimates in the column also indicate a negative and statistically significant break in infant mortality trend.

In the second column, I report estimates after controlling for air temperature. The general pattern of the results is little changed. However, the evidence of a negative and insignificant policy's effect five years after implementation is substantially weaker using this specification, with a reduction in the infant mortality rate of 0.36 per 1,000 live births. In the third column, I additionally control for precipitation and its quadratic. Inclusion of these meteorological variables reduces the estimated impact of the CAT policy on infant mortality further to -0.29 per 1,000 live births, which is about a third of the size of GH's original estimate. Other results are largely unchanged, including a positive and statistically significant policy dummy coefficient and negative and significant trend break.

Finally, in the last column of Table 5, I add wind speed as a control variable. In contrast to the results in previous columns, the estimated effect of the policy five years after implementation turns positive but remains insignificant. CAT policy is associated with a statistically insignificant increase in the infant mortality rate of 0.59 per 1,000 live births five years after implementation. Controlling for wind speed reduces the size of the trend break coefficient and eliminates its significance. However, the sign and significance of the policy dummy coefficient are robust to the inclusion of meteorological controls, although its magnitude increases compared to those reported in previous columns.

2.6 Discussion

How should the evidence in Sections 4 and 5 be interpreted in terms of the policies' effectiveness? To facilitate response to this question, Appendix Table A6 provides a summary of the estimated CAT policy's effects five years after its implementation expressed in % of the 1987–1990 nationwide mean air pollution concentrations. Shown this way, the magnitudes of the policy's effects become comparable across all data-sample combinations and improve the understanding of the reexamination: testing the sensitivity of GH's findings to the revised air pollution outcomes, extended number of observations, and meteorological controls. The CAT policy was found GH as the most strongly related to improvements in air quality.

The analysis in Section 4 indicates that GH's findings are highly sensitive to the revised air pollution outcomes and the extended number of observations. The changes in the patterns of the policies' effects include changes in the size, significance, sign of the estimates, and reinforce the conclusion made in Section 3 based on the observation of the opposite trends in air pollution outcomes.

GH's findings do not generally hold after replacing original air pollution outcomes by those constructed using satellite-derived data. Environmental regulations found in GH to be strongly associated with air quality improvements do not appear to have helped reduce air pollution. The only exception pertains to the CAT policy's effect on SO2. The statistically significant policy dummy coefficient from the one-step specification suggests a modest reduction in SO2 pollution. The policy's effects five years after implementation, however, remain insignificant. Thus, adding revised data casts doubts on the effectiveness of air pollution control policies.

Nevertheless, GH's findings seem somewhat less fragile after extending the sample size to the full number of observations from the satellite-derived data. Alongside the coefficient on the policy dummy, the estimate from the one-step specification indicates that the CAT policy is associated with a statistically significant decline in SO2 concentrations five years after implementation. However, the effect remains substantially smaller than that obtained by GH. There is still little empirical support for the effectiveness of air pollution control policies for other policy-pollutant pairs.

Estimates from the richest specifications in Section 5 that additionally incorporate a complete set of meteorological controls point to further convergence in the policies' effects estimated using GH's and satellite-based data. Similarly to GH, the CAT policy induces reductions in PM2.5 and SO2 concentrations five years after implementation. Although weaker than those found using GH's data, the CAT policy's effects five years after implementation estimated using satellite-based data point to a decline of 11.7% against 19.3% of the 1987–1990 nationwide mean concentrations for PM2.5 and 25.7% against 69.5% for SO2. The fact that this study finds a similar pattern of the CAT policy's effects using alternative data is particularly remarkable given substantive differences between data sources and differential trends in air pollution. Likewise, the estimated impact of the CAT policy on infant mortality confirms GH's finding that regulation-induced improvements in air quality need not improve infants' health.

A natural question that arises from these findings is whether GH's and satellite-based data lead to the same results. Analysis of the disparities in the outcomes generated by two data sources provides a reasonable basis for answering this question. At least two of them deserve attention.

First, the qualitative patterns of the policies' effects estimated using GH's and satellite-based data differ considerably. For the CAT policy's effects on SO2, GH's data indicate insignificant coefficients on policy dummy and negative and significant breaks in SO2 trend, whereas satellite-based data point to the opposite effects. Estimates suggest that GH might overlook the effectiveness of the SCAP policies. The policy dummy coefficient turns statistically significant after estimating the two-step approach using satellite-based data, indicating a reduction in SO2 pollution by 19% of the 1987–1990 nationwide mean concentrations. For the CAT policy's effects on infant mortality, the estimates point to the opposite conclusion from that reached by GH. The policy is associated with a modest and insignificant increase in infant mortality five years after implementation.

Second, the policies' effects estimated using satellite-based data are not always robust across various data-sample combinations and across two-step and one-step specifications that are supposed to return numerically identical estimates. For the CAT policy's effects on PM2.5, the coefficients that quantify the policy's effects five years after implementation turn significant only in the richest combination but across both GH's specifications. In contrast, for the CAT and SCAP policies' effects on SO2, the coefficients on policy dummy and five-year effect become significant in several data-sample combinations but only in one of the GH's specifications. For example, the CAT policy's effect on SO2 five years after implementation turns significant in the one-step specification, whereas the estimate from the two-step specification remains insignificant. Not only does the significance of the estimates vary dramatically but also their sign and size. The CAT policy's effects on infant mortality are similarly sensitive to the inclusion of additional controls.

After controlling for wind speed, the five-year effect reverses the sign from all previous specifications using GH's and satellite-derived data.

Observed disparities do not provide strong empirical support for a complete similarity in the results based on the findings from two data sources. Therefore, reexamination using satellite-based data can confirm the conclusions drawn from GH's data, but with reservations. Equally, it seems unreasonable to interpret the results from satellite-derived data as sufficiently compelling.

2.7 Conclusion

This chapter reexamines empirical evidence on the effectiveness of environmental regulations in India from a recent study by Greenstone and Hanna (2014). GH demonstrate that air pollution control policies have been effective in improving air quality but arrive at the surprising conclusion that the policy-led reductions in air pollution need not improve infants' health. These somewhat counterintuitive findings are likely due to the limited availability of air pollution data and the absence of critical meteorological confounders. This conclusion motivated a reexamination of GH's findings using alternative data sources.

Using satellite-based estimates for air quality and meteorological conditions, I test the sensitivity of GH's findings to revised air pollution outcomes, an extended number of observations, and meteorological controls. Three findings emerge. First, air pollution outcomes constructed using GH's and satellite-based data demonstrate opposite trends. While concentrations of air pollutants were falling in GH, concentrations of the revised air pollution outcomes are continuously increasing. Second, GH's findings are highly sensitive to the revised air pollution outcomes and the extended number of observations. There is little empirical support in satellite-derived data for the effectiveness of the air pollution control policy found in GH to be strongly associated with air quality improvements. Third, meteorological controls matter. Additionally controlling for meteorological confounders revealed similar effects of policies on air pollution to those reported in GH. Likewise, the estimated impact on infant mortality confirms that regulation-induced improvements in air quality do not necessarily result in improved health. However, the qualitative patterns estimated using GH's and satellite-derived data differ substantially. Further, the effects of policies estimated using satellite-derived data are not robust across various data-sample combinations and specifications. Thus, based on the complementary empirical evidence from satellite-derived data, it seems reasonable to confirm GH's findings and interpret air pollution control policies in India as effective, although with substantially weaker effects on air pollution.

The next important empirical step in this line of research will be to explore further the prospects for using satellite-based data in a meaningful examination of important issues related to the effectiveness of environmental regulations. Such research would be particularly valuable for developing countries where air pollution control policies are especially contentious, and their effectiveness is hampered by weak institutions and limited data availability. Understanding whether and to what extent satellite-based estimates can be reliable complements to the observed indicators will be critical in uncovering the effects of environmental regulations and recommending sensible interventions aimed at mitigating air pollution and protecting population health.

2.8 Appendix

Fig. A1. Vital Statistics of India 1995, example page with city names

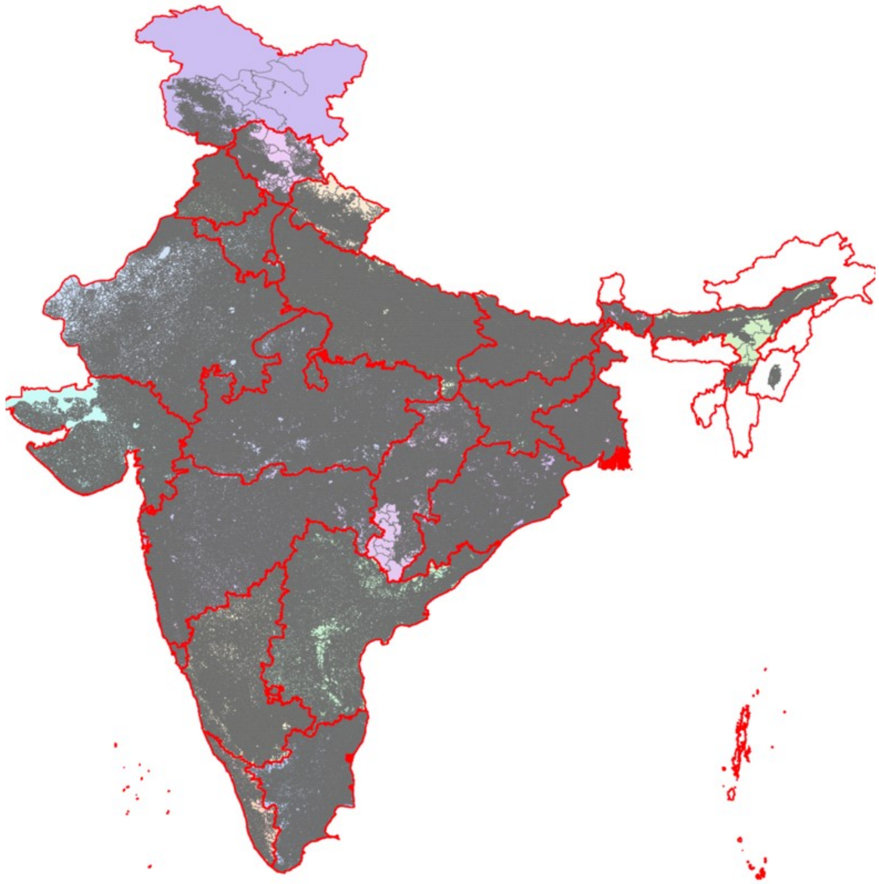
Table 5 - Live births, deaths, infant deaths and maternal deaths in towns with population 100,000 and above during 1993-95

India/State/Union territory/Town	Birth			Death			Infant Death			Maternal Death			India/State/Union territory/Town	
	1991	1992	1993	1994	1995	1995	1993	1994	1995	1993	1994	1995		
1	2	3	4	5	6	7	8	9	10	11	12	13	1	
INDIA (all towns)	**2,976,305**	**3,020,746**	**3,053,505**	**814,277**	**806,887**	**773,183**	**66,783**	**68,610**	**67,018**	**1,660**	**2,162**	**1,468**	**INDIA (all towns)**	
Andhra Pradesh (all towns)	**281,283**	**300,049**	**284,283**	**66,022**	**63,407**	**63,370**	**5,116**	**4,322**	**4,700**	**155**	**98**	**87**	**Andhra Pradesh (all towns)**	
1. Adoni	2,680	2,824	3,202	720	692	714	57	65	91	4	3	3	Adoni	1.
2. Anantapur	4,485	6,203	5,959	1,480	1,309	1,595	149	143	151	4	8	10	Anantapur	2.
3. Bheemavaram	3,232	3,820	4,003	526	480	478	13	8	6	-	-	-	Bheemavaram	3.
4. Chirala	2,676	2,610	2,696	532	529	478	10	9	2	1	-	-	Chirala	4.
5. Chittoor	5,236	5,469	5,756	713	734	691	7	11	14	-	-	-	Chittoor	5.
6. Cuddapah	4,692	4,795	5,287	994	851	947	93	38	39	-	-	-	Cuddapah	6.
7. Eluru	4,557	4,778	4,837	1,442	1,485	1,463	68	45	52	3	-	-	Eluru	7.
8. Gudivada	3,271	3,775	3,750	586	612	648	27	34	21	-	-	-	Gudivada	8.
9. Guntakal	1,709	1,935	2,037	591	478	530	8	2	15	-	-	-	Guntakal	9.
10. Guntur	12,428	12,350	12,452	4,866	4,775	4,545	551	40	520	-	10	19	Guntur	10.
11. Hindupur	1,602	16,006	1,456	393	403	403	27	36	39	-	-	-	Hindupur	11.
12. Hyderabad	96,454	101,984	102,279	19,749	19,220	19,302	1,662	1,251	908	29	12	14	Hyderabad	12.
13. Kakinada	6,752	7,641	7,539	3,202	3,214	3,104	281	310	300	-	-	-	Kakinada	13.
14. Karimnagar	8,128	8,889	8,826	1,234	1,138	1,156	216	184	184	31	27	12	Karimnagar	14.
15. Khammam	5,358	N.A.	N.A.	495	N.A.	N.A.	16	N.A.	N.A.	-	N.A.	N.A.	Khammam	15.
16. Kurnool	7,977	8,247	8,533	2,993	2,812	3,386	357	312	460	-	-	-	Kurnool	16.
17. Machilipatnam	5,238	5,205	5,383	1,113	1,125	1,126	107	114	81	-	3	-	Machilipatnam	17.
18. Mahabubnagar	1,644	1,526	N.A.	860	803	N.A.	75	-	N.A.	-	-	N.A.	Mahabubnagar	18.
19. Nandyal	4,033	4,487	4,446	463	455	472	2	-	9	-	-	-	Nandyal	19.
20. Nellore	10,251	9,815	10,403	2,055	1,915	1,931	69	72	54	6	1	-	Nellore	20.
21. Nizamabad	6,845	N.A.	8,264	1,212	N.A.	1,112	26	N.A.	69	1	N.A.	7	Nizamabad	21.
22. Ongole	3,583	4,050	N.A.	564	725	N.A.	14	20	N.A.	2	4	N.A.	Ongole	22.
23. Prodatur	3,903	3,771	4,053	494	475	412	8	5	1	1	-	-	Prodatur	23.
24. Qutubullapur	1,698	2,382	N.A.	142	131	N.A.	-	12	N.A.	-	-	N.A.	Qutubullapur	24.
25. Rajahmundri	7,764	8,188	8,504	1,751	1,701	1,913	24	32	26	-	-	-	Rajahmundri	25.
26. Ramagundam	3,297	5,643	N.A.	609	439	N.A.	108	7	N.A.	-	-	N.A.	Ramagundam	26.
27. Tenali	5,251	5,334	5,450	792	720	685	11	-	8	-	-	-	Tenali	27.
28. Tirupati	5,956	6,827	7,028	2,207	2,299	2,537	312	324	358	2	4	2	Tirupati	28.
29. Vijaywada	15,784	15,871	16,322	3,859	4,037	4,211	276	168	258	7	16	18	Vijaywada	29.
30. Vishakhapatnam	14,730	15,123	15,590	4,738	5,202	4,686	38	419	353	23	-	-	Vishakhapatnam	30.
31. Vizianagaram	2,592	2,449	2,471	1,181	1,312	1,111	4	8	4	39	10	2	Vizianagaram	31.
32. Warangal	17,477	18,052	17,757	3,466	3,336	3,734	500	653	677	2	-	-	Warangal	32.

136 137

Fig. A2. ML InfoMap digital maps with village and town borders as of 2011

A. All India, 619000 polygons



B. State of Madhya Pradesh

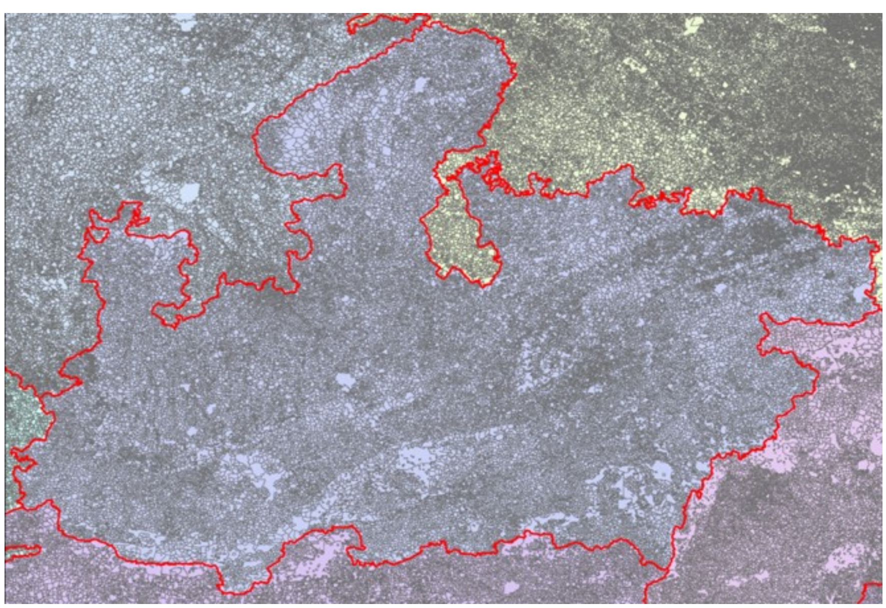
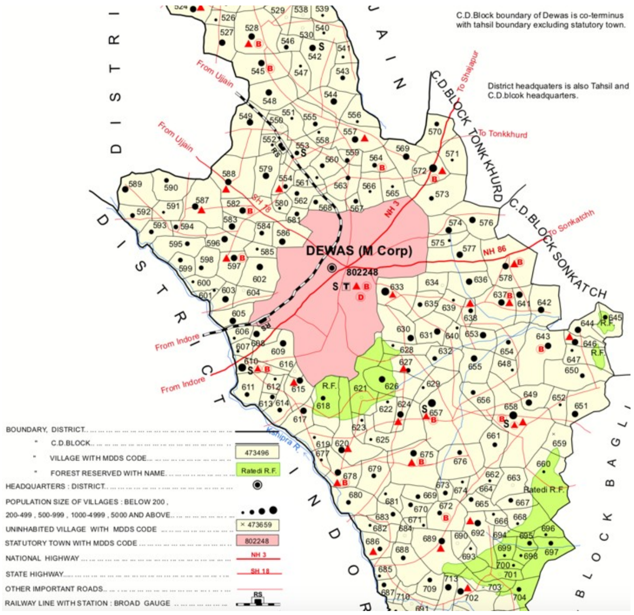


Fig. A3. Example of city extent polygon selection

A: District Census Handbook, Dewas city, Dewas district, Madhya Pradesh state



B: Dewas city, selected urban extent polygon, ML InfoMap 2011 digital maps

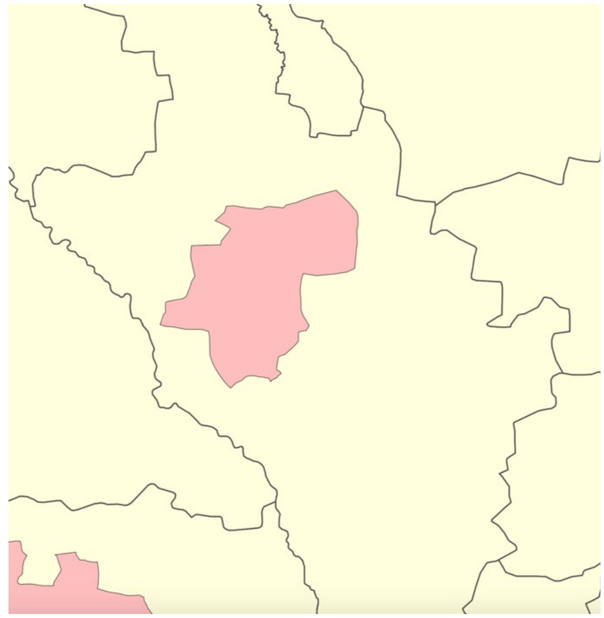
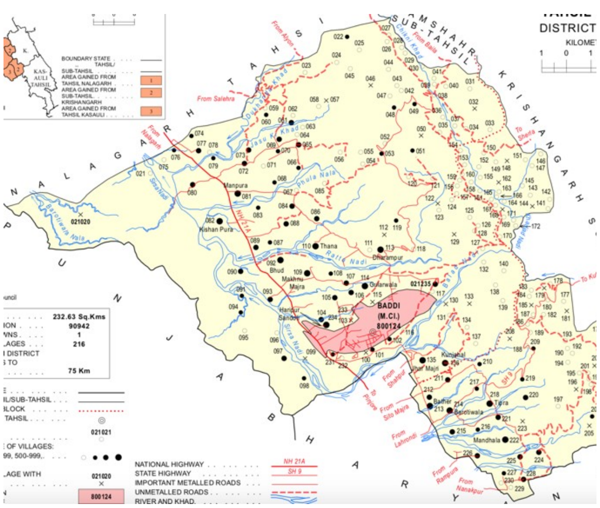


Fig. A4. Example of digitized city extent polygon

A: District Census Handbook, Baddi city, Solan district, Himachal Pradesh state



B: Baddi city, selected urban extent polygon, digitized from the District Census Handbook

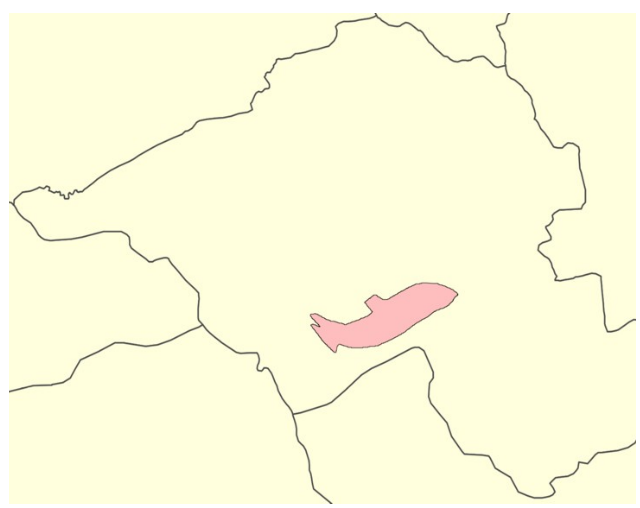


Fig. A5. Selected city extent polygons

A. All selected cities, 140 polygons

B. Selected cities, a closer look

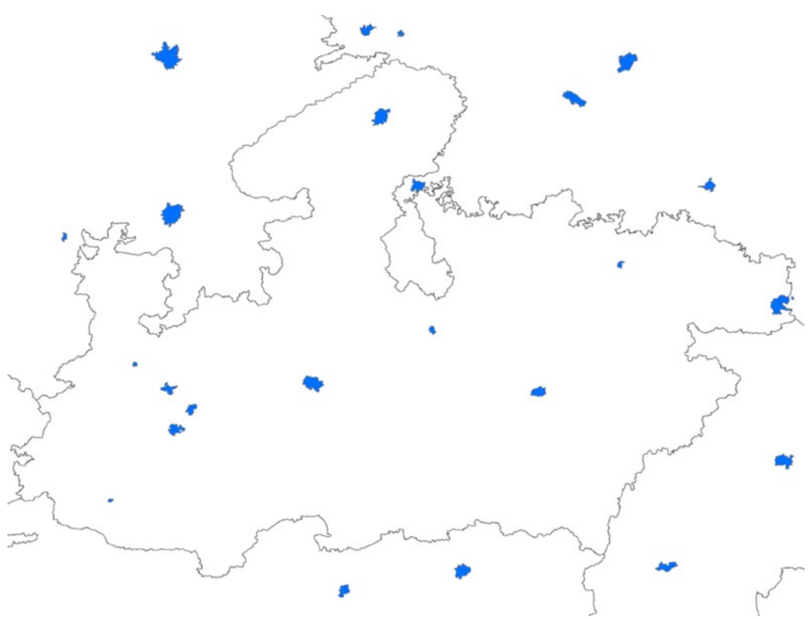
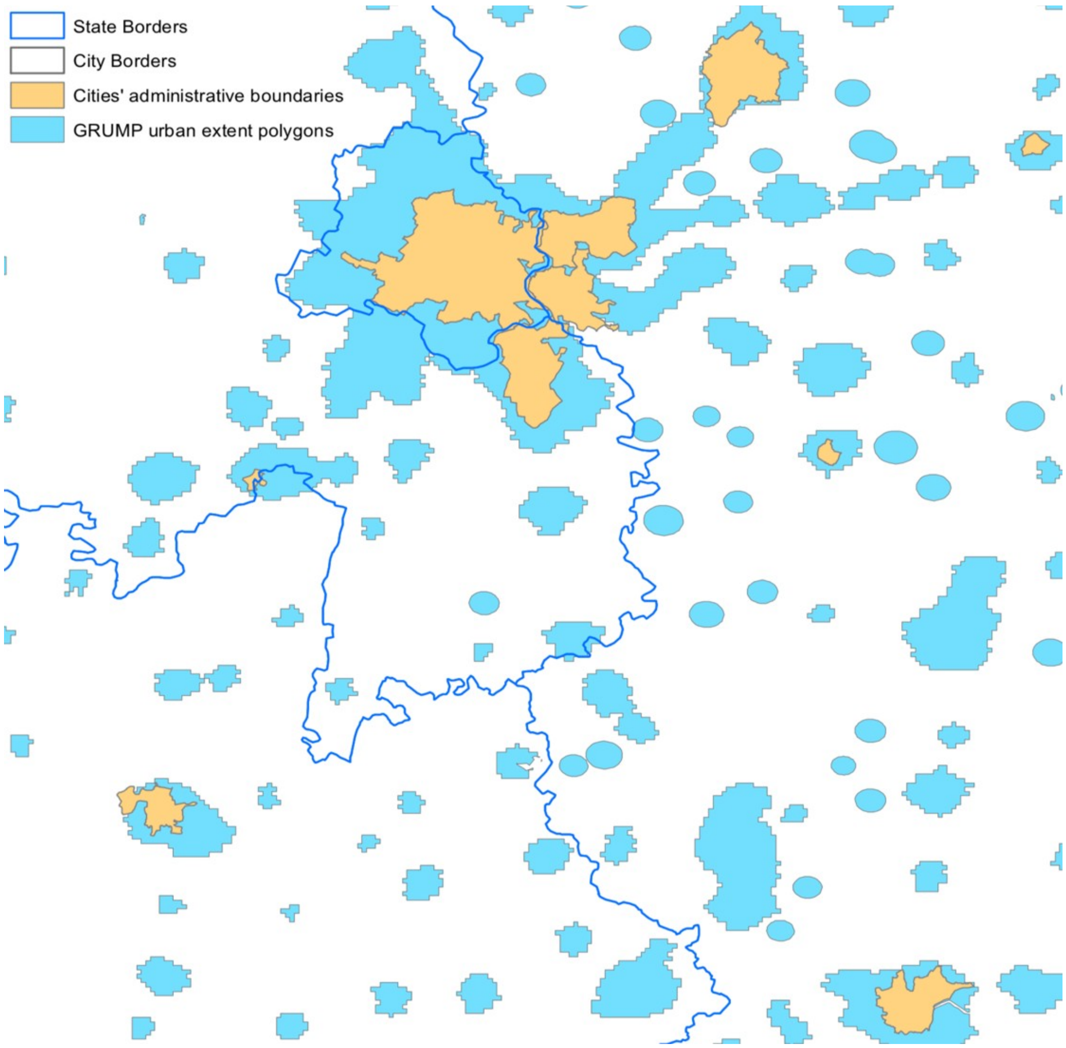


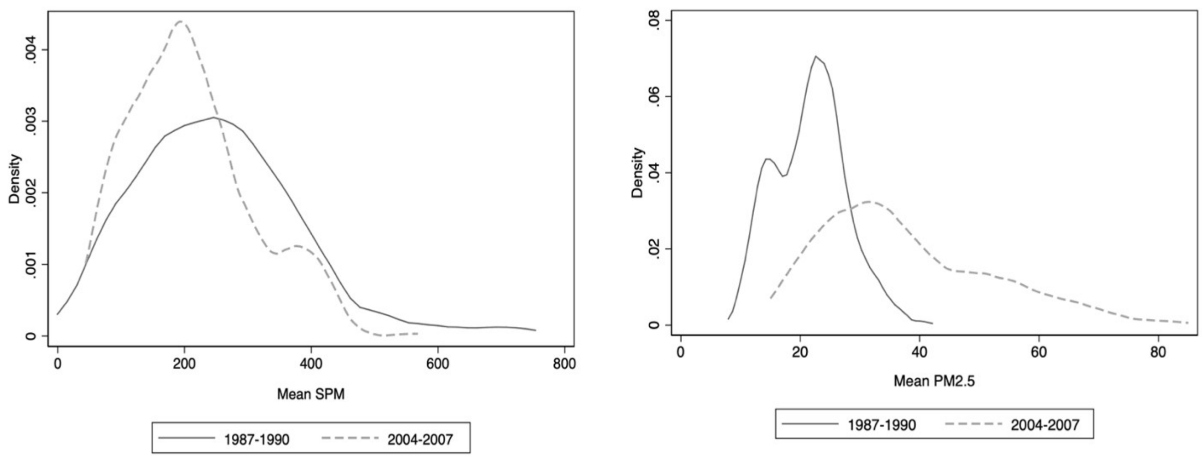
Fig. A6. Comparison of the cities' administrative boundaries with GRUMP urban extent polygons



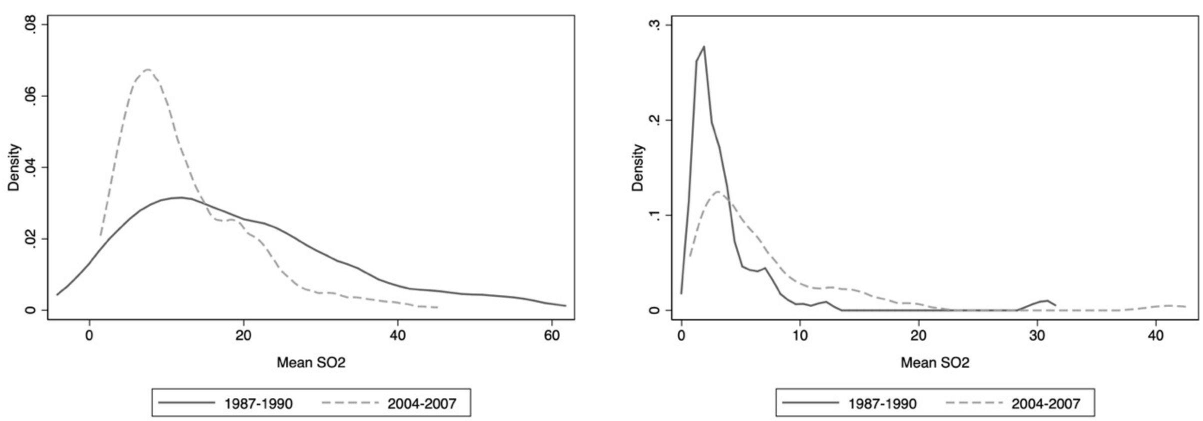
Notes: The figure compares urban extent polygons defined by the cities' administrative boundaries in this study with those defined by the combination of the night-time lights and buffered settlement centroids in the Global Rural-Urban Mapping Project (GRUMP). More information about the GRUMP can be found at https://sedac.ciesin.columbia.edu/data/collection/grump-v1/about-us.

Fig. A7. Comparison of kernel density graphs of air quality

A. Particulate air pollution: GH (left) vs. This study (right)



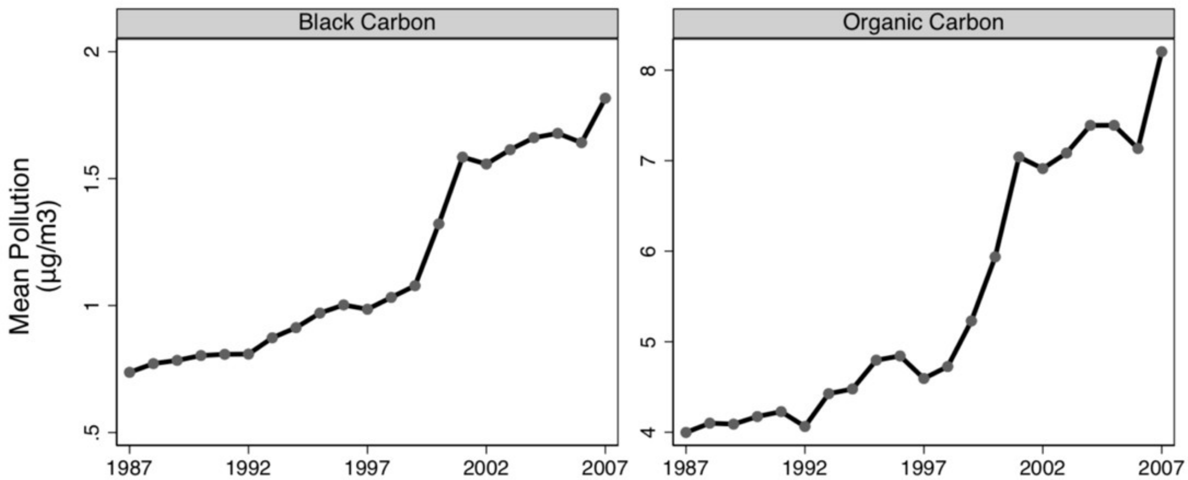
B. SO2 air pollution: GH (left) vs. This study (right)



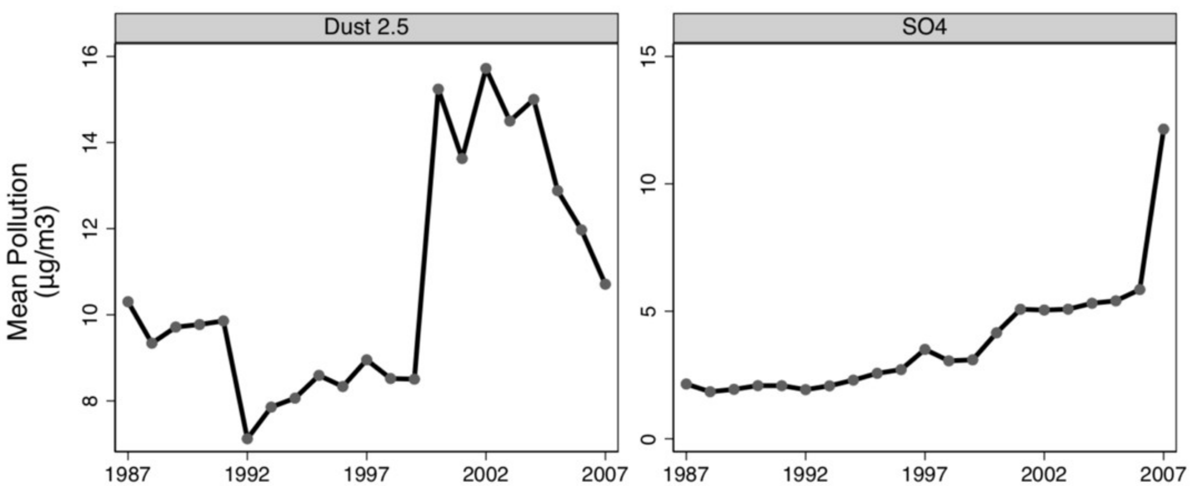
Notes: The figure provides additional evidence on the opposite trends. It compares kernel density estimates of GH's and revised air pollutant distributions across Indian cities for two periods, 1987-1990 and 2004-2007.

Fig. A8. Trends in PM2.5 components, 1987-2007

A. PM2.5 components 1



B.   PM2.5 components 2



Notes: The figure shows the trends in the components of PM2.5 that shed some light on the developments in the overall PM2.5 air pollution.

Table A1 – GH replication: Comparison of outcome variables

	Replication GH data, GH sample			
	SPM		PM2.5	
	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4
	Panel A. Supreme Court Action Plans			
π1: 1(Policy)	7.50	0.30	1.66	0.07
	(20.59)	(21.51)	(4.56)	(4.76)
π2 : time trend	-3.60	-2.85	-0.80	-0.63
	(2.78)	(4.28)	(0.61)	(0.95)
π3: 1(Policy)*time trend	-1.54	0.12	-0.34	0.03
	(7.13)	(5.97)	(1.58)	(1.32)
5-year effect: π1+5π3	-.21	.92	-.05	.20
p-value	[.99]	[.98]	[.99]	[.98]
Observations	11	1,165	11	1,165
	Panel B. Mandated Catalytic Converters			
π1: 1(Policy)	5.55	7.62	1.23	1.69
	(12.76)	(12.26)	(2.82)	(2.71)
π2: time trend	7.75***	7.81**	1.72***	1.73**
	(2.50)	(3.29)	(0.55)	(0.73)
π3: 1(Policy)*time trend	-10.82***	-11.20**	-2.40***	-2.48**
	(2.89)	(4.57)	(0.64)	(1.01)
5-year effect: π1+5π3	-48.56**	-48.39*	-10.75**	-10.71*
p-value	[.04]	[.06]	[.04]	[.06]
Observations	17	1,165	17	1,165

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table replicates GH's results exactly using their data. It reports estimated coefficients from fitting the second-step equation (2), odd columns, and its one-step version, even columns, for the effects of SCAP (Panel A) and CC (Panel B) policies on particulate air pollution. The outcome variable in columns 1-2 is the original GH's SMP, while the outcome variable in columns 3-4 is PM2.5 converted from GH's SPM using SPM/PM10/PM2.5 ratios: PM10 = 0.5053SPM, PM2.5 =0.438PM10. PM10 is particulate matter with a diameter less than 10 µm. Both PM10 and PM2.5 are the fractions of SPM. Columns 1-2 correspond to panels A, columns 1-2 and 7-8 of Table 3 in the main text. Standard errors are in parentheses. The liner combination of the coefficients $\pi_1+5\pi_3$ is an estimate of the policies' effects 5 years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Table A2 – Effectiveness of air quality policies: Effects of meteorological controls

	Reexamination: Full set of meteorological controls					
	GH data GH sample		New data GH sample		New data Full sample	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6
	Supreme Court Action Plans					
	Panel A. PM2.5					
π1: 1(Policy)	3.94	1.17	-0.41	-1.05	-1.41	-1.63
	(5.07)	(4.30)	(2.78)	(1.76)	(2.35)	(1.65)
π2 : time trend	-0.45	-0.35	0.53	0.45	0.50	0.48
	(0.68)	(0.86)	(0.38)	(0.52)	(0.32)	(0.47)
π3: 1(Policy)*time trend	-1.60	-0.66	1.39	1.76*	1.57*	1.64*
	(1.75)	(1.41)	(0.96)	(1.06)	(0.81)	(0.91)
5-year effect: π1+5π3	-4.06	-2.13	6.55	7.77**	6.42*	6.55*
p-value	[.59]	[.79]	[.14]	[.05]	[.09]	[.06]
Observations	11	1165	11	1165	11	2720
	Panel B. SO2					
π1: 1(Policy)	-1.51	-1.70	-0.70**	-0.43	-0.71**	-0.43
	(0.91)	(2.28)	(0.27)	(0.42)	(0.29)	(0.38)
π2: time trend	0.24*	0.09	0.11**	0.09	0.07	0.05
	(0.12)	(0.61)	(0.04)	(0.12)	(0.04)	(0.11)
π3: 1(Policy)*time trend	-0.02	0.33	0.05	-0.01	0.08	0.01
	(0.32)	(0.94)	(0.09)	(0.11)	(0.10)	(0.09)
5-year effect: π1+5π3	-1.61	-.05	-.46	-.47	-.32	-.36
p-value	[.25]	[.99]	[.27]	[.47]	[.47]	[.49]
Observations	11	1158	11	1158	11	2720
	Mandated Catalytic Converters					
	Panel C. PM2.5					
π1: 1(Policy)	1.99	2.08	2.03*	1.85	1.58**	1.52
	(3.36)	(2.80)	(1.12)	(1.25)	(0.72)	(0.93)
π2 : time trend	1.69**	1.72**	0.42*	0.36	0.30*	0.25**
	(0.66)	(0.71)	(0.22)	(0.23)	(0.14)	(0.12)
π3: 1(Policy)*time trend	-2.62***	-2.64***	-0.98***	-0.88***	-0.82***	-0.76***
	(0.76)	(0.98)	(0.25)	(0.31)	(0.16)	(0.23)
5-year effect: π1+5π3	-11.13*	-11.1*	-2.86	-2.53	-2.53**	-2.28*
p-value	[.07]	[.06]	[.15]	[.14]	[.05]	[.09]
Observations	17	1165	17	1165	17	2720
	Panel D. SO2					
π1: 1(Policy)	0.09	-0.46	-0.87*	-0.89***	-1.07**	-0.98***
	(1.92)	(2.74)	(0.48)	(0.25)	(0.38)	(0.17)
π2: time trend	1.88***	1.75**	-0.00	-0.01	0.08	0.07*
	(0.38)	(0.73)	(0.09)	(0.08)	(0.08)	(0.04)
π3: 1(Policy)*time trend	-2.45***	-2.14**	0.09	0.09	0.02	0.01
	(0.43)	(0.98)	(0.11)	(0.10)	(0.09)	(0.07)
5-year effect: π1+5π3	-12.15***	-11.18**	-.41	-.43	-.96	-.95**
p-value	[00]	[.05]	[.61]	[.51]	[.15]	[.03]
Observations	17	1158	17	1158	17	2720

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to additional controlling for meteorological confounders. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) concentrations. Both specifications include a full set of meteorological controls, specifically air temperature, precipitation, its quadratic, and wind speed. The enumeration of columns corresponds to that of columns in Table 3. Columns 1-2 use GH's data. I substitute GH's SPM by GH's PM2.5 for comparability with the policies' effects on MERRA-2 PM2.5. GH's PM2.5 is converted from GH's SPM using SPM-PM10-PM2.5 ratios. Columns 3-4 exploit the same number of cities as in GH and modified PM2.5 and SO2 air pollution outcomes. Columns 5-6 use new outcome variables and fit equation (2) and its one-step version to full sample of cities. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1+5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Table A3 – Detailed effects of meteorological controls, GH data/GH sample

	GH data, GH sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
π1: 1(Policy)	1.66	0.07	4.18	2.23	4.71	2.59	3.94	1.17
	(4.56)	(4.76)	(4.89)	(4.21)	(4.96)	(4.22)	(5.07)	(4.30)
π2 : time trend	-0.80	-0.63	-0.71	-0.54	-0.81	-0.61	-0.45	-0.35
	(0.61)	(0.95)	(0.66)	(0.92)	(0.67)	(0.92)	(0.68)	(0.86)
π3: 1(Policy)*time trend	-0.34	0.03	-1.23	-0.72	-1.23	-0.72	-1.60	-0.66
	(1.58)	(1.32)	(1.69)	(1.44)	(1.72)	(1.40)	(1.75)	(1.41)
5-year effect: π1+5π3	-.05	.20	-1.98	-1.37	-1.44	-.99	-4.06	-2.13
p-value	[.99]	[.98]	[.78]	[.87]	[.84]	[.90]	[.59]	[.79]
Observations	11	1165	11	1165	11	1165	11	1165
	Panel B. SO2							
π1: 1(Policy)	-1.44	-1.25	-1.09	-1.20	-1.49**	-1.53	-1.51	-1.70
	(0.88)	(2.13)	(0.87)	(2.17)	(0.63)	(2.13)	(0.91)	(2.28)
π2 : time trend	0.20	0.09	0.29**	0.18	0.31***	0.19	0.24*	0.09
	(0.12)	(0.55)	(0.12)	(0.59)	(0.08)	(0.59)	(0.12)	(0.61)
π3: 1(Policy)*time trend	-0.06	0.10	-0.28	-0.03	-0.13	0.10	-0.02	0.33
	(0.31)	(0.98)	(0.30)	(0.92)	(0.22)	(0.89)	(0.32)	(0.94)
5-year effect: π1+5π3	-1.74	-.78	-2.49*	-1.36	-2.12**	-1.05	-1.61	-.05
p-value	[.21]	[.87]	[.08]	[.77]	[.05]	[.83]	[.25]	[.99]
Observations	11	1158	11	1158	11	1158	11	1158
	Mandated Catalytic Converters							
	Panel C. PM2.5							
π1: 1(Policy)	1.23	1.69	1.57	1.72	1.23	1.46	1.99	2.08
	(2.82)	(2.71)	(2.90)	(2.66)	(2.97)	(2.65)	(3.36)	(2.80)
π2 : time trend	1.72***	1.73**	1.61**	1.68**	1.67**	1.74**	1.69**	1.72**
	(0.55)	(0.73)	(0.57)	(0.71)	(0.58)	(0.70)	(0.66)	(0.71)
π3: 1(Policy)*time trend	-2.40***	-2.48**	-2.43***	-2.51**	-2.46***	-2.55***	-2.62***	-2.64***
	(0.64)	(1.01)	(0.66)	(0.97)	(0.67)	(0.96)	(0.76)	(0.98)
5-year effect: π1+5π3	-10.75**	-10.71*	-10.59**	-10.82*	-11.05**	-11.29**	-11.13*	-11.1*
p-value	[.04]	[.06]	[.05]	[.06]	[.04]	[.05]	[.07]	[.06]
Observations	17	1165	17	1165	17	1165	17	1165
	Panel D. SO2							
π1: 1(Policy)	-0.53	-0.76	-0.38	-0.80	-0.36	-0.88	0.09	-0.46
	(1.52)	(2.56)	(1.56)	(2.64)	(1.55)	(2.67)	(1.92)	(2.74)
π2 : time trend	2.02***	1.91***	1.98***	1.88***	1.94***	1.85**	1.88***	1.75**
	(0.29)	(0.70)	(0.30)	(0.71)	(0.30)	(0.72)	(0.38)	(0.73)
π3: 1(Policy)*time trend	-2.58***	-2.39**	-2.50***	-2.28**	-2.44***	-2.22**	-2.45***	-2.14**
	(0.34)	(0.98)	(0.35)	(0.96)	(0.35)	(0.96)	(0.43)	(0.98)
5-year effect: π1+5π3	-13.45***	-12.69**	-12.86***	-12.21**	-12.58***	-11.95**	-12.15***	-11.18**
p-value	[.00]	[.02]	[00]	[.03]	[00]	[.03]	[00]	[.05]
Observations	17	1158	17	1158	17	1158	17	1158

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It uses original GH data like in Columns 1-2 of Table 3 to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) concentrations. I substitute GH's SPM by GH's PM2.5 for comparability with the policies' effects on MERRA-2 PM2.5. GH's PM2.5 is converted from GH's SPM using SPM-PM10-PM2.5 ratios. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1+5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Table A4 – Detailed effects of meteorological controls, New data/GH sample

	New data, GH sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
π1: 1(Policy)	-0.69	-1.70	-0.40	-1.22	-0.12	-1.04	-0.41	-1.05
	(2.79)	(1.90)	(2.45)	(1.86)	(2.56)	(1.75)	(2.78)	(1.76)
π2 : time trend	0.67	0.58	0.53	0.44	0.55	0.46	0.53	0.45
	(0.38)	(0.54)	(0.33)	(0.55)	(0.34)	(0.55)	(0.38)	(0.52)
π3: 1(Policy)*time trend	1.83	2.28*	1.59	1.97*	1.49	1.92*	1.39	1.76*
	(0.97)	(1.33)	(0.85)	(1.11)	(0.89)	(1.12)	(0.96)	(1.06)
5-year effect: π1+5π3	8.46*	9.68**	7.55*	8.65**	7.31*	8.55**	6.55	7.77**
p-value	[.07]	[.05]	[.07]	[.04]	[.08]	[.05]	[.14]	[.05]
Observations	11	1165	11	1165	11	1165	11	1165
	Panel B. SO2							
π1: 1(Policy)	-0.27	-0.12	-0.34	-0.17	-0.36	-0.20	-0.70**	-0.43
	(0.30)	(0.44)	(0.27)	(0.42)	(0.22)	(0.44)	(0.27)	(0.42)
π2 : time trend	0.12**	0.09	0.10**	0.07	0.11***	0.09	0.11**	0.09
	(0.04)	(0.14)	(0.04)	(0.13)	(0.03)	(0.13)	(0.04)	(0.12)
π3: 1(Policy)*time trend	-0.03	-0.03	0.04	0.03	0.03	0.02	0.05	-0.01
	(0.10)	(0.12)	(0.09)	(0.12)	(0.08)	(0.12)	(0.09)	(0.11)
5-year effect: π1+5π3	-.4	-.28	-.12	-.03	-.2	-.08	-.46	-.47
p-value	[.37]	[.71]	[.75]	[.97]	[.55]	[.90]	[.27]	[.47]
Observations	11	1158	11	1158	11	1158	11	1158
	Mandated Catalytic Converters							
	Panel C. PM2.5							
π1: 1(Policy)	2.26*	1.96*	2.39*	2.07	2.41*	2.11	2.03*	1.85
	(1.24)	(1.15)	(1.23)	(1.45)	(1.22)	(1.50)	(1.12)	(1.25)
π2 : time trend	0.32	0.23	0.41	0.34	0.40	0.33	0.42*	0.36
	(0.24)	(0.25)	(0.24)	(0.23)	(0.24)	(0.24)	(0.22)	(0.23)
π3: 1(Policy)*time trend	-0.95***	-0.79**	-1.03***	-0.89***	-1.01***	-0.88***	-0.98***	-0.88***
	(0.28)	(0.39)	(0.28)	(0.32)	(0.28)	(0.32)	(0.25)	(0.31)
5-year effect: π1+5π3	-2.48	-1.99	-2.74	-2.38	-2.64	-2.31	-2.86	-2.53
p-value	[.25]	[.19]	[.20]	[.22]	[.21]	[.24]	[.15]	[.14]
Observations	17	1165	17	1165	17	1165	17	1165
	Panel D. SO2							
π1: 1(Policy)	-0.75	-0.88***	-0.74	-0.86***	-0.70	-0.81***	-0.87*	-0.89***
	(0.49)	(0.22)	(0.48)	(0.21)	(0.47)	(0.22)	(0.48)	(0.25)
π2 : time trend	-0.03	-0.03	0.01	0.00	-0.00	-0.01	-0.00	-0.01
	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.08)
π3: 1(Policy)*time trend	0.11	0.12	0.07	0.08	0.08	0.09	0.09	0.09
	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)
5-year effect: π1+5π3	-.22	-.28	-.41	-.48	-0.32	-.38	-.41	-.43
p-value	[.79]	[.62]	[.61]	[.42]	[.69]	[.52]	[.61]	[.51]
Observations	17	1158	17	1158	17	1158	17	1158

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It exploits the same number of cities as in GH and MERRA-2 PM2.5 and SO2 air pollution outcomes, like in Columns 3-4 of Table 3, to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) concentrations. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Table A5 – Detailed effects of meteorological controls, New data/Full sample

	New data, Full sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
π1: 1(Policy)	-1.41	-1.85	-0.71	-1.15	-0.60	-1.07	-1.41	-1.63
	(2.18)	(1.74)	(1.92)	(1.79)	(2.02)	(1.74)	(2.35)	(1.65)
π2 : time trend	0.55	0.54	0.41	0.40	0.44	0.43	0.50	0.48
	(0.29)	(0.50)	(0.26)	(0.52)	(0.27)	(0.51)	(0.32)	(0.47)
π3: 1(Policy)*time trend	2.11**	2.21*	1.80**	1.92*	1.72**	1.86*	1.57*	1.64*
	(0.76)	(1.26)	(0.67)	(1.06)	(0.70)	(1.05)	(0.81)	(0.91)
5-year effect: π1+5π3	9.12**	9.19*	8.30**	8.45**	7.98**	8.21**	6.42*	6.55*
p-value	[.02]	[.06]	[.02]	[.05]	[.03]	[.05]	[.09]	[.06]
Observations	11	2720	11	2720	11	2720	11	2720
	Panel B. SO2							
π1: 1(Policy)	-0.34	-0.14	-0.45	-0.23	-0.46	-0.25	-0.71**	-0.43
	(0.33)	(0.45)	(0.30)	(0.42)	(0.27)	(0.42)	(0.29)	(0.38)
π2 : time trend	0.07	0.05	0.05	0.03	0.06	0.04	0.07	0.05
	(0.04)	(0.12)	(0.04)	(0.11)	(0.04)	(0.11)	(0.04)	(0.11)
π3: 1(Policy)*time trend	0.07	0.04	0.11	0.08	0.11	0.07	0.08	0.01
	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)
5-year effect: π1+5π3	-.01	.04	.12	.15	.08	.11	-.32	-.36
p-value	[.98]	[.94]	[.78]	[.80]	[.84]	[.84]	[.47]	[.49]
Observations	11	2720	11	2720	11	2720	11	2720
	Mandated Catalytic Converters							
	Panel C. PM2.5							
π1: 1(Policy)	2.15**	1.95**	1.95**	1.76	1.98**	1.81	1.58**	1.52
	(0.84)	(0.97)	(0.74)	(1.15)	(0.75)	(1.16)	(0.72)	(0.93)
π2 : time trend	0.19	0.15	0.24	0.21	0.24	0.21	0.30*	0.25**
	(0.17)	(0.11)	(0.14)	(0.13)	(0.15)	(0.13)	(0.14)	(0.12)
π3: 1(Policy)*time trend	-0.82***	-0.73***	-0.81***	-0.74***	-0.82***	-0.74***	-0.82***	-0.76***
	(0.19)	(0.27)	(0.17)	(0.25)	(0.17)	(0.25)	(0.16)	(0.23)
5-year effect: π1+5π3	-1.93	-1.71	-2.1	-1.95	-2.1	-1.92	-2.53**	-2.28*
p-value	[.19]	[.15]	[.11]	[.20]	[.11]	[.21]	[.05]	[.09]
Observations	17	2720	17	2720	17	2720	17	2720
	Panel D. SO2							
π1: 1(Policy)	-0.89**	-0.86***	-0.90**	-0.87***	-0.90**	-0.85***	-1.07**	-0.98***
	(0.38)	(0.19)	(0.39)	(0.16)	(0.39)	(0.17)	(0.38)	(0.17)
π2 : time trend	0.06	0.06	0.07	0.07*	0.07	0.07*	0.08	0.07*
	(0.07)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)
π3: 1(Policy)*time trend	0.03	0.02	0.02	0.00	0.02	0.01	0.02	0.01
	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)
5-year effect: π1+5π3	-.73	-.75*	-0.83	-.85**	-0.82	-.83**	-.96	-.95**
p-value	[.27]	[.07]	[.22]	[.04]	[.22]	[.05]	[.15]	[.03]
Observations	17	2720	17	2720	17	2720	17	2720

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It uses the full sample of cities and MERRA-2 PM2.5 and SO2 air pollution outcomes, like in Columns 5-6 of Table 3, to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on PM2.5 (panels A and C) and SO2 (panels B and D) concentrations. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Table A6 – Magnitudes of the estimated CAT policy's effects: A quantitative summary

	Replication	Reexamination		Reexamination		
	GH data / GH sample	New data / GH sample	△, revised air pollution	New data / Full sample	△, extended sample	△, cumulative
	1	2	3	4	5	6
			Mandated Catalytic Converters			
			Panel A. PM2.5			
5-year effect: $\pi 1+5\pi 3$, %	-19.27**	-10.96	8.31	-8.92	2.04	10.35
1987–1990 mean PM2.5	55.8	22.63			21.64	
			Panel B. SO2			
5-year effect: $\pi 1+5\pi 3$, %	-69.47***	-3.46	66.01	-19.57	-16.11	49.9
1987–1990 mean SO2	19.36	6.36			3.73	
Observations	17	17			17	

	Replication		Reexamination		Reexamination	
	GH data / GH sample	△, meteo controls	New data / GH sample	△, meteo controls	New data / Full sample	△, meteo controls
	1	2	3	4	5	6
			Panel C. PM2.5			
5-year effect: $\pi 1+5\pi 3$, %	-19.95*	-0.68	-12.64	-1.68	-11.69**	-2.77
1987–1990 mean PM2.5	55.8		22.63		21.64	
			Panel D. SO2			
5-year effect: $\pi 1+5\pi 3$, %	-62.76***	6.71	-6.45	-2.99	-25.74	-6.17
1987–1990 mean SO2	19.36		6.36		3.73	
Observations	17		17		17	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: The table summarizes the estimated CAT policy's effects five years after its implementation () expressed in % of the 1987–1990 nationwide mean concentrations of PM2.5 (panels A and C) and SO2 (panels B and D). Shown this way, the magnitudes of the policy's effects become comparable across all data-sample combinations and improve the understanding of the reexamination: testing the sensitivity of GH's findings to the revised air pollution outcomes, extended number of observations, and meteorological controls. Estimates are obtained by fitting the second-step equation (2) of GH's two-step econometric approach. The coefficients in columns 1-2 and 4 of Panels A and B mirror the respective coefficients from Table 3 and characterize the effects of the revised air pollution outcomes and the extended number of observations, respectively. Columns 3 and 5 quantify the differences in the CAT policy's effects on PM2.5 and SO2 concentrations estimated using GH data/GH sample, New data/GH sample, and New data/Full sample. Column 3 shows the net effects of the revised air pollution data captured by the differences between the effects in columns 2 and 1 (column 2 - column 1). Column 5 shows the net effects of the extended number of observations captured by the differences between the effects in columns 4 and 2 (column 4 - column 2). Column 6 shows the cumulative effect of the revised air pollution outcomes and the extended number of observations (column 4 - column 1). Columns in Panels C and D show the effects of controlling for meteorological conditions. The estimates in the odd columns correspond to the respective coefficients from Tables 4 and A4-A6. The even columns show the differences in the CAT policy's effects on PM2.5 and SO2 concentrations across data-sample combinations. Column 2 shows the difference between the effects in column 1 in Panels C and D and column 1 in Panels A and B for GH data/GH sample. Similarly, columns 4 and 6 show the net effects of meteorological controls for the New data/GH sample (column 3 in Panels C and D - column 2 in Panels A and B) and New data/Full sample (column 5 in Panels C and D - column 4 in Panels A and B), respectively.

3 The Impact of the Crisis-Induced Reduction in Air Pollution on Infant Mortality in India: A Policy Perspective

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3.1 Introduction

Air pollution is a grave concern in the developing world, where it kills millions, leads to enormous costs, and constrains economic development (IHME, 2013a; Lim et al., 2013).[54] Despite this, many developing countries avoid committing themselves to the reduction of air pollution because of the natural fear that the economic costs of pollution abatement may outweigh the health benefits (Tanaka, 2015). Thus, measuring the benefits resulting from improvements in air quality has important policy implications. Such measures would allow the evaluation of potential regulations and ensure that their costs are justified. However, empirical studies estimating health benefits associated with reductions in air pollution in developing countries are still scarce (Arceo, Hanna, and Oliva, 2015; Tanaka, 2015; Heft-Neal et al., 2018).

This chapter addresses this literature gap by quantifying the impact of air pollution reductions on infant mortality in India.[55] Specifically, it takes advantage of the economic slowdown caused by the Global Financial Crisis of 2008 and exploits the episode of synchronous

[54] Of the 7 million annual deaths linked to air pollution, 5.9 million occurred in low and middle-income countries of South-East Asia and the Western Pacific (WHO, 2014a). Newborns and infants are particularly vulnerable to air pollution exposure. Around 6.3 million children under the age of five died in 2013, of which 70% and 41% were infants and newborns. About half of under-five deaths were concentrated in just five countries of Africa and South-East Asia, including India with a share of 21% (WHO, 2011, 2014b). The prime cause of these deaths is respiratory diseases attributable to air pollution (WHO, 2014c). The costs of premature mortality caused by the exposure to particulate matter and ozone in 2013 translated into USD 5.11 trillion and USD 225 billions of global losses in total welfare and forgone labor income. Developing countries, mostly in Africa, East and South Asia, incurred the record high losses equivalent to up to 9% of the country's GDP (WB, 2016). India's annual GDP growth was 6.6% in 2013 (WB, n.d.) implying that the pollution-related losses could have offset the whole year of the country's economic development. If no abatement policies are implemented, the number of premature deaths due to exposure to just such air pollutant as particulate matter (PM) will likely more than double, mostly because of an increasing number of deaths in China and India (OECD, 2012).

[55] Infant mortality is defined as the death of children under one year old.

decline in industrial production, reduction in air pollution, and improvement in infant mortality.[56] The specific questions this study addresses are whether the crisis-induced reductions in air pollution caused a decline in infant mortality, and what the transmission channels are through which reductions in air pollution affect infants' health. I also examine the benefits of the decline in infant mortality resulting from the improvement in air quality.

India provides a compelling setting for this study for several reasons. First, two decades of industrialization and rapid economic growth led to severe air pollution in India. Of the 20 most polluted cities in the world, 13 are located in India, including the capital city Delhi, which is ranked as the most polluted (Greenstone et al., 2015; WHO, 2014d). India has the world's highest proportion of deaths caused by respiratory diseases (WHO, 2014e). The Global Burden of Disease ranks air pollution as the second leading health risk factor in India (IHME, 2013b). Second, despite the severity of the Global Financial Crisis, India escaped a full-scale recession and suffered instead from the delayed second-order effects that led to a temporary economic downturn. According to the Index of Industrial Production (IIP), the output of the integrated industrial sector in India hit a record low of -7.20% in March 2009, from about 20% of its pre-crisis level (MOSPI, n.d.). Also, the average contraction of trade was around 20% during the period from October 2008 to September 2009 (EAC, 2009; Kumar and Alex, 2009). Third, the contribution of the global financial turmoil to the reductions in air pollution in the U.S. and Europe is well documented (Davis et al., 2010; Castellanos and Boersma, 2012; Vrekoussis et al., 2013), but it is still understudied in the case of India. Taken together, the substantial drop in IIP and the dominant share of the manufacturing and energy sectors in the index (78% and 8%, MOSPI, n.d.) imply that the economic slowdown affected areas in India differentially, based on the pre-crisis industrial structure and industry-specific pollution intensities. As I demonstrate below, this led to substantial reductions in air pollution in some areas, but not in others. Indian districts with larger shares of the manufacturing, mining, construction, or energy sectors experienced a more substantial decline in air pollution than districts without these pollution-intensive sectors. Altogether, such a setting allows me to study the relationship between air pollution reductions and infant mortality at greater pollution concentration levels and to do so using a credible quasi-experimental approach.

[56] I exploit the economic slowdown caused by the Global Financial Crisis of 2008 rather than environmental regulations as a natural experiment. This is because environmental regulations in developing countries, even if they are designed similarly to those in the developed ones, often involve implementation problems that complicate the estimation of the effect of interest (Arceo et al., 2015; Duflo, Greenstone, Pande, and Ryan, 2013, 2018).

To implement the analysis, I combine state-of-the-art satellite-based estimates for annual concentrations of fine particulate matter (PM2.5)[57] with survey-based household information on nearly 2 million births and 150 thousand deaths and their determinants for 284 districts across 9 states during 2007-2011. I use a quasi-experimental difference-in-differences approach in an attempt to isolate the role of the reductions in PM2.5 pollution from other confounding factors that affect infant mortality. This approach exploits both the timing of the crisis and its differential effect across districts, depending on their pre-crisis industrial specialization. However, using the crisis as a source of treatment variation exposes this approach to two conceptual challenges: unknown timing of the crisis-induced effects on air pollution and sorting the districts into treated and control groups. I overcome these challenges by exploiting such methodological innovations as a time-series econometric test for structural trend break and a spatial Hot Spot Analysis. Based on the results of these analyses, my preferred specification compares pre- vs. post- 2010 levels and trends in infant mortality rates between treated and control districts. The key identifying assumptions are that, conditional on district-specific trends, any pre- versus post-2010 changes in infant mortality rates caused by factors besides air pollution are the same for the treated and control districts, and that air pollution is the only factor differentially affecting the treated districts beginning in 2010.

Answering the first question, I find that the crisis-induced reductions in PM2.5 pollution led to a statistically significant decline in district-level infant mortality rates. Regression coefficients indicate that the infant mortality rate in the treated districts fell by about 24% more than in the control districts between pre- and post-crisis periods. The estimates are robust to a variety of specifications and falsification tests. Addressing the second question, I examine the impact of the changes in PM2.5 concentrations on the mortality of infants at different ages and from various diseases. My findings suggest that the PM2.5 reductions affected infant mortality mainly through respiratory diseases and two biological mechanisms: in utero and post-birth PM2.5

[57] The United States Environmental Protection Agency [U.S. EPA] defines particulate matter (PM) as “a complex mixture of extremely small particles and liquid droplets that get into the air” (U.S. EPA., n.d.a). Particulate air pollution can be categorized in a number of ways, including size and sources of emissions. Size is an important indicator of the particles’ penetrating ability, which highlights the most probable region of the respiratory tract where inhaled particulates could be deposited. By this criterion, particulate air pollution can be broken down into total suspended particles with an aerodynamic diameter of less than 100 μm, coarse or inhalable (less than 10 μm in diameter), fine or respirable (smaller than 2.5 μm) and ultra fine (less than 0.1 μm). Particulate matter can be originated from anthropogenic (human-made) or natural sources. The former sources include industrial activity, transport exhaust, power generation, household heating, cooking and fuel combustion, while the latter add sea salt, dust, volcanic and fire ash (van Donkelaar et al, 2010; van Donkelaar et al., 2016).

exposure. Heterogeneity analysis further emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution. Finally, I use the quantified relationship to measure health benefits and monetary gains from the crisis-induced episode of PM2.5 pollution reduction. My calculations suggest that 1338 infant lives were saved, implying a contribution of 11% to the overall decline in infant mortality during the post-crisis period and leading to monetary benefits of USD 312.5 million.

The research design used in this study allows me to overcome or substantially mitigate some of the frequent empirical challenges of the endogeneity of air pollution exposure. First, the temporary nature of the economic crisis in India allows me to address one of the major causes of endogeneity – residential sorting.[58] In my research design, it is unlikely that households migrate in search of new employment or because of their preferences for better air quality in the short crisis time frame. The limited geographical mobility of infants and pregnant women also helps to alleviate this threat to identification.[59] Second, since the reduction in air pollution concentrations was caused simultaneously by global and nationwide phenomena, unobserved behavioral changes within the treatment group that could also affect health and invalidate research design are unlikely in this study's settings. In addition, the control group of districts accounts for any common responses to the crisis. Finally, it is also critical to control for other changes accompanying the crisis, including changes in per capita income and meteorological confounders. I address these challenging issues in the study.

The study builds on economic and epidemiological literature that uses quasi-experimental designs to quantify the causal relationship between various health outcomes and reductions in air pollution. Prominent epidemiological studies by Pope (1989), Pope, Schwartz, and Ransom (1992), Ransom and Pope (1995), Parker, Mendola, and Woodruff (2008) exploit closure and reopening of a steel mill in the Utah Valley to show that improvements in air quality are associated with the decline in respiratory morbidity, mortality, and preterm births. Related studies from economic

[58] Residential sorting is the optimizing behavior of individuals choosing residential locations based on attributes, including air quality, that can lead to the non-random assignment of air pollution (Graff Zivin and Neidell, 2013; Currie et al., 2014).

[59] Although statistics on mobility or migration of pregnant women do not exist, numerous indirect evidence can be found in the literature. For example, the 2001 Census reports that only 1.6% of all Indian households, both urban and rural, migrated in 2001. Similarly, Bošković et al. (2023), using data from the 2005 round of the India Human Development Survey, which is a nationally-representative survey of households, shows that only 1% of the sample households moved from elsewhere. Another evidence of typically low migration of households in India can be found in National Sample Survey Office (2010).

literature by Lavaine and Neidell (2013), Currie et al. (2013), and Hanna and Oliva (2015) also estimate the health effects from the variations induced by operational distortions of specific polluters, oil refineries or toxic plants, in both developed and developing countries. However, these studies rarely exploit recession as a source of exogenous variation, with the remarkable exception represented by Chay and Greenstone (2003b), who link changes in infant mortality to the reduction in total suspended particles (TSP) across U.S. counties caused by the U.S. 1981-1982 recession.[60] They show that a 1% reduction in TSP resulted in a 0.35-0.45% decline in infant deaths at the county level. Other quasi-experimental studies focus on regulation-induced changes in air quality. This strand of literature benefits from the contribution by Chay and Greenstone (2003a) and Sanders, Barreca, and Neidell, (2020) for the U.S. and Luechinger (2014) for Germany. Until recently, much of what we knew from the literature came from the developed countries. However, as these countries are generally wealthier, have much lower mortality rates and air pollution concentrations, the transferability of estimates from developed to developing countries remained unvalidated in most cases. Currently, a growing literature provides causal evidence on the effects of environmental policies on infant mortality in developing countries: Greenstone and Hanna (2014) for India, Ebenstein et al. (2015) and Tanaka (2015) for China, and Cesur, Tekin, and Ulker (2016) for Turkey. My study builds on the successful design of the previous studies and contributes to overcoming the scarcity of studies that link infant mortality and reductions in air pollution in developing countries, using a different quasi-experimental setting. Additionally, the study estimates the health benefits of reducing air pollution, which could be used as a benchmark to assess potential policies designed to improve air quality.

3.2 Data

To implement the analysis, I constructed a panel of district-by-year data on infant mortality, mortality-related controls, fine particulate matter, and confounding factors for 2007-2011. Raw data are from a variety of survey-based and satellite-based sources.

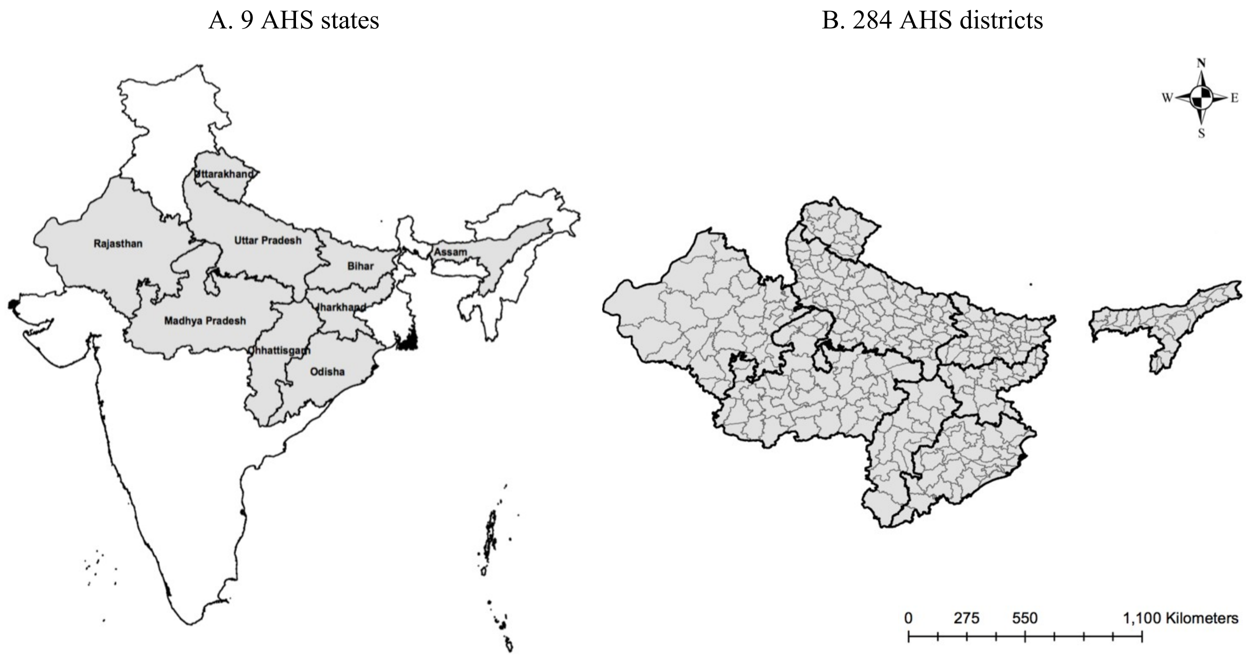
[60] Sanders (2012) investigates the relationship between early-life exposure to air pollution and long-term outcomes (Currie et al. 2014). Similar to Chay and Greenstone (2003b), the author uses the U.S. 1981-1982 recession and the related decline in manufacturing employment as a source of variation to estimate the impact of the reduction in fetal TSP exposure on educational outcomes in Texas. Sanders (2012) finds that a one standard deviation decline in TSPs around the time of students' birth increases high school test performance by 6% of standard deviation.

3.2.1 Mortality Data

Data on infant births and deaths came from the Annual Health Survey (AHS) of India. The AHS is the first population-representative longitudinal demographic survey in India designed to collect health-related information at the district level, with the infant mortality rate taken as the decisive indicator for the sample size. The survey structure corresponds to the typical structure of demographic and health surveys (DHS) conducted in many low- and middle-income countries.

The AHS is a sub-national survey that covers 284 districts across 9 states from 2007 to 2011 (Fig. 1). These districts are a particularly relevant study area. They represent nearly 50% of the overall population and account for 60% of all births and 70% of all infant deaths in the country. The AHS was conducted during 2010-2013 in three consecutive rounds and four schedules, specifically House-listing, Household, Woman, and Mortality. Each round recorded health-related information at the individual and household levels for 12 months before the survey was taken. A representative sample of 20694 Primary Sample Units, selected based on a uni-stage (two-stage in cases of larger rural villages) stratified simple random sample without replacement, covered around 20.6 million individuals and 4.3 million households (Census of India, n.d.). I downloaded the AHS data from the Health Management Information System, a digital initiative of the Ministry of Health and Family Welfare, Government of India (HMIS, n.d.).

Overall, my sample includes 1,883,456 individual births and 148,398 deaths. The outcome of interest for this study is the infant mortality rate (IMR), which is conventionally expressed as the number of infant deaths per 1000 live births. I derived information on the number of deaths within one year of life from the Mortality schedule and further aggregated the number at the district-by-year level. As the numerator for infant mortality rate I used the total number of infant deaths due to all causes, within one day, within 28 days, between one and eleven months, and between eleven months and one year. I collected data on the total district-by-year number of live births for the denominator from the Woman schedule reporting the outcomes of pregnancies. I further disaggregated the total number of deaths using information on different symptoms of death pertaining to the deceased infants. I also use a perinatal or a stillbirth mortality rate as the outcome variable. This measure of mortality is computed as the number of stillbirths or fetal deaths per 1000 total live births and stillbirths combined. The average annual infant mortality rate for all causes is 87.4 per 1000 live births.



Notes: The figure demonstrates the 284 districts (as per Census 2001) across 9 states in India covered by the Annual Health Survey. These districts are a particularly relevant study area. They represent nearly 50% of the overall population and account for 60% of all births and 70% of all infant deaths in the country.

Fig. 1. Annual Health Survey (AHS) study area

3.2.2 Mortality-Related Controls

The Mortality and Woman AHS schedules are the primary sources of the mortality-related controls. From the former schedule, I derived three groups of control variables: characteristics of the deceased infants, characteristics and habits of the infants' Heads of the households (HH)[61], and deceased infants' household characteristics. These variables include a percentage of male infants, share of infant deaths in rural areas and average birth order; the share of the male HHs, percentage of the HHs affiliated with social groups, including scheduled castes and scheduled tribes, HHs' educational qualification, religion and occupation, as well as the percentage of HHs smoking and drinking alcohol; the percentage of houses with filtered water, different sources of lightning, type of cooking fuel used, whether households cook inside the house and use open defecation as a toilet

[61] I use characteristics and habits of the deceased infants' Heads of the households as a proxy for parental characteristics.

facility. The purpose of these controls is to capture the effects of either changes in indoor air pollution or potential sources of deadly infectious diseases, for example, malaria.

Some of the district-specific attributes and indicators of the utilization of medical services by mothers and infants were extracted from the Woman schedule. The controls from this survey are the average number of births and population, average age of mothers and percentage of those married. Indicators of the utilization of medical services by mothers and infants include percentage of mothers who did not receive any ante natal care during pregnancy, percentage of deliveries at the government medical facilities, share of newborns who did not receive any checkups after birth and percentage of babies who received any vaccination. These variables highlight the importance of the medical services in saving infant lives.

3.2.3 Pollution Data

Satellite-derived data for the construction of the main variable of interest, the annual district-level average PM2.5 concentrations, were obtained from the Atmospheric Composition Analysis Group (ACAG) at Dalhousie University. The data represent global gridded datasets of annual bias-corrected average surface PM2.5 concentrations at 0.01^{o} x 0.01^{o} spatial resolution (1 x 1 km at the equator) estimated by combining Aerosol Optical Depth[62] retrievals from multiple satellite sources (MODIS, MISR, SeaWIFS) with simulations in the GEOS-Chem chemical transport model, subsequently calibrated against ground-based monitor data using geographically weighted regressions (van Donkelaar et al., 2016; ACAG, 2016). AOD-based PM2.5 estimates are widely considered as a good proxy of air pollution over India (Dey et al., 2012). I downloaded ArcGIS-compatible files with dust and sea-salt removed estimates, which allowed me to focus on anthropogenic, human-made particulate air pollution. PM2.5 concentrations were calculated by taking averages of annual mean concentrations at all grid points within districts' administrative boundaries overlying the ACAG gridded PM2.5 data using the ArcGIS platform. I downloaded shapefiles with districts' boundaries for such computations from the Global administrative areas

[62] Aerosol Optical Depth measures the amount of sunlight absorbed, reflected, and scattered by the particles suspended in the air. Satellite observations of AOD make it possible to estimate surface PM2.5 concentrations at granular spatial resolution and with comprehensive geographical and temporal coverage.

[GADM] (2015) spatial database.[63] The average annual PM2.5 concentration in my sample during the study period is 54.4 μg/m3.

3.2.4 Economic Data

Controlling for cross-districts differences in income changes during the crisis is important to mitigate potential confounding bias. However, official district-level data on income per capita do not exist. I thus constructed a proxy for this confounder using satellite-derived nighttime lights imagery. Evidence suggests that nighttime lights expressed in the form of a natural logarithm adequately explain GDP at the district-level for India (Chaturvedi, Ghosh, and Bhandari, 2011; Bhandari and Roychowdhury, 2011).[64] I obtained nighttime lights satellite images from the repository at the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA). These images were captured by the Operational Linescan System sensor onboard the Defense Meteorological Satellite Program satellites. The values of the pixels from the stable lights data show brightness in Digital Numbers and are cleaned from ephemeral lights from fires, gas flares and other similar events (NGDC, n.d.). Using ArcGIS, I first sum all lit pixels within the GADM districts' boundaries for each year as suggested by Lowe (2014). Then, relating the sums obtained to the district-level population and taking log-transformation, I derived a measure of the natural logarithm of the district-level GDP per capita.

District-level population data were retrieved from the world's gridded population count dataset for 2000, 2005, 2010 and 2015, obtained from the Center for International Earth Sciences Information Network (CIESIN) at Columbia University. The population count grids are consistent with national Censuses and population registers and contain estimates of the number of persons per grid cell (CIESIN, 2016). To construct a district-by-year population, I summed the number of persons in the cells within the overlaid GADM districts' boundaries. For missing years, the population was imputed by linear interpolation. I also use the CIESIN's population data to weight regressions and compute population-weighted dimensions of the variables.

[63] I adjusted districts' borders in the GADM shapefiles so that they correspond to the districts' administrative boundaries as they were in 2001. As a reference, I used maps of the AHS districts downloaded from the Census of India website (Census of India, n.d.)

[64] This early evidence is supported by several most recent papers (Singhal et al., 2020; Asher et al., 2021; Dasgupta, 2022), showing that night lights are highly significant proxies for economic activity in India at very disaggregated geographical levels and can reliably capture even short-term impact of economic shocks.

3.2.5 Weather Data

As atmospheric conditions influence both air pollution and health, meteorological covariates are also potential confounders. Addressing this concern, I control for temperature, precipitation, wind direction and speed. I use gridded datasets of average monthly temperature and precipitation from the Climatic Research Unit (CRU) at the University of East Anglia (Harris at al., 2014; CRU, 2017). The raw monthly means gridded data for u-wind (west-east), v-wind (south-north) vectors and wind speed were obtained from the NOAA's NCEP/NCAR Reanalysis 1 (Kalnay et al.,1996). By analogy to air pollution, I processed raw data in the ArcGIS to construct annual average air temperature, precipitation, wind directions and speed at the district level.

3.2.6 Descriptive Statistics and Data Insights

Table 1 presents descriptive statistics for the districts from Fig. 1. The table shows that the reduction in district-level PM2.5 pollution during 2009-2011 is visibly larger than the changes in the majority of other variables during the same period.

Appendix Fig. A1 illustrates the evolution of the district-level annual mean concentration of PM2.5 in the study area for 1998-2015. Two observations deserve closer attention. First, air quality has been deteriorating continuously during the last two decades. The PM2.5 level increased from an average of 43 μg/m3 in 1999 to more than 60 μg/m3 in 2015, a change of almost 40%. The worsening of air quality during this period could obviously be associated with rapid economic growth during the pre-crisis wave of globalization, accompanied by industrialization and urbanization, as well as a fast-growing population and deterioration of the natural environment (CPCB, 2014). Second, the figure documents two episodes of abrupt reduction in PM2.5 concentrations, 2005-2006 and 2009-2012, followed by the comparably sharp reversals of the trends. The timing of the first episode is somewhat unfortunate for this study as it is close in time to the period of interest. In the next section, I conduct a formal test to ensure that my findings are not related to this period.

Table 1 – Descriptive statistics

	2007	2008	2009	2010	2011
Panel A: District-specific characteristics					
Number of districts	283	283	283	257	281
Population in sample	605872070	617397169	628922276	598644463	648405359
Total number of live births	414075	373871	336085	335528	423897
Total number of infant deaths (all causes):	32310	31718	33515	25058	25797
early neonatal	14781	14271	15065	11199	11797
late neonatal	4897	4747	4976	4034	4088
postneonatal	9659	9486	10111	7488	6984
Infant Mortality Rates (all causes)	82.43	89.56	111.61	88.74	64.73
early neonatal	36.43	38.59	47.72	38.14	29.99
late neonatal	13.86	14.65	18.80	16.38	9.97
postneonatal	24.72	27.11	33.86	25.97	17.49
Mean district-level air pollution ($PM_{2.5}$)	52.35	57.97	56.27	54.03	51.43
Average age of mothers	28.21	27.35	26.72	26.41	26.40
% of Married mothers	98.92	99.09	99.24	99.46	99.40
Panel B: Deceased infants characteristics					
% of Male infants	50.97	51.21	50.13	50.93	50.40
% of Infant deaths in rural areas	86.86	87.89	87.43	87.56	85.84
Average birth order	2.75	2.79	2.76	2.52	2.41
Panel C: Head of the household characteristics					
% of Male Head of the household	90.09	89.91	89.80	86.27	84.50
% of Heads from Scheduled Castes	21.58	22.15	22.06	22.74	22.39
% of Heads from Scheduled Tribes	12.40	12.54	12.82	11.69	12.50
% of Illiterate Heads	40.70	40.16	40.88	39.81	40.04
% of Hindu Heads	82.59	82.47	82.77	82.70	82.84
% of Muslim Heads	15.82	15.86	15.46	14.60	14.64
% of Unemployed Heads	8.56	8.05	8.53	10.55	11.57
% of Smoking Heads	29.44	28.61	29.47	26.89	27.10
% of Alcohol-drinking Heads	24.98	24.52	24.40	22.13	22.30
Panel D: Deceased infants household characteristics					
% of Houses with filtered water	16.45	16.68	16.95	16.75	16.48
% of Houses with electrical lightning	40.32	40.08	40.17	38.39	37.15
% of Houses with kerosene lightning	58.09	58.13	58.16	60.05	61.10
% of Households cooking on firewood	54.57	54.45	54.52	52.79	55.24
% of Households cooking on cow dung cake	22.34	22.62	22.10	23.98	22.55
% of Households cooking on coal/charcoal	1.54	1.50	1.63	1.50	1.35
% of Households cooking on electricity	0.08	0.07	0.07	0.05	0.06
% of Households cooking inside	81.09	81.65	81.02	82.66	81.46
% of Households without toilet	74.24	74.12	74.01	74.42	75.17
Panel E: Medical services utilization					
% of Mothers with no ante natal care	17.12	15.04	13.51	1.61	1.67
% of Deliveries at government facilities	34.27	40.03	43.77	46.09	49.95
% of Newborns with no after births checkups	29.94	26.10	23.82	18.36	13.91
% of Vaccinated babies	93.29	94.13	94.54	92.64	95.22
Panel F: Meteorological covariates					
Mean district-level air temperature (p/a)	25.71	25.55	26.37	26.38	25.59
Mean district-level precipitation (p/a)	87.93	95.30	73.06	76.81	108.68

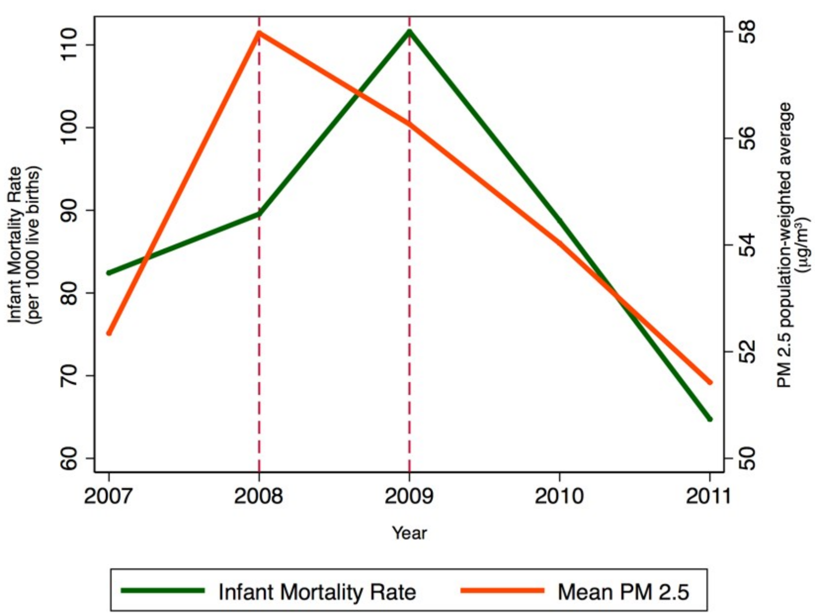
Notes: The table presents descriptive statistics for the districts from Fig. 1. The table shows that the reduction in district-level PM2.5 pollution during 2009-2011 is visibly larger compared to the changes in the majority of other variables during the same period.

Improvement in air quality during the 2009-2012 episode is the focus of my study. The PM2.5 curve does show a change in its trend around the alleged outbreak of the Global Financial Crisis. After reaching its record high maximum in 2008 at 58 μg/m3, fine particulate air pollution fell by almost 9 μg/m3, slightly above 15%, making improvement in air quality during this episode the largest for the entire 1998-2015 interval. This downward trend in PM2.5 pollution was offset by the steep reversal during 2013-2015, when average PM2.5 concentrations reached a record high of 60.25 μg/m3, representing an increase of about 23%. This period coincides with the accelerating recovery of the Indian economy and its transit from volatile to stable real GDP growth (IMF, 2016).

Appendix Fig. A2 compares kernel density estimates of the annual mean PM2.5 distributions across the districts for 2008, 2012 and 2015, representing pre-crisis, crisis and post-crisis year-end points. Panel A demonstrates that the entire distribution shifted substantially to the left in 2012 compared to 2008. In contrast, Panel B documents a shift of the distribution to the right again in 2015. Panel A of Appendix Table A1 provides summary statistics for these changes. It demonstrates that the 2009-2012 improvement episode was remarkable in several aspects. While the mean PM2.5 level declined by more than 15%, the tenth percentile of the distribution as well as observed minimums remained unchanged. However, the drop in the ninetieth percentile was particularly noteworthy with a decrease of about 14 μg/m3, more than 17%. The shift in observed maximums by almost 44 μg/m3, representing 36%, is especially striking. During the post-crisis period, the sharp reversal of the improvement trend led to a substantial deterioration in air quality that was comparable to the pre-crisis period.

Taken together, Appendix Fig. A3 and Panel A of Appendix Table A1 support the initial hypothesis that districts with high pre-crisis levels of air pollution likely experienced more substantial improvement in air quality than districts with initially low pollution concentrations. Appendix Fig. A3 provides an overview of the spatio-temporal distributions of annual mean PM2.5 concentrations across the study area for 2008, 2012 and 2015, which visually support this conclusion. Panel B of Appendix Table A1 relates changes in PM2.5 concentrations from Appendix Fig. A3 to population exposure, providing suggestive evidence that improvements in infant mortality could be more pronounced in districts with high pre-crisis levels of air pollution.

Fig. 2 illustrates the evolution of the district-level annual means of PM2.5 air pollution and the infant mortality rate during 2007-2011. The infant mortality rate followed a similar pattern to that of air pollution. The IMR increased to achieve its highest rate by 2009. Then, during the following two years, 2010-2011, the infant mortality rate decreased sharply from about 112 to 65 deaths per 1000 live births, an unprecedented 42%, and supposedly continued this path till the end of the time frame of the crisis in 2012. Further, Table 1 indicates that while the number of infant deaths from all causes declined substantially after 2009, the number of births remained almost unchanged. This implies that the decline in the IMR was likely driven by the substantial reduction in the number of deaths during the period, which I relate to the crisis-induced decline in air pollution. As analysis of different death categories suggests, the dynamics observed in the total number of deaths was caused mainly by the reduction in early neonatal and postneonatal mortality.



Notes: The figure shows the evolution of the district-level annual means of PM2.5 air pollution and the infant mortality rate during 2007-2011. The infant mortality rate followed a similar pattern to that followed by air pollution. Both data series provide visual evidence of structural breaks marked by the dashed lines and reversals in upward trends started after 2008 and 2009, respectively for air pollution and mortality. Although with a time lag, both breaks correspond well to the crisis' time frame, cautiously suggesting the presence of a direct relationship within the crisis-pollution-mortality nexus.

Fig. 2. Trends in mean PM2.5 concentrations and Infant mortality rates, study area, 2007-2011

Both data series presented in Fig. 2 provide visual evidence of structural breaks, marked by the dashed lines, and reversals in upward trends, beginning after 2008 and 2009, respectively for air pollution and mortality. Albeit with a time lag, both breaks correspond well to the time frame of the crisis, cautiously suggesting the presence of a direct relationship within the crisis-pollution-mortality nexus.

3.3 Empirical Strategy

This section introduces the empirical strategy that I use to answer the first research question. Specifically, in an attempt to isolate the causal relationship between the crisis-induced reductions in PM2.5 and the infant mortality rate, I use a quasi-experimental difference-in-differences (DID) technique.

3.3.1 Standard Model

The standard DID model in a two-way fixed effect regression framework is as follows:

$$\log(IMR)_{dt} = \alpha + \delta_1 (Treated_d \cdot Post_t) + \beta_1 W_{dt} + \beta_2 X_{dt} + \mu_d + \gamma_t + \varepsilon_{dt} \quad (1)$$

where $\log(IMR)_{dt}$ denotes a natural logarithm of the infant mortality rate[65] in district d and year t. $Treated_d$ is an indicator variable for whether district d belongs to the treatment group; $Post_t$ is an indicator variable for the years after a specific year τ_0, indicating a post-crisis time period. I delve into the more precise definition of the latter two variables further below. W_{dt} is a set of district-level meteorological covariates; X_{dt} is a set of observable time- and/or district-varying controls for a set of covariates in the mortality-pollution nexus. μ_d are district fixed effects that capture time-invariant heterogeneity between treated and control districts; γ_t are year fixed effects controlling for the year-specific common shocks for both types of districts; ε_{dt} are idiosyncratic

[65] The reason for modeling infant mortality rate in a log-form is as follows. I hypothesize that the crisis-induced changes in air pollution could have had proportional effects on infant mortality. Specifically, districts with initially higher mortality rates could experience a larger decline in the level of mortality, due to changes in air pollution concentrations, than the districts with an initially lower rate. Using proportional changes also facilitates between-districts comparisons.

error term, robust and clustered at the district level to account for serial correlation between districts over time (Bertrand, Duflo, and Mullainathan, 2004; Wooldridge, 2003). To account for differences in the size of the districts, equation (1) is weighted by the district-level population.

The coefficient of interest, δ_1, captures the difference between the districts from the treatment and control groups in changes in $\log(IMR)_{dt}$ before and after the crisis-induced decline in PM2.5 pollution. If the crisis-induced reductions in air pollution contributed to a more substantial decline in infant mortality in the districts from the treatment group than those from the control group, $\widehat{\delta_1}$ will be negative. The interpretation of the coefficient would be that the crisis-induced reductions in PM2.5 pollution are associated with a $100 \cdot (e^{\hat{\delta}_1} - 1)$ percent lower infant mortality rate in the treated districts than in the control districts between pre- and post-crisis periods.

Using the crisis as a natural experiment exposes this empirical strategy to two conceptual challenges: unknown timing of the crisis-induced effects on air pollution (variable $Post_t$), and sorting of the districts into the treatment and control groups (variable $Treated_d$).

3.3.2 Timing of the Crisis-Induced Effects

To address the first challenge, I associate the timing of the crisis-induced effects on air pollution with the break in the upward trend of PM2.5 concentrations that occurred in a particular year. Then, this year can be considered as the year of critical changes in air pollution caused by the crisis and can be used to divide the whole period of interest into pre- and post- crisis intervals. Even though Fig. 2 provides visual support that PM2.5 pollution does indeed show a trend break around 2008[66], the timing of the effects of the crisis on air pollution requires more credible justification.

Therefore, I perform a time-series econometric test for a structural trend break, specifically supremum Wald and likelihood-ratio (LR) tests designed for cases when the breakpoints are unknown (Andrews, 1993, 2003; Hansen, 1997). The idea is to determine a statistically significant trend break in the aggregated average PM2.5 pollution time series and check whether it corresponds to the initial point of the global financial crisis around 2008. Finding a statistically

[66] I assume that this year can be considered as the first year when the crisis could potentially affect air pollution.

significant break in proximity to the alleged starting point of the crisis would suggest that the crisis might have had an impact on the level of particulate air pollution. Exploiting supremum tests for the purpose of finding structural breaks in time series was shown to be a reliable in contexts similar to that of this study and was adopted by economists in a number of papers (Piehl et al., 2003; Jayachandran, Lleras-Muney, and Smith, 2010; Greenstone and Hanna, 2014).[67]

I test for the structural break in PM2.5 pollution time series in the year of the possible breakpoint, τ, using a model similar to Jayachandran et al. (2010):

$$\Delta PM_{t,t-1} = \alpha + \delta_0 D_t(\tau) + \varepsilon_t \tag{2}$$

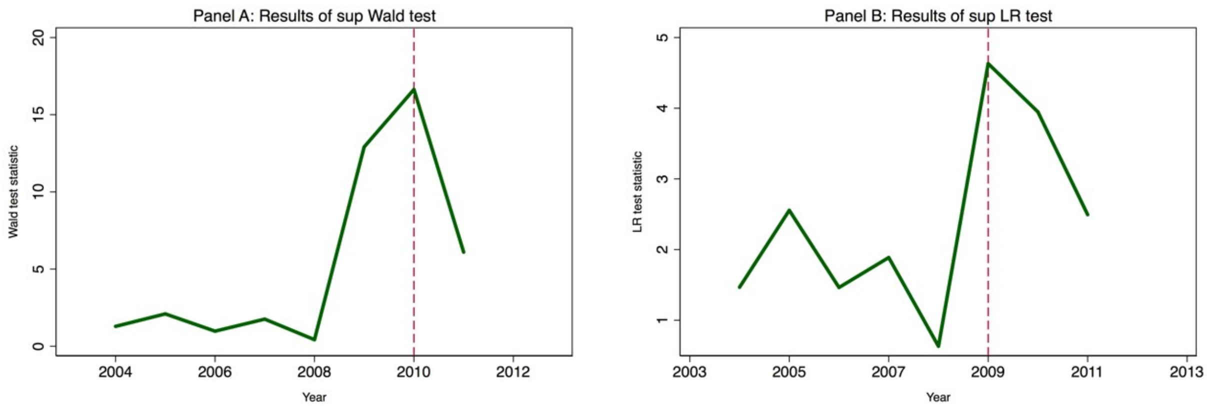
where $\Delta PM_{t,t-1}$ is the first difference in the PM2.5 pollution time series[68]; $D_t(\tau)$ is an indicator variable equal to zero for the years before τ and equal to one for those after τ; ε_t - robust standard errors.

Formally, sup Wald and LR tests are applied sequentially to test for constancy in the coefficients from the regression of model (2) with τ taking on each year within the interval of possible trend breaks, a test window, and calculate the W- and F-statistic associated with the null hypothesis of no trend break, $\delta_0 = 0$, for each tested year. The test window is shorter than the whole time series. For the test not to be misleading, it should have enough data points before and after the test window to estimate regressions before and after the breakpoint (Andrews, 1993; Piehl et al., 2003; Jayachandran et al., 2010; Greenstone and Hanna, 2014). I test for the single possible break in an eight-year test window, including a range of years in the 2004-2011 interval. Given quite a short time series, this is the maximal length of test window I could allow; it corresponds to a symmetric trimming of the pollution time series by 25%[69]. The test then selects the maximal among the resulting test statistics to define the best possible breakpoint, τ_0, and returns the

[67] Several reasons make application of this technique in our research attractive. Firstly, both tests are robust to heteroscedasticity and overcome limitations inherent in the traditional Chow test that assumes homoscedasticity. Secondly, as Piehl et al. (2003) summarize, the intuition of sup Wald and LR tests is appropriate in the program evaluation context, the purpose similar to our aims in that the effect of the crisis can be treated in a way similar to the effect of a policy intervention. Finally, formal testing improves earlier attempts undertaken by Chay and Greenstone (1999, 2003b), Sanders (2012), Tanaka (2015) to overcome the same difficulties in the similar settings.

[68] The reason for using the first difference of the dependent variable is that by doing so I achieve stationarity of air pollution time series. To be valid, supremum tests require data to be stationary (Andrews, 1993; Piehl et al., 2003), a condition that my time series does not satisfy. Both Augmented Dickey-Fuller and Phillips-Perron tests fail to reject the null hypothesis of nonstationarity; however, they do reject the null in the case of the first-differenced series.

associated p-value to gauge the significance of the detected break. Since the test statistics do not converge to any known distribution, the reported p-values are calculated by the method introduced in Hansen (1997). Fig. 3 and Appendix Table A2 present the results of the tests for structural break on an unknown year.[70]



Notes: The figure presents the results of the time-series econometric test for structural trend break, specifically supremum Wald and likelihood-ratio (LR) tests designed for the cases when the breakpoints are unknown (Andrews, 1993, 2003; Hansen, 1997). Both supremum tests identify structural breaks within the 2009-2012 air quality improvement episode, thus associating them with the respective reversal of the upward trend in PM2.5.

Fig. 3. W- and F-statistics from sup Wald and sup LR tests for trend break

Both supremum tests identify structural breaks within the 2009-2012 air quality improvement episode, thus associating them with the respective reversal of the upward trend in PM2.5. Sup Wald reports 2010 as a year of statistically significant break, while sup LR selects 2009 as a break year, although insignificant[71]. Panel A of Appendix Table A2 shows that whenever 2010 is included in the test window, the maximal W-statistics are concentrated at this year, and the null hypothesis can be rejected at the 1 percent level. When tested by the sup LR, the same applies to 2009 except that neither of the F-statistics is significant. As another specification test, in addition to different lengths of test window and trimming percentages, I test for possible trend

[69] For comparison, a common approach suggested by Andrews (1993) is to trim 15% from both ends. However, it is common to select a trimming percentage up to 49%.

[70] I also perform a Chow-type test for structural trend break on a known year (Chow, 1960). Using the same model and data, I construct a heteroscedasticity robust Wald statistic to test the null hypothesis of no trend break for each year within the same test window, separately. Thus, I pretend I know that each year from 2004 to 2011 might be a breakpoint. The test works similarly to supremum tests except that it is not conducted sequentially and the limiting distribution of the test-statistic is known. Conducted together, both tests complement each other.

[71] It is worth noting that the statistical insignificance of the latter breakpoint could potentially be caused by the relatively low statistical power of the test due to short pollution time series.

breaks in the parameters after estimation of the log form of the model (2). The results are robust to different ranges of possible break years, trimming, or log-level model specifications. Panel B of Appendix Table A2 shows that neither of the years within the 2005-2006 interval, or the years of the largest pre-crisis drop in PM2.5, are trend break years. This finding relaxes my previous concern about the possible confounding role of these years in my results. Thus, I consider 2010 in further analysis as the time of the effects of the crisis and on air pollution, τ_0, and the most important year when the crisis could affect air pollution in the sample districts.

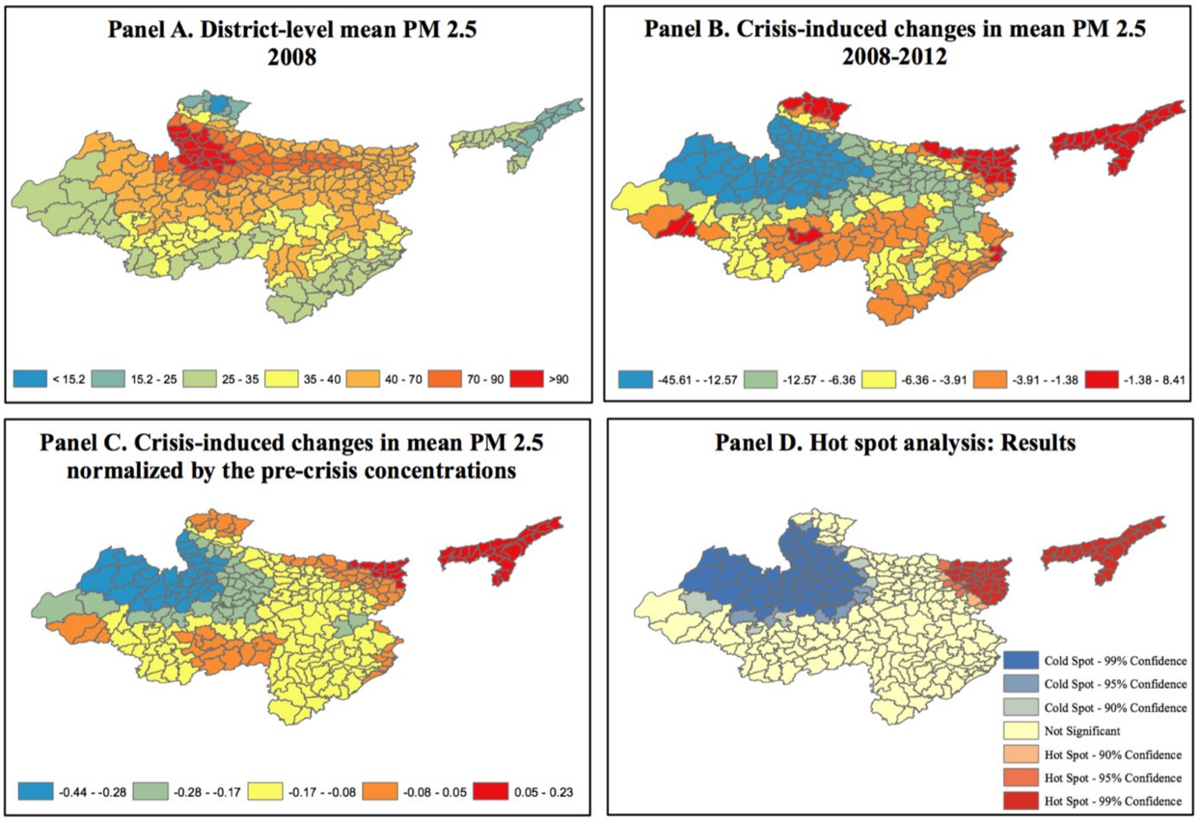
3.3.3 Selection of the Treatment and Control Groups

Addressing the second challenge, I designate districts with large improvements in air quality during the 2009-2012 improvement episode, those most impacted by the crisis, to the group of the treated districts, while districts with small or no changes, unaffected or least affected, are designated to the control group. I use several approaches that, nevertheless, lead to a very similar result.[72]

Panel B of Fig. 4 demonstrates a geographical distribution of the district-wise changes in average PM2.5 during 2009-2012. For comparison, Panel A illustrates the spatial variation in the pre-crisis levels of PM2.5 pollution. The following observations are noteworthy. First, the two maps correlate very well visually. Thus, the levels of average PM2.5 before the crisis could potentially be a good predictor for the effects of the crisis-induced reduction in air pollution. Second, in contrast to my expectations, some of the districts experienced worsening of air quality. Independent of the sign of the changes, these districts should be taken into account similarly to those with reductions in air pollution. Third, the variation in the magnitude of the crisis-induced changes in the PM2.5 levels varied substantially across districts with a reduction or increase in air pollution. These changes are significantly larger in the former group and vary from zero to a substantial 45 μg/m3 or almost 10 μg/m3 on average. In the latter group, the maximum and average values of the increase in the level of fine particulate pollution are slightly above 8 μg/m3 and 4 μg/m3, respectively. Finally, it may well be that the districts are spatially clustered

[72] Chay and Greenstone (1999, 2003b) divided U.S. counties into three groups with large, medium and small changes. These groups include quartiles of the counties with the largest reduction (upper quartile, >75%), smallest reduction (lower quartiles, <25%) and all other counties (combined second and third quartiles, between 25% and 75%).

depending on the magnitude of the changes. This is especially relevant to the districts with a larger reduction or increase in air pollution.



Notes: Panel A illustrates spatial variation in the pre-crisis levels of PM2.5 pollution. Panel B demonstrates a geographical distribution of the district-wise changes in average PM2.5 during 2009-2012. Panels C and D provide visual representation of the Hot Spot Analysis results. Panel C shows spatial distribution of the HSA input values – crisis-induced changes in mean PM2.5 concentrations during 2008-2012 normalized by the pre-crisis 2008 concentrations. Panel D shows the resulting HSA output with hot spot and cold spot districts depicted in red and blue. There is a striking correspondence between the hot spots and the districts that experienced statistically significant increase in air pollution, and the cold spots and the districts that experienced statistically significant reduction in air pollution. The remaining districts, depicted in beige, are the ones in which relative changes in particulate air pollution are not statistically significant, implying that they could likely happen by random chance or that these districts would experience such changes in the absence of the crisis. I consider districts belonging to the hot and cold spots as treated districts with worsened and improved air quality, respectively, while districts depicted in beige are control districts.

Fig. 4. Spatial relationship between pre-crisis PM2.5 and crisis-induced changes

In view of the latter observation, I experiment with a Getis-Ord Hot Spot Analysis (Getis and Ord, 1992; Ord and Getis, 1995), applying this technique to PM2.5 pollution data to sort districts into treatment and control groups. Appendix A1 provides more details about the Getis-Ord Hot Spot Analysis. The Getis-Ord Hot Spot Analysis (HSA) is in essence a test for spatial dependence[73], designed to assess the extent of clustering between units based on their attributes, and to draw inference about its statistical significance.

Putting HSA in context, it is highly probable that the highly-polluted districts are surrounded by other similarly polluted districts. Moreover, air pollution in the latter could originate either from the districts' own sources or transported from outside. Such a scenario is quite possible given the ability of air pollution to travel across regions. In this case, even districts without pollution-intensive industries would likely demonstrate some degree of spatial association with heavily-polluted neighbors. More importantly, such districts could also experience the effects of the crisis related to a decrease or increase in pollution levels in nearby districts. In contrast, districts without polluting sectors, or districts located farther from the neighbors that have such sectors, might not exhibit any spatial association based on pollution-related attributes, and might not experience any impact of the crisis on air quality. Apart from the identification of spatial clusters in crisis-induced changes in air pollution, the HSA also provides a means to assess whether such a pattern of spatial dependence is statistically significant. Applying HSA, I am interested in identifying spatial clusters of districts with unusually large and statistically significant changes in PM2.5 concentrations during the 2009-2012 improvement episode, relative to the pre-crisis 2008 PM2.5 pollution levels. Therefore, HSA output allows me to assign districts within statistically significant clusters into the treatment group, while districts outside such clusters are assigned into the control group.

Technically, HSA boils down to the testing of the null hypothesis of "no spatial dependence". The null implies that the assignment of the input attribute values to the particular districts does not depend on spatial location; the value of the attribute itself is all that matters. The alternative hypothesis focuses instead on the cases where districts with large and small attribute values are systematically surrounded by other districts with respectively large and small values. Rejection of the null hypothesis would imply the presence of statistically significant spatial clusters of similar attribute values (Anselin, 1992). Statistically significant spatial clusters of high

[73] In spatial statistics, the notion of spatial dependence, reflecting the tighter relationship between near rather than distant units, means that the similar values of some attribute or characteristic for one unit will likely also occur in neighboring units, leading to the formation of spatial clusters (Anselin, 1992).

values are referred to as hot spots, while cluster of low values are referred to as cold spots. I implement HSA using ArcGIS's Getis-Ord G_i^* tool.

Panels C and D of Fig. 4 provide visual representation of the HSA's results. Panel C shows the spatial distribution of the HSA input values – crisis-induced changes in mean PM2.5 concentrations during 2008-2012 normalized by the pre-crisis 2008 concentrations. Panel D shows the resulting HSA output with hot- and cold-spot districts depicted in red and blue colors. There is a striking correspondence between the hot spots and the districts that experienced a statistically significant increase in air pollution, and also between the cold spots and the districts that experienced a statistically significant reduction in air pollution. The remaining districts, depicted in beige, are those in which relative changes in particulate air pollution are not statistically significant, implying that changes could likely occur by random chance or that these districts would experience such changes in the absence of the crisis. For the rest of the chapter, I consider districts in hot and cold spots as treated districts with worsened and improved air quality, while those depicted in beige as control districts.

Appendix Table A3 displays detailed descriptive statistics separately for treated and control districts before and after the crisis. Generally, before the crisis, both districts looked very similar across many key characteristics, including infant mortality rate, but they differ substantially by mean PM2.5 pollution, with a higher concentration of the pollutant observed in the treated districts. This observation leaves less room for the possibility that there is a selection or contamination of the control group. It is also consistent with the conclusion that the levels of average PM2.5 before the crisis can predict the effects of the crisis-induced changes in air pollution. After the crisis, both groups of districts experienced a decline in infant mortality and air pollution level, with an especially pronounced decline in the group of the treated districts. This finding supports the hypothesis that the crisis-induced reductions in PM2.5 pollution led to a statistically significant decline in district-level infant mortality rates.

3.3.4 Identifying Assumptions

The key identification assumption for equation (1) can be formulated in terms of the idiosyncratic error term, for t = 1, 2, …, T:

$$E(\varepsilon_{dt}|\mu_d, \gamma_t, Treated_d \cdot Post_t, W_{dt}, X_{dt}) = 0 \quad (3)$$

In the DID context, this assumption is known as a parallel or common trends assumption, implying that, irrespective of the levels, comparison groups should have equally-sloped trajectories in the pretreatment outcomes of interest. Then, the unobserved average trend in the outcome variable of the treatment group in the absence of treatment should be equal to the observed trend of the control group. Further, the treatment is assumed to be the only process that induces deviations from the common trends between the comparison groups[74]. This assumption implies that districts from the control group provide valid counterfactual changes in infant mortality for the districts from the treatment groups in the absence of crisis-induced changes in air pollution.

One possible reason for violation of the assumption in equation (3) is the presence of time-varying unobservables as an additional source of heterogeneity, causing districts' individual trajectories in infant mortality to diverge from the parallel trends. As the baseline model in equation (1) controls only for time-constant unobservables, it would likely fail to produce unbiased estimates of the effect of interest. To overcome this concern, I extend the baseline specification to allow for heterogeneous trends by including district-specific slopes in equation (1):

$$\log(IMR)_{dt} = \alpha + \delta_1(Treated_d \cdot Post_t) + \beta_1 W_{dt} + \beta_2 X_{dt} + \mu_d + \gamma_t + \lambda_d t + \xi_{dt} \quad (4)$$

where $\lambda_d t$ is a time-varying unobserved heterogeneity that allows the possibility for each district to have differential trends through the distinct values of λ_d. Technically, the latter term represents time-invariant, either observed or unobserved, effects interacted with time to produce district-specific trajectories of outcomes. t is a continuous year variable centered on 2010 and normalized so that it equals zero in this year.

Based on the results of the trend break and Hot Spot analyses, the DID model in equation (4) compares pre- versus post-2010 levels and trends in infant mortality rates between the treated

[74] This latter assumption is often referred to as a common shocks assumption (Dimick and Ryan, 2014; Kreif et al., 2015).

and control districts. The key identifying assumption is that, conditional on district-specific trends, any pre- versus post-2010 changes in infant mortality rates caused by factors besides air pollution are the same for the affected and control districts, and that air pollution is the only factor differentially affecting the treated districts, beginning in 2010.

Taking into account the fact that the impact of the crisis could accelerate and decelerate over time, I further extend equation (4) to the following specification:

$$\begin{aligned}\log\left(IMR\right)_{dt} = \alpha + \delta_1 (Treated_d \cdot Post_t) + \delta_2 (Treated_d \cdot Post_t \cdot t) + \\ + \beta_1 W_{dt} + \beta_2 X_{dt} + \mu_d + \gamma_t + \lambda_d t + \xi_{dt}\end{aligned} \quad (5)$$

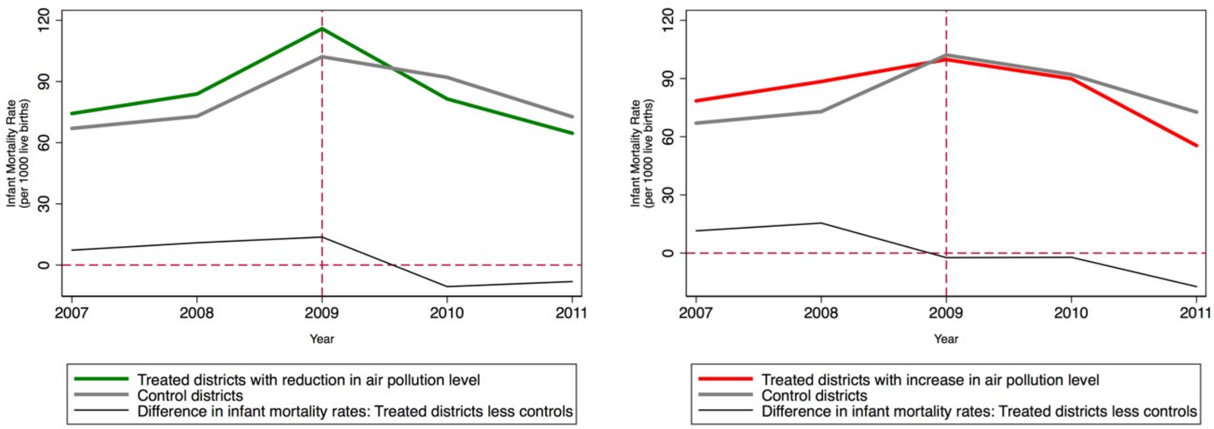
where $Treated_d \cdot Post_t \cdot t$ allows for the effects of the crisis to evolve over time. Equation (5) is a trend-break model allowing a change in the slope after 2010. The statistical question of interest is whether $\widehat{\delta_1}$ and $\widehat{\delta_2}$ are jointly statistically significant after the trend-adjustment. The following concern should be taken into account while interpreting the estimation results. On the one hand, equation (5) introduces a dynamic structure that is consistent with the visual evidence from Fig. 2, showing that the decline in infant mortality in the treated districts does not look like a one-time drop. On the other hand, the short length of our panel data set, especially the number of the post-crisis years, might mean that there could be limited statistical power to estimate a model with changes in slope. Therefore, the model in equation (4) might be more preferable.

I estimate models in equations (4) and (5) using an estimation method based on within transformation of data known as detrending. I prefer this approach because it is more efficient than others, especially in cases with relatively short and unbalanced panel datasets similar to mine (Brüderl and Ludwig, 2015). The idea of detrending is to subtract time-varying estimates of the individual-specific trends from the original variables. Applying this estimation approach essentially boils down to the following four-step procedure. First, for each district I estimate the regression of the form $\log\left(IMR\right)_{dt} = \mu_d + \lambda_d t + \zeta_{dt}$ to obtain predicted values of the outcome variable $\log\left(\widehat{IMR}\right)_{dt} = \hat{\mu}_d + \hat{\lambda}_d t$. Time-varying predicted values, $\log\left(\widehat{IMR}\right)_{dt}$, represent expected district-specific trends. Second, I subtract values predicted in step (1) from the original values of outcome to obtain the detrended dependent variables $\log\left(\widetilde{IMR}\right)_{dt} = \log\left(IMR\right)_{dt} - \log\left(\widehat{IMR}\right)_{dt}$. After this step, the only variation left in the dependent variable is the variation around the district-specific trend. Third, I apply steps (1) and (2) to detrend all explanatory variables $\tilde{x}_{jdt} = x_{jdt} - \hat{x}_{jdt}$ for any variable x_j. Detrending all variables of the model means that the estimation of the causal effect of interest is based solely on within around-trend variation. Finally, I run regressions on the detrended variables.

To further validate the DID identifying assumption of the model in equation (4), I formally address two violations common in the literature (Tanaka, 2015). First, the existence of a systematic difference in the pre-crisis trends in infant mortality rates. Second, the orthogonality of the impact of the crisis on other factors affecting the dependent variable in the post-crisis period.

To address the first concern, I examine the pre-crisis trends graphically. Fig. 5 depicts the evolution of the average infant mortality rates across comparison groups, adjusted for the district-specific linear trends and some basic characteristics of the deceased infants. The figure provides graphical evidence that trends in infant mortality rates are almost parallel in the pre-crisis period between control and treated districts with reduction in air pollution. However, adjustment for the district-specific trends fails to improve the presentation for the treated districts with an increase in air pollution. The parallel trends assumption is apparently violated in the case of these districts. Visual examination also provides evidence of the trend break for the treatment group right after the onset of the crisis.

To address the second concern, I follow Altonji, Elder, and Taber (2005) and examine whether the impact of the crisis has any association with changes in observable characteristics. I first successively regress my empirical model with every observable characteristic as the dependent variable. Then, I check whether the coefficients on the interaction term, $\widehat{\delta_1}$, are statistically significant. Although this is not a formal test for exclusion restrictions, the absence of statistically significant association with observable characteristics would suggest that there should not be a correlation with unobservable variables either (Altonji et al., 2005). Appendix Table A4 presents results for both types of treated districts. Although some of the point estimates are statistically significant, the vast majority show no evidence of the systematic difference in trends between districts from the treated and control groups. This is especially true for the group of districts with improvement in air quality, for which most of the coefficients are small or close to zero. It is noteworthy that, the impact of the crisis-induced reductions in PM2.5 pollution is not associated with important determinants of infant mortality, including mother's age, household amenities and proxied parental characteristics. Although significant, the coefficients on the meteorological confounders are quite small.



Notes: The figure depicts the evolution of the trends in infant mortality rates across comparison groups adjusted for the district-specific linear trends and some basic characteristics of the deceased infants. The dashed vertical line indicates the time of the effects of the crisis on air pollution started between years 2009-2010. The thin black line represents the difference in infant mortality rates between treatment and control groups of districts, allowing a rough comparison of the relative pre- and post-crisis trends.

Fig. 5. Visual examination of the parallel trend assumption

Overall, the results provide suggestive evidence that the changes in PM2.5 pollution attributable to the global financial crisis is orthogonal to other factors affecting the dependent variable in the post-crisis period. Therefore, the selected empirical strategy is unlikely to be biased due to changes in unobservable covariates. Additional falsification tests and robustness checks will further support this conclusion.

3.4 Results

I first present baseline estimates of the impact of the crisis-induced changes in PM2.5 on the infant mortality rate at the district level. I then perform sensitivity analysis to ensure that the proposed empirical strategy provides unbiased estimates. Finally, I perform a number of falsification tests and robustness checks to support the validity of the main findings.

3.4.1 Baseline Results

Table 2 presents baseline results of the regression analysis by reporting the key estimates resulting from fitting equations (4) and (5). The dependent variable is the infant mortality rate for all causes of deaths. For both types of treated districts, columns (1) report the estimate of coefficient δ_1 after the estimation of equation (4), which tests for the effects of the crisis-induced changes in PM2.5 on the infant mortality rate after adjustment for district fixed effects, year fixed effects and differential trends. The second columns report the results from the equation (5) allowing for both level and slope changes during the post-crisis period. All regressions are run on the variables detrended as described in previous section.

The coefficients in both columns for the treated districts with reduction in PM2.5 pollution suggest that these districts experienced a statistically significant decline in all-cause infant mortality after 2010. Moreover, column (2) provides evidence of a negative and statistically significant change in the slope of the infant mortality rate after 2010. Therefore, regression analysis confirms the visual impression that reduction in air pollution that occurred during the post-crisis period was strongly associated with a decline in infant mortality. In contrast, the regression coefficients for the treated districts with increase in PM2.5 pollution captured by the variable Treated · Post are positive, small and insignificant. Thus, there is little evidence of the impact of the crisis-induced increase in air pollution on infant mortality. However, similarly to the districts with a decline in air pollution, the infant mortality rate in districts with worsened air quality demonstrates a negative and statistically significant change in slope after 2010. For both types of districts and across both specifications, the coefficients on Treated · Post are insensitive to the inclusion of the variable allowing change in the slope, Treated · Post · t.

These findings are consistent with the evidence from Appendix Table A5, which reports estimates from fitting equations similar to equations (4) and (5) testing if the crisis-induced economic slowdown reduced PM2.5 pollution in the treatment districts relative to control districts. The table shows that the treated districts with improved air quality experienced a statistically significant decline in PM2.5 concentration of 11.89 mg/m3 relative to the control districts between the pre- and post-crisis, or of 9.05 mg/m3 if the change in the slope is also accounted for. The regression coefficients for the treated districts with the increase in PM2.5 pollution are positive, much smaller, and significant. In contrast to districts with a decline in air pollution, PM2.5

concentrations in these districts do not demonstrate a sign of a statistically significant change in slope after 2010. Thus, there is little evidence of the trend-break impact of the crisis on air pollution in these districts. Overall, regression analysis confirms the visual impression that air pollution reduction occurred during the post-crisis period.

Table 2 – Effects of the changes in particulate air pollution on infant mortality

Dependent variable = ln(Infant Mortality Rate)	Districts with improved air quality		Districts with worsened air quality	
	(1)	(2)	(1)	(2)
	Detrended district-level data, all causes of death, 2007-2011			
Treated · Post	-0.26***	-0.25***	0.08	0.09
	(0.08)	(0.08)	(0.13)	(0.13)
Treated · Post · t		-0.17**		-0.24***
		(0.07)		(0.08)
Observations	1,115	1,115	1,007	1,007
R-squared	0.37	0.38	0.27	0.29
District FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
District-specific trends	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents baseline results of the regression analysis by reporting the key estimates from fitting equations (4) and (5). The dependent variable is the infant mortality rate for all causes of deaths. For both types of treated districts, columns (1) report the estimate of coefficient δ_1 after the estimation of equation (4), which tests for the effects of the crisis-induced changes in PM2.5 on the infant mortality rate after adjustment for district fixed effects, year fixed effects and differential trends. The second columns report the results from equation (5) allowing for both level and slope changes during the post-crisis period. All regressions are run on the variables detrended as described in section 3 of the study. Standard errors clustered at the district level are shown in parentheses.

I further use the resulting coefficients reported in Table 2 to assess the magnitude of the crisis-induced changes in PM2.5 pollution on infant mortality. For that purpose, I focus on treated districts with improved air quality, which demonstrate a significant decline in infant mortality rates. The coefficient in column (1) indicates that the infant mortality rate in this group of treated districts fell by about 23% ($100 \cdot (e^{\hat{\delta}_1} - 1)$) more than in the group of control districts between the pre- and post-crisis period. The estimated decline is associated with 4.9 fewer infant deaths per

1000 live births.[75] Coefficients in column (2) from the model that allows for changes in the level and slope show an even larger effect of about 28%. I computed the total effect from equation (5) as $\hat{\delta}_1 + 0.5 \cdot \hat{\delta}_2$, where the factor of 0.5 is equal to the average value of the continuous year variable t for two post 2010 years ((0+1)/2; t is set to be equal to zero in 2010). A 28% decline translates into a total of 6.09 fewer infant deaths per 1000 live births.

3.4.2 Sensitivity Analysis

Table 2 provides estimates of the baseline effect of interest without control variables. To address the concern that changes in the dependent variable may be explained by changes in the observable time-varying characteristics that potentially correlated with the impact of PM2.5 pollution changes attributable to the effect of the crisis, I perform a sensitivity analysis. Appendix Table A6 reports results for both types of districts. Every pair of columns represents estimates from fitting equations (4) and (5).

First, I included confounders to the baseline specification, namely a natural logarithm of the district-level GDP per capita and meteorological covariates. In all specifications, the coefficient on GDP per capita is close to zero, not statistically significant and does not fluctuate much across specifications, apparently not affecting the point estimates on either Treated · Post and Treated · Post · t. This relaxes the concern about the income channel through which the crisis could also have affected infant mortality.

Columns (3) and (4) control for the average district-level temperature, precipitation, wind directions and speed. Inclusion of these factors makes the estimates larger but preserves their sign and significance. The wind-related controls dominate with the larger and significant coefficients. The coefficient on the west-east wind is the most important in terms of the magnitude. In contrast to previous specifications, the Treated · Post · t coefficient drops to almost zero and becomes insignificant.

[75] My baseline results are quite similar to those reported in Tanaka (2015) who estimated the impact of the 1998 "Two Control Zones" environmental regulation on infant mortality in China, i.e. in similar pollution-mortality settings. The author found that a TZP status is associated with 3.3 fewer infant deaths per 1000 live births and a 20% reduction in infant mortality in the post-reform period.

Columns (5) and (6) control for characteristics of the deceased infants. None of the coefficients on these variables are statistically significant. The inclusion of these controls does not have any effect on the coefficients of interest. Columns (7) and (8) control for characteristics and habits of the Heads of households. The coefficients of the main interest remained virtually unchanged. I also observe small, negative and statistically significant coefficients on the share of the Heads belonging to the Sikh and Buddhist religions, as well as the share of the Heads who are alcohol drinkers. The picture is very much the same with the next specification, columns (9) and (10), including the deceased infants' household characteristics, although the coefficients of interest become slightly smaller. However, the resulting coefficients on these control variables are close to zero and insignificant.

Columns (11) and (12) report coefficients from the regressions controlling for the district-specific indicators of the utilization of the medical services by mothers and infants. The main effect remains robust and statistically significant. As in the previous specification, the coefficient on Treated · Post · t remains small and insignificant. This makes equation (4), with a combination of W_{dt} and X_{dt} vectors as specified in column (11), my preferable specification.

The coefficient in column (11) indicates that the infant mortality rate in the group of treated districts with improved air quality fell by about 24% more than in the group of the control districts between pre- and post-crisis periods. The estimated decline is associated with a total of 5.226 fewer infant deaths per 1000 live births. Combining changes in particulate air pollution with the estimated changes in infant mortality, I obtain an implied elasticity equal to 0.35.[76] The elasticity is within the range of elasticities reported in economic studies of the effects of air pollution on infant mortality in developed and developing countries. Chay and Greenstone (2003b) calculated elasticities for the effects of TSP equal to 0.35-0.5 in the U.S., while Arceo et al. (2015) find elasticity of 0.415 for exposure to PM10 in Mexico. The marginal effects of SO2 found in Tanaka (2015) translates into an implied elasticity of 0.9 in China; Knittel, Miller, and Sanders (2016) provide evidence of a 1.827 elasticity for the impact of automobile air pollution on infant health in the U.S.; Currie and Schmieder (2009) report elasticity for chronic effects of toxic chemicals in a range of 1.82-6.49 in the U.S. On the lower end of the elasticities reported in economic studies are

[76] In the context of the study, implied elasticity is a ratio of percentage changes in the infant mortality rate to the same period percentage changes in air pollution.

the estimates for the effects of SO2, in the range of 0.07-0.13 in Germany from Luechinger (2014), and of 0.04-0.09 for acute effects of CO in the U.S., from Currie and Neidell (2005).

Finally, sensitivity analysis also supports the previous conclusion concerning the effects of the crisis-induced changes in PM2.5 pollution on the infant mortality rate in the group of districts with worsened air quality. The main coefficient of interest remained close to zero and insignificant despite differences in specifications. In contrast to the analysis of the treated group of districts with improved air quality, the slope coefficients from the regressions fitting equation (5) become close to zero and insignificant only after controlling for district characteristics and utilization of medical services. Coefficients on the west-east wind and its speed are large, comparable in magnitude, and highly statistically significant, but have different signs. Therefore, the sensitivity analysis fails to capture any sign of the effects that documented an increase in PM2.5 pollution attributable to the crisis could have on infant mortality in these districts, which is in line with the baseline results.

Experimentation with different specifications in this section provides evidence that the magnitude, sign and statistical significance of the coefficient of interest are insensitive to the inclusion of the control variables. This supports the credibility of my research design and estimates. Although there is always room for non-causal explanations between the variables of interest in non-experimental studies, the results of the sensitivity analysis do not directly contradict the causal nature of the relationship between the crisis-induced changes in air pollution and district-level infant mortality.

3.4.3 Falsification Tests and Robustness Checks

Conditional on the results of Altonji et al. (2005) test and sensitivity analysis, equation (4) is likely to produce valid estimates of the crisis-induced reduction in PM2.5 pollution on infant mortality in the Indian districts. Nevertheless, I provide further support for this conclusion by conducting a number of falsification tests and robustness checks.

For the first falsification test, I replace the dependent variable with another outcome variable that is not affected by the crisis-induced changes in air pollution. One of the most plausible candidates is infant mortality due to external causes of deaths, which include deaths caused by accidents and homicides that are not associated with air pollution. However, AHS contains disaggregated information only on internal causes of deaths. Nevertheless, I could select an internal disease that is potentially not associated with particulate air pollution for the test. The most promising candidate for this role is diarrheal diseases. To the best of my knowledge, there is no evidence of obvious causal links between exposure to air pollution and infant mortality due to diarrhea/dysentery. Another reason to think that the choice of this disease for the falsification test is appropriate is the evidence that diarrheal diseases are the concurrent cause of death to respiratory infections and have a comparable share of infant fatalities in my study area (Bassani et al., 2010).

Therefore, I use the infant mortality rate due to diarrhea/dysentery as the alternative dependent variable to evaluate the internal validity of the previous estimates. As Table 4 indicates, regressions return statistically insignificant coefficients. The result also provides evidence that the crisis-driven reduction in air pollution had no additional effect on infant mortality through other diseases. Therefore, my specifications are likely unbiased.

As another falsification test, I re-estimate the model using observations only from the pre-crisis period where the effects of the crisis-induced reduction in air pollution could not exist. For this purpose, I assign 2008 as a placebo trend break point and thus consider 2007 as the pre-crisis period, and 2008 as the post-crisis period. Specifically, the variable $Post_t$ became equal to 1 for the year 2008, not after the formally identified τ_0. Thus, I use a classic two-periods model. The results are in Appendix Table A7. The table reports point estimates after fitting equation (4) with different combinations of W_{dt} and X_{dt} vectors for the districts from both treated groups with improved (Group 1) and worsened (Group 2) air quality. Since estimated coefficients using a pre-crisis sample and placebo trend break point are statistically insignificant and close to zero, my specifications can be considered as likely unbiased.

Further, I apply the model equation (4) to the alternative control group. For this purpose, I limit this group to the districts selected, based on the common support propensity score that restricts the sample to the districts that have similar observable characteristics to the districts from the treatment group of districts with improved air quality. I first computed the common support propensity score of being in the treatment group using available characteristics of the districts with significant crisis-induced air pollution reductions. Then, I constructed an alternative control group, including only those districts from the initially identified control group that are matched based on the propensity score. Finally, I re-estimated the model with this alternative control group. Appendix Table A8 reports the results of this falsification test. Since the sign, magnitude and the order of statistical significance of the estimated coefficient on the main effect of interest are not substantially different from that in the main analysis, I again concluded that my model is likely unbiased.

Performing robustness checks, I address concern that there may still be unobserved factors affecting infant mortality due to the differential response of air pollution concentrations within the similar geographic regions. To control for this issue, I include in the preferable specification additional National Sample Survey (NSS) region*year fixed effects. NSS regions do not represent administrative units but rather collections of districts grouped based on similar agro-climatic conditions. Thus, this specification identifies the effect of interest using variation in crisis-induced changes in PM2.5 pollution within the NSS regions with similar characteristics. Thus, any potentially possible changes caused by any differences are purged at the level of NSS regions. This exercise does not affect either the sign or magnitude of the estimated effect.

Further, I use a number of other specifications to re-estimate the most preferable model in the analysis. First, I use different weighting schemes to check how sensitive the model is to these changes. The results show that the point estimate of the main effect of interest did not change in response to not weighting at all, and reacted by a not substantial reduction in the magnitude on the weighting by the number of births. Second, I cluster standard errors at the state and NSS regions levels, as well as at the state*year and region*year levels. The estimated effect of interest remained robust to these alternative specifications. Third, I run a regression with one dependent variable expressed in level rather than in the log-form to see that the coefficient on Treated · Post had the same sign and significance level. Appendix Table A8 summarizes results.

Complementing the robustness checks above, the Appendix provides two additional tests. The first is based on the model in equation (4) and focuses on alternative options for sorting sample districts into treatment and control groups. Appendix Table A9 compares the resulting estimates. Each column of the table corresponds to one of the eight options, which are intuitively illustrated by the graphs in Fig. A4. The sign, magnitude and order of statistical significance of the estimated coefficients on Treated · Post remain similar between each other and to the coefficient estimated using my preferable specification.

The second additional test checks whether the main finding would remain robust to different estimation strategies, namely the detrending used in this study, conditioning on the explanatory variables and district-specific trends, and a method combining matching on pre-crisis explanatory variables and trends with subsequent difference-in-differences. The results are presented in Appendix Table A10, which indicates that all specifications return estimated coefficients of interest that are not substantially different from each other, thus confirming the credibility of the main analysis.

Overall, conditional on the results of the falsification tests and robustness checks, I conclude that the main findings of the study justify the causal impact of the crisis-induced reduction in air pollution on the infant mortality rate in the sample of the selected Indian districts.

3.5 Mechanism

Addressing the second research question, I examine the impact of the changes in PM2.5 concentrations on the mortality of infants at different ages and from various diseases. I then complement this analysis by exploring whether the crisis-induced decline in PM2.5 air pollution had a heterogeneous impact on infant mortality across several infant and the head of household characteristics. The analysis based on the specifications in columns (11) and (12) from Appendix Table A6 focuses solely on the treated group of the districts with improved air quality.

Table 3 presents the estimated effects of the reductions in PM2.5 pollution on the infant mortality rate within 1 day, 28 days, between 28 days and 11 months, within 11 months and between 11 and 12 months of life.[77] The second category is also known as the neonatal infant mortality rate, which in turn is broken down into early and late neonatal mortality rates corresponding to the deaths occurring within 0-7 and 8-27 days from births, respectively. The third category is usually referred to as a postneonatal mortality rate. Separate analysis of these categories is performed purposefully. The large and statistically significant estimate in the neonatal period would likely suggest that particulate air pollution affects infant mortality through the

[77] Ideally, I would also examine how the reductions in PM2.5 air pollution affected fetuses at different gestational terms. However, I could not implement this analysis because of the mismatch in the data. It is possible to determine gestational age at the time of crisis from the AHS data, but it is impossible to match air pollution exposure for the months before birth. The reason is that the satellite-based PM2.5 data I used in the chapter is only available at the annual level.

adverse effects on fetal development, via in utero exposure to PM2.5. Newborns whose mothers were exposed to high PM2.5 concentrations during pregnancy have a higher probability of dying in the neonatal than the postneonatal period. In contrast, a large and statistically significant effect in the postneonatal period would highlight the importance of post-birth PM2.5 exposure in the biological mechanism through which air pollution affects infants directly. However, the exact biological channels are not yet well-studied (Chay and Greenstone, 2003b; Tanaka, 2015).

The estimates reveal that both biological mechanisms are important in explaining the overall effect found above. However, the response of infant mortality during the postneonatal period (column (5)) is substantially larger than in the neonatal period (column (4)). The coefficients suggest that the neonatal IMR fell by 21% more in the districts with improved air quality, with a corresponding elasticity of 0.31, which is lower than the implied elasticity for infant mortality of 0.35. In contrast, postneonatal mortality shows a decline of almost 32% with the implied elasticity of 0.45, which is significantly larger than the elasticity for both overall infant and neonatal mortality. I estimate that the contribution of the reduction in PM2.5 to the overall decline in neonatal mortality and postneonatal mortality is equal to 9% and 15%, respectively. Therefore, the effect of particulate air pollution on infant mortality is not larger in the neonatal period and is more likely disproportionally associated with the probability of dying during the postneonatal period.

Several aspects of the biological mechanism are worth noting. First, there is no effect on infant deaths within one day of birth. Although negative, the point estimates are small and statistically insignificant. Second, disaggregation of the overall neonatal mortality into early and late neonatal periods, presented in columns (2)-(3), reveals the important regularity of the biological mechanism. The response of neonatal mortality to the reduction in particulate air pollution is completely driven by the decline in infant mortality during the early neonatal period. Therefore, I cannot rule out the channel of in utero PM2.5 exposure. Third, point estimates on the deaths of infants aged between eleven and twelve months (column (7)) are large and negative, but insignificant, additionally highlighting the importance of the postneonatal mortality and post-birth PM2.5 exposure as the channel through which air pollution affects infant mortality. Finally, as presented in column (6), the estimated effects of the reduction in PM2.5 concentrations on infant deaths within eleven months are identical to those I found for the all-cause infant mortality and thus support my main findings.

Table 3 – Pathophysiological mechanism: Timing of infants' deaths

Dependent variable = ln(Infant Mortality Rate)	within 1 day	early neonatal	late neonatal	neonatal (28 days)
	(1)	(2)	(3)	(4)
Treated · Post	-0.10	-0.22***	-0.13	-0.24***
	(0.12)	(0.08)	(0.14)	(0.07)
Observations	1,110	1,110	1,110	1,110
R-squared	0.48	0.63	0.35	0.69

Dependent variable = ln(Infant Mortality Rate)	postneonatal 1-11 months	within 11 months	between 11-12 months	stillbirth
	(5)	(6)	(7)	(8)
Treated · Post	-0.38***	-0.30***	-0.21	0.17
	(0.09)	(0.07)	(0.14)	(0.17)
Observations	1,110	1,110	1,110	1,110
R-squared	0.63	0.73	0.41	0.20

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results from examination of the channels through which air pollution affects infant mortality. It presents the estimated effects of the reductions in PM2.5 pollution on the infant mortality rate within 1 day, 28 days, between 28 days and 11 months, within 11 months and between 11 and 12 months of life. The second category is also known as the neonatal infant mortality rate, which in turn is broken down into early and late neonatal mortality rates corresponding to the deaths occurring within 0-7 and 8-27 days from birth, respectively. The third category is usually referred to as a postneonatal mortality rate. Separate analysis of these categories is performed purposefully. The large and statistically significant estimate in the neonatal period would likely suggest that particulate air pollution affects infant mortality through the adverse effects on fetal development, via in utero exposure to PM2.5. Newborns whose mothers where exposed to high PM2.5 concentrations during pregnancy have a higher probability of dying in the neonatal than the postneonatal period. In contrast, a large and statistically significant effect in the postneonatal period would highlight the importance of post-birth PM2.5 exposure in the biological mechanism through which air pollution affects infants directly. The analysis is based on the specifications in columns (11) and (12) from Appendix Table A6 and focuses on the treated group of the districts with improved air quality. All regressions include district FE, year FE, district-specific trends; Controls: income per capita, meteorology characteristics of the deceased infants, head of household, household, medical services utilization, other. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses

These findings are in contrast to conclusions made in Chay and Greenstone (1999, 2003b) and Tanaka (2015) about the disproportionate effect of air pollution on infant mortality during the neonatal period. For the U.S., Chay and Greenstone (2003b) attributed 80% of the effect of the reduction in TSPs on infant mortality to the decline in neonatal mortality, of which 60-70% is driven by fewer infant deaths within one day of birth. For China, Tanaka (2015) found that 26% and 63% of the effect of the TCZ regulation on infant mortality occurred within one day of births and during the neonatal period. On the other hand, my estimates are in line with the statistics for the districts in the study area according to which the decline in the number of infant deaths during the post-crisis period was due to a decline in the early neonatal and postneonatal periods, with respective shares of 42% and 41%.

I then examine the effect of the crisis-induced changes in PM2.5 pollution on infant mortality disaggregated by various diseases. Table 4 presents the results from the regressions with IMR due to fifteen causes of deaths as the dependent variable. Although the AHS does not provide exact codes for different symptoms, I used the tenth International Classification for Diseases (ICD-10) to identify all of them except the category "Other" as internal causes of deaths. Internal causes of deaths are defined as health-related, non-accidental causes in contrast to non-health related external causes such as accidence, injury, homicides, poisoning and other similar causes. Since the exact pathology of diseases caused by particulate air pollution is not well-known, some of the internal diseases could potentially be associated with air pollution. Particularly, chronic exposure of infants to high PM2.5 concentrations is expected to result in deaths due to respiratory infections. In contrast, there could well be internal diseases without any association with particulate air pollution.

Table 4 provides evidence of a large, negative and statistically significant impact of the crisis-induced reduction in PM2.5 pollution on mortality from respiratory infections (column (1)). The effect is associated with 24% fewer infant deaths in the districts with improved air quality, translated into implied elasticity of 0.34. The calculations suggest that the crisis-induced reduction in particulate air pollution is associated with 15% of the overall improvement in infant mortality due to respiratory infections. The magnitude of the estimated effect is comparable to the impact on the all-cause infant mortality.

Table 4 - Pathophysiological mechanism: Causes of deaths

Dependent variable = ln of Infant Mortality Rate due to	Respiratory diseases	Diarrhea / Dysentery	Congenital / Birth Defects	Preterm Birth Low Weight	Convulsions
	(1)	(2)	(3)	(4)	(5)
Tretaed · Post	-0.441*	-0.399	-0.024	0.161	-0.592**
	(0.260)	(0.263)	(0.310)	(0.314)	(0.276)
Observations	1,110	1,110	1,110	1,110	1,110
R-squared	0.779	0.700	0.725	0.745	0.749

Dependent variable = ln of Infant Mortality Rate due to	Hypothermia	Fever with Jaundice	Asphyxia	Bleeding (umbilicus)	Infections
	(6)	(7)	(8)	(9)	(10)
Tretaed · Post	-0.058	-0.566**	-0.160	0.036	-0.184
	(0.287)	(0.265)	(0.301)	(0.224)	(0.282)
Observations	1,110	1,110	1,110	1,110	1,110
R-squared	0.789	0.701	0.772	0.679	0.826

Dependent variable = ln of Infant Mortality Rate due to	Birth Injuries	Jaundice	Fever with Convulsions	Fever with Rash	Other
	(11)	(12)	(13)	(14)	(15)
Tretaed · Post	-0.170	-0.133	-0.482*	-0.397	-0.085
	(0.285)	(0.288)	(0.251)	(0.252)	(0.154)
Observations	1,110	1,110	1,110	1,110	1,110
R-squared	0.680	0.766	0.785	0.761	0.869

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table shows the results from one of the falsification test and the results from examination of the channels through which air pollution affects infant mortality. For the falsification test, I replace the dependent variable in equation (4) with another outcome variable that is not affected by the crisis-induced changes in air pollution. Specifically, I use the infant mortality rate due to diarrhea/dysentery as the alternative dependent variable to evaluate the internal validity of the previous estimates. As expected, regressions return statistically insignificant coefficients. For examination of the channels, the table reports the effect of the crisis-induced changes in PM2.5 pollution on infant mortality disaggregated by various diseases. The results indicate that the effects of PM2.5 pollution on infant mortality are specific for respiratory infections and might be related to some of the infectious diseases. The analysis is based on the specifications in columns (11) and (12) from Appendix Table A6 and focuses on the treated group of the districts with improved air quality. Each column presents results from the regressions with IMR due to fifteen causes of deaths as the dependent variable. All regressions include district FE, year FE, district-specific trends; Controls: income per capita, meteorology characteristics of the deceased infants, head of household, household, medical services utilization, other. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses

Additionally, this finding supports the conclusion about the dominance of the post-birth PM2.5 exposure channel and more frequent incidence of infants' deaths during the postneonatal period. In the case of the states from the study area, the prevalence of pneumonia or respiratory infections as the causes of children deaths directly attributable to air pollution is indeed much higher in the postneonatal period than in the neonatal period (Bassani et al., 2010). Moreover, my findings are consistent with evidence that respiratory diseases less probably cause infant death during the neonatal period since newborns spend the most of their time indoors, but are the major cause of death for infants in the postneonatal period (Woodruff, Grillo, and Schoendorf, 1997; Bobak and Leon, 1999; Woodruff, Parker, and Schoendorf, 2006). Thus, disproportional association of the infants' deaths due to respiratory infections in the postneonatal period is justified.

It is notable that for the majority of other cases representing quite a broad range of diseases, the estimated effect of the crisis-induced reduction in particulate air pollution is small and not statistically significant. The exceptions are convulsions and two types of fever, with jaundice and convulsions. Although large and statistically significant, the coefficients on these diseases are sensitive to the inclusion of additional variables, particularly the second variable of interest that allows changes in the slopes. While there are no obvious causal links between air pollution and infant mortality due to these diseases, Clay, Lewis, and Severnini (2015), using the 1918 influenza pandemic in the U.S. as a natural experiment, provide rare evidence that air pollution could adversely affect the susceptibility of infants to infectious disease. This is consistent with my findings for fever.

Next, I test the hypothesis that the crisis-induced decline in PM2.5 air pollution may have a heterogeneous impact on infant mortality across several subsamples based on infant and head of household characteristics. The infant characteristics include gender and location, while the head of household includes literacy. Table 5 reports the estimated effects for each of the subsamples.

The coefficients in columns (1)-(2) and (3)-(4) show that the impact of the crisis-induced reduction in PM2.5 concentration on infant mortality is significant and similar in magnitude for boys and girls and infants living in rural and urban locations. However, the estimated effects are somewhat larger for the boys living in rural areas. The interpretation of the results can be complicated[78], but it is more likely the heterogeneity in the impact between boys and girls can be due to biological gender differences. Specifically, the literature suggests that male fetuses are more

[78] For a more detailed discussion, see Tanaka (2015).

sensitive to pollution exposure than female fetuses (Tanaka, 2015; Sanders and Stoecker, 2015). Another possible interpretation reflects gender discrimination channel: if sons are preferred to daughters, they will likely be better protected from air pollution exposure. The impact of pollution would then be larger for daughters, which is not the case. Thus, this channel can be left out of consideration. The larger magnitude of the impact for the rural sample could be explained by the fact that rural households can be more sensitive to changes in air pollution and, generally, are more vulnerable to air pollution. It can be the case because rural households typically have lower socioeconomic status and fewer means to protect infants from exposure to higher air pollution.

Table 5 – Heterogeneity in impact: Infant and head of household characteristics

Dependent variable	Infant's Characteristics				HH's Characteristics	
= ln(Infant Mortality Rate)	Gender		Location		Literacy	
	Boys	Girls	Rural	Urban	Illiterate	Literate
	(1)	(2)	(3)	(4)	(5)	(6)
Treated · Post	-0.272***	-0.232***	-0.300***	-0.266*	-0.170*	-0.344***
	(0.065)	(0.074)	(0.100)	(0.153)	(0.094)	(0.081)
Observations	1,109	1,106	1,106	1,022	1,105	1,107
R-squared	0.625	0.635	0.347	0.253	0.370	0.389

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of the heterogeneity analysis, which explores whether the crisis-induced decline in PM2.5 air pollution had a heterogeneous impact on infant mortality across several subsamples based on infant and head of household characteristics. The infant characteristics include gender and location, while the head of household includes literacy. The analysis is based on the specifications in columns (11) and (12) from Appendix Table A6 and focuses on the treated group of districts with improved air quality. Each column reports the estimated coefficients from a separate regression with IMR of a specific subsample as the dependent variable. Each pair of columns reports the estimated effects for each of the subsamples, which indicate the dimensions of heterogeneity: columns (1)-(2) – infant gender, columns (3)-(4) – infant locational status, and columns (5)-(6) – head of household literacy. The heterogeneity analysis emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution and justifies the need for interventions targeting low-income households. All regressions include district FE, year FE, district-specific trends; Controls: income per capita, meteorology characteristics of deceased infants, head of household, household, medical services utilization, and other. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses

In contrast, columns (5)-(6) indicate the impact of the crisis-induced reduction in PM2.5 pollution on infant mortality is disproportionally smaller for infants from households with illiterate heads than for infants from households with literate heads. Generally, the impact of air pollution reduction on infant mortality would be stronger for illiterate households, which being presumably lower-socioeconomic are more vulnerable to the effects of air pollution. However, the impact can also be smaller. Children born in less educated households generally have lower initial health endowments, which makes them susceptible to other health risks besides air pollution. Alternatively, the impact of pollution reduction could be smaller for illiterate households because such households could be located in highly polluted areas and prefer to keep infants indoors (Tanaka, 2015).

Overall, my findings suggest that the crisis-induced reductions in PM2.5 pollution affect infant mortality through two biological mechanisms, particularly the adverse impact on fetal development and infants' early-life exposure. However, the estimates indicate that the former mechanism is not the primary channel as infants' deaths are more likely to occur during the postneonatal period. Moreover, the results indicate that the effects of PM2.5 pollution on infant mortality are specific for respiratory infections and might be related to some of the infectious diseases. Heterogeneity analysis emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution and justifies the need for interventions targeting low-income households. The absence of differential impact of air pollution reduction on infants by gender reinforces the critical hypothesis that the decline in infant mortality was due to air pollution. Nevertheless, the results should be interpreted with caution since the model designed for all-cause infant mortality could not capture effectively all underlying factors affecting some of the diseases and heterogeneity, as an indicator of model fit suggests.

3.6 Policy Perspective: Health Benefits

Finally, I use the quantified relationship to measure health benefits from the crisis-induced episode of air quality improvement. Moving the analysis to a policy perspective, this section demonstrates how the resulting estimates can be applied to measure the effectiveness of the potential policies designed to improve air quality.

For this purpose, I first use estimated coefficients to assess the contribution of the crisis-induced reduction in PM2.5 pollution to the overall improvement in infant mortality. Then I calculate the number of infant lives saved by the improvement in air quality. Further, using available life-years and life-expectancy metrics, I convert the number of infant lives saved into the number of infant life years saved. Finally, I use available estimates of the value of a statistical life to monetize potential gains from the crisis-induced improvement in air quality.

The average decline in district-level infant mortality in the group with the reduction in PM2.5 concentrations fell by about 59 infant deaths per 1000 live births during the post-crisis period. In terms of marginal effects, my computations imply that a decline in PM2.5 by 1 μg/m3 results in about 1.09 fewer infant deaths per 1000 live births. Dividing the product of the implied marginal effects with respective average reduction in PM2.5 levels of 5.75 μg/m3, I find that an 11% overall decline in the infant mortality rate during the period of interest occurred due to improvement in air quality. Interestingly, had all districts in the study area experienced the same reduction in air pollution as the treated districts, the contribution would be of the same magnitude. For comparison, Jayachandran et al. (2010) show that the introduction of sulfa drugs, a groundbreaking medical innovation in 1930s in the U.S., resulted in a 17-32% decline in pneumonia mortality, 24-36% decline in maternal mortality, and 52-65% decline in scarlet fever mortality during 1937-1943. Among more recent economic studies, Luechinger (2014) finds that 25-44% of the infant mortality decrease in Germany in 1985-2003 was associated with the reduction in SO2 concentrations. Therefore, although with a little lower magnitude, the contribution of improvement in air quality to the overall decline in infant mortality rates in the sample of Indian districts during the period of interest is comparable.

Knowing that the average district-level decline in PM2.5 concentrations during the period of interest is 5.75 μg/m3, and that the number of live births in the treated districts with reduction in PM2.5 pollution is 214,173 out of 759,425 for the whole sample in the post-crisis period, I apply implied marginal effects to calculate the number of saved infant lives. The calculation suggests that the crisis-induced reduction in air pollution resulted in 1338 infant lives saved in the treated districts. This number is lower but still comparable with that in Chay and Greenstone (2003b), where the authors claim 2500 fewer infants died during the U.S. economic recession in 1980-1982. Assuming that there could be an environmental regulation that would have the equivalent impact for all sample districts, the number of infant lives saved by such an improvement in air quality could reach 3589.

Having calculated the number of infant lives saved, I convert it into the number of infant life years saved. For that purpose, I use official life tables published on the web page of the Ministry of Home Affairs' Office of the Registrar General and Census Commissioner of India. A life table states the probabilities of survival and life expectancies of the hypothetical group or cohort at different ages (Census of India, 2016). Particularly, a Sample Registration System's life table for the 2009-2013 period shows that the average life expectancy for individuals within one year of life is 67.5 years. Multiplying the number of infant lives saved by this life expectancy, I obtain a gain in life years saved of 90,319.1 for the treated districts and 242,282.02 for the whole sample of districts.

Finally, however impressive the estimated benefits from the improvement in air quality are, they would be pointless without an opportunity to compare them with the costs of environmental regulation. Therefore, all gains need to be monetized. For that purpose, estimates of the value of a statistical life are usually used.[79] As there is no standard concept for the value of a human life in economics, the authors typically use different measures varying from USD 1.7 million (USD 2000) in Ashenfelter and Greenstone (2004) to USD 6.7 million (USD 2000) in Viscusi and Aldy (2003) and the U.S. EPA (n.d.b) estimate of USD 7.4 million (USD 2006). I use the value of a statistical life estimated specifically for India by Madheswaran (2007), who finds it equals to 15 million INR or USD 233,619.

I monetize the estimated number of infants lives saved of 1338 for the treated districts and 3589 for the whole sample during 2010-2011 to obtain monetary values of health benefits in the range of USD 313 million and USD 839 million, respectively. Knowing that the average number of the households surveyed in the treated districts and in the whole sample is 1,081,727 and 4,280,315, an annual average per-household monetized benefit from the estimated reduction in PM2.5 pollution is in the range of USD 289 for the treated districts, and USD 196 for the whole sample. For comparison, Luechinger (2014) reports that annual monetized benefit from the environmental regulation aimed at the reduction of SO2 concentrations in West Germany in the year 1989/1990 varies from USD 50 to USD 343 per household.

[79] In a statistical sense, the value of a statistical life is the cost of reducing the average number of deaths by one. Conducting a cost-benefit analysis of environmental policies in practice, the U.S. EPA, for example, estimates how much people are willing to pay for a marginal reduction in the risk of dying from the pollution-related adverse health conditions and refers to such estimates as the values of a statistical life (U.S. EPA, n.d.b).

It is worth mentioning that the overall health benefits of the crisis-induced reduction in air pollution could be underestimated in this study. My research design does not account for the effects of the decline in the concentrations of other air pollutants, as well as the crisis-driven impact on morbidity or labor productivity of the older cohorts of the Indian population. Nevertheless, the resulting monetary values of health benefits can be used as a benchmark against which the costs of the current or potential policies aimed at improving air quality can be compared. Thus, my estimates could be of considerable interest for policymakers aimed at finding the optimal balance between the costs and benefits of air pollution regulation in the specific context of early-life health in developing countries.

3.7 Conclusion

This study has attempted to isolate the causal relationship between the reductions in PM2.5 pollution presumably caused by the Global Financial Crisis of 2008 and decline in infant mortality in India using a quasi-experimental difference-in-differences research design.

Combining state-of-the-art satellite-based estimates with household survey-based information for 284 districts across 9 states during 2007-2011, I find that the infant mortality rate fell by 24% more in the most affected districts, implying 1338 fewer infants deaths than would have occurred in the absence of the crisis. The analysis of the pathophysiological mechanism indicates that the effect of interest is strongest in the postneonatal period, specific for respiratory infections and might be related to infectious diseases. The findings also highlight the importance of two biological mechanisms: in utero and post-birth PM2.5 exposure. Heterogeneity analysis further emphasizes the role of parental education in alleviating the adverse consequences of infants' exposure to air pollution and justifies the need for interventions targeting low-income households. The estimates are within the range reported in other economic studies and appear to be robust to a variety of specifications and falsification tests, prompting the belief that the relationship between crisis-induced reduction in particulate air pollution and decline in infant mortality is causal in nature.

Moving the analysis further into the policy perspective, I demonstrate how the resulting estimates of the health effects attributable to the crisis-induced reduction in PM2.5 pollution could be applied to measure the effectiveness of the current and potential policies aimed at controlling air quality in India. For that purpose, I measured actual gains from improving air quality in the Indian districts during the crisis time-frame. The resulting gains comprise a number of infant lives saved, the corresponding increase in life expectancy at birth and monetary values of the improvements obtained.

Back-of-the-envelope calculations suggest that the estimated decline in infant mortality translates into a three-year after crisis total of USD 312.5 million. The resulting health benefits attributable to the crisis-induced reduction in air pollution can be used as a benchmark to assess the effectiveness of potential policies designed to improve air quality in the selected Indian districts.

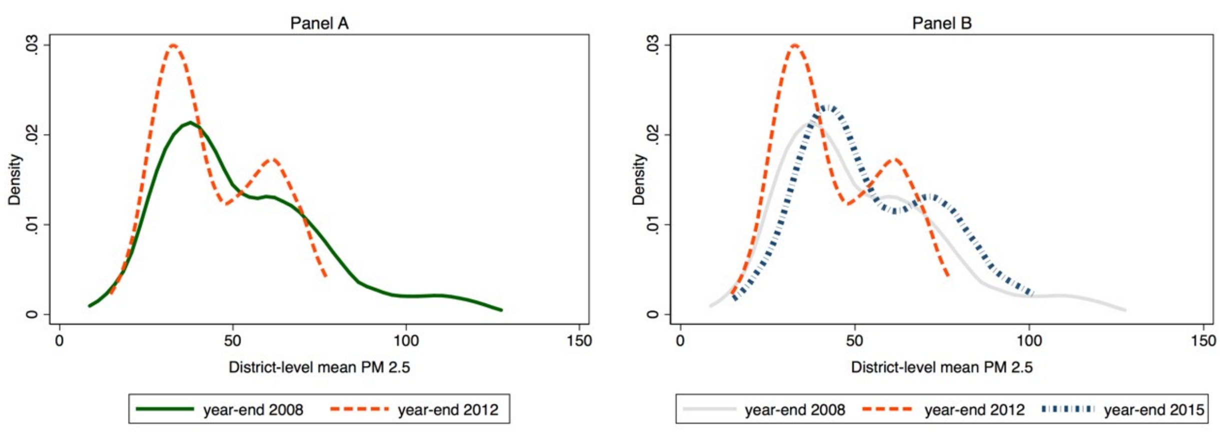
Therefore, this study addresses more precisely the needs of policymakers aimed at finding the optimal balance between the costs and benefits of air pollution reduction in the specific context of developing countries.

3.8 Appendix

Fig. A1. PM2.5 concentrations in study area, 1998-2015

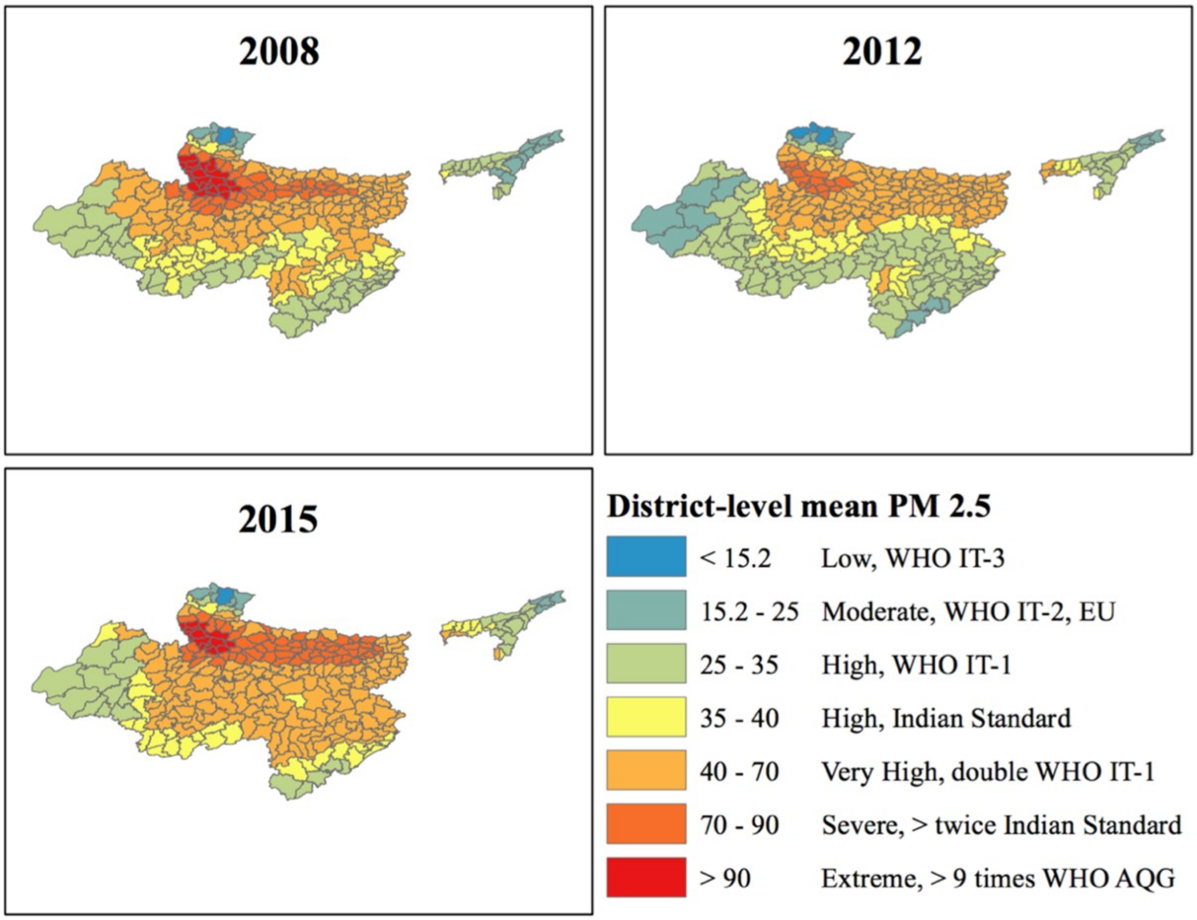
Notes: The figure shows the evolution of the district-level annual mean PM2.5 levels in the study area for 1998-2015. Two observations emerge. First, air quality has been continuously deteriorating during the last two decades. Second, the figure documents two episodes of abrupt reduction in PM2.5 concentrations, 2005-2006 and 2009-2012, followed by comparably sharp reversals of the trends. Air quality improvement during the 2009-2012 episode is the focus of my study.

Fig. A2. Kernel density graphs of air quality



Notes: The figure compares kernel density estimates of the annual mean PM2.5 distributions across the districts in the study area for 2008, 2012 and 2015, representing pre-crisis, crisis and post-crisis cut-off points. Panel A demonstrates that the entire distribution shifted substantially to the left in 2012 compared to 2008. In contrast, Panel B documents the shift of the distribution to the right again in 2015.

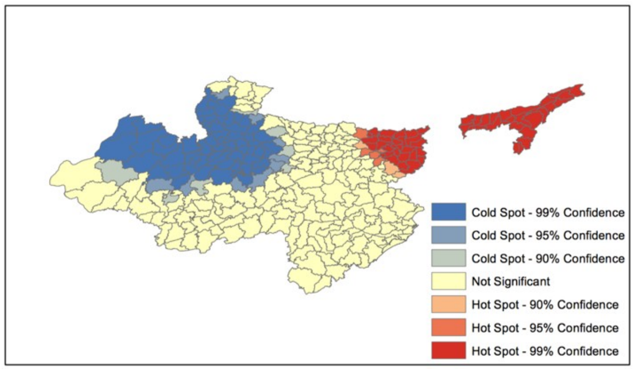
Fig. A3. Spatio-temporal distribution of district-level annual mean PM2.5



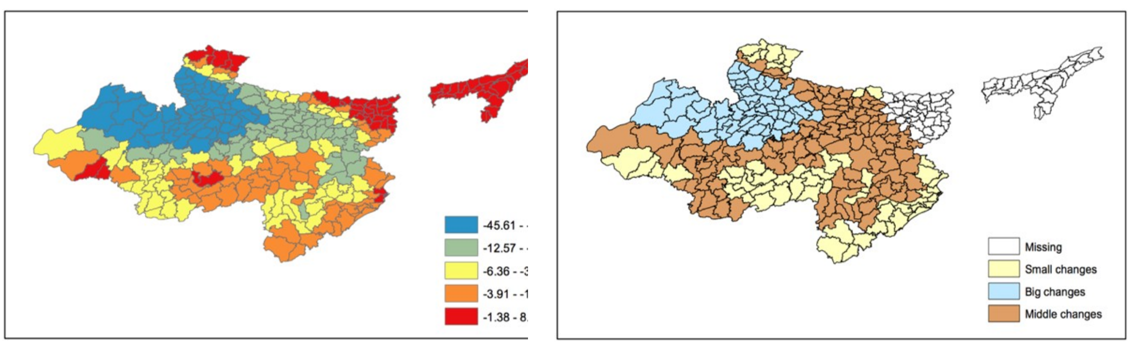
Notes: The figure depicts spatio-temporal distribution of district-level annual mean PM2.5 concentrations in the study area for 2008, 2012 and 2015, representing pre-crisis, crisis and post-crisis cut-off points. The districts are classified into six categories using air quality thresholds adopted by the WHO, EU and Indian environmental agencies (similar to Chowdhury & Dey, 2016). I define "Low", "Moderate", "High", "Very High", "Severe" and "Extreme" categories in a way that their upper limits correspond to one of the standards. The limits for the first two categories are set to meet the WHO interim targets 3 (IT-3) and 2 (I-2), equal to 15 and 25 μg/m3 respectively. The latter threshold also corresponds to the European Environmental Agency target value for European countries. The upper limit of 35 μg/m3 in the lower "High" category is the WHO IT-1, while the limit in the upper "High" category is equivalent to the Indian National Ambient Air Quality Standard of 40 μg/m3, the least stringent of the standards. The limits of the remaining categories are designed to highlight extremely high levels of air pollution in India. The "Very High" category corresponds to the PM2.5 concentration equivalent to the double of the least demanding WHO IT-1, "Severe" pollution exceeds twice the Indian Standard and is nine times the WHO air quality guideline value of 10 μg/m3, which is excluded from our classification. The last "Extreme" category comprises the remaining concentrations of fine particulate pollution exceeding 90 μg/m3. More details about air quality standards and guidelines are in Panel B of Appendix Table A1, WHO (2006a), EEA (2014) and CPCB (2009).

Fig. A4. Location of the treated and control districts: Illustrations to columns of the Appendix Table A9

A. The location of the treated and control districts as in Column (1): Hot Spot Analysis (HSA)



B. The location of the treated and control districts as in Column (2): 2008-2012 simple changes in PM2.5 concentrations as in Chay and Greenstone (2003b)



C. The location of the treated and control districts as in Column (3): as in Chay and Greenstone (2003b) but alternatively based on 2008-2012 % changes in PM2.5

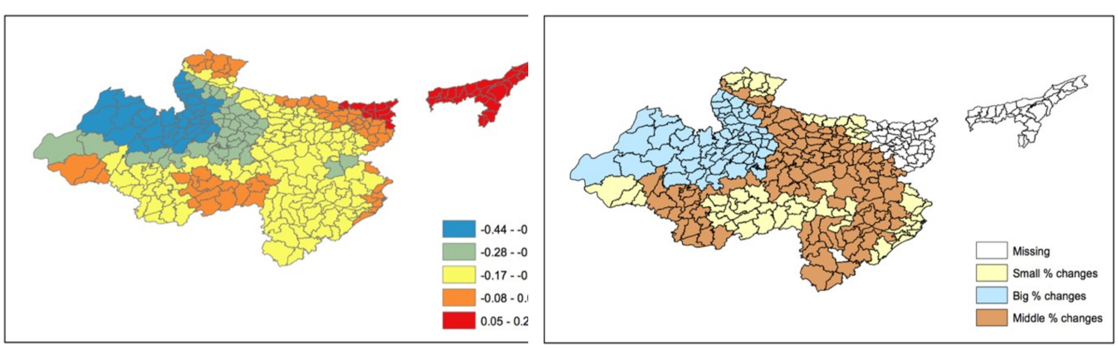
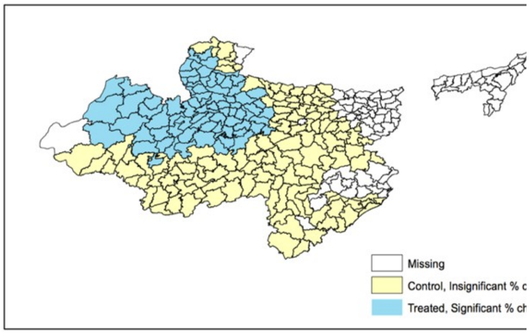
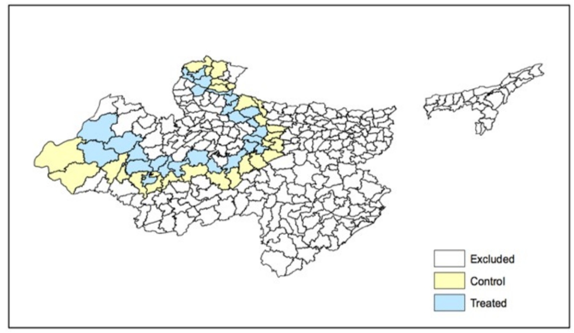


Fig. A4 (continued). Location of the treated and control districts

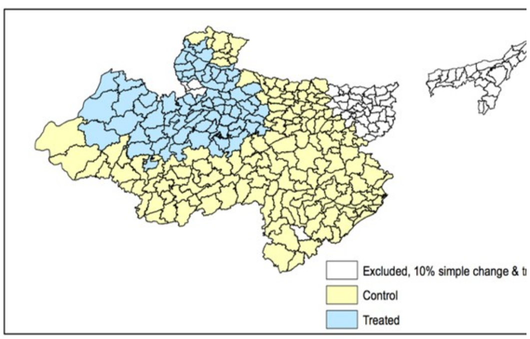
D. The location of the treated and control districts as in Column (4): HSA, balanced panel



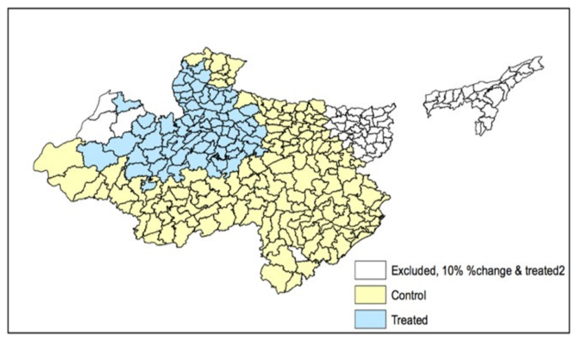
E. The location of the treated and control districts as in Column (5): HSA, adjacent districts



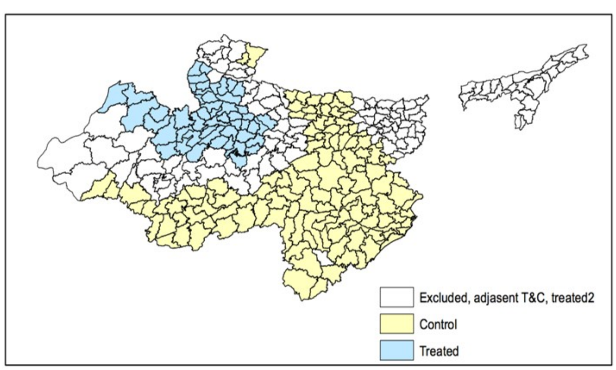
F. The location of the treated and control districts as in Column (6): HSA, after drop of 10% of the most affected districts based on PM2.5 change



G. The location of the treated and control districts as in Column (7): HSA, after drop of 10% of the most affected districts based on % change in PM2.5



Panel H. The location of the treated and control districts as in Column (8): HSA, after drop of the adjacent districts



Notes: The figure illustrates a column-wise location of the treated and control districts for the Appendix Table A9.

Table A1 – Summary statistics of changes in PM2.5 and population

Panel A: Summary statistics of changes in annual mean PM 2.5

	a) 2008	b) 2012	c) 2015
Mean	51.91	44.45	54.37
Standard deviation	22.25	15.54	19.43
Min	15.12	14.64	15.16
Max	120.92	77.32	101.61
10th percentile	28.93	27.43	32.54
90th percentile	80.44	66.54	80.81
Observations	284	284	284

Panel B: Classification of the PM 2.5 levels and population exposure

a) 2008

Annual PM2.5	Category	# of districts	% of districts	# of exposed population	% of exposed population	Exposed % > Indian standard	Comments
< 15.2	low	1	0.35	425428	0.07	28.59	WHO IT-III
15.2-25	moderate	14	4.93	11568477	1.87		WHO IT-II, EU AQS
25-35	high	63	22.18	102100000	16.5		WHO IT-I
35-40	high	38	13.38	62735096	10.14		Indian standard
40-70	very high	114	40.14	279800000	45.22	71.41	2*WHO IT-I
70-90	severe	35	12.32	106600000	17.23		>2*Indian standard
>90	extreme	19	6.7	55488672	8.97		>9*WHO AQG

b) 2012

Annual PM2.5	Category	# of districts	% of districts	# of exposed population	% of exposed population	Exposed % > Indian standard	Comments
< 15.2	low	3	1.05	1380248	0.21	39.97	WHO IT-III
15.2-25	moderate	17	5.99	24321796	3.64		WHO IT-II, EU AQS
25-35	high	91	32.04	159300000	23.87		WHO IT-I
35-40	high	37	13.03	81711800	12.24		Indian standard
40-70	very high	123	43.31	361700000	54.19	60.03	2*WHO IT-I
70-90	severe	13	4.58	38989920	5.85		>2*Indian standard
>90	extreme	0	0	0	0		>9*WHO AQG

c) 2015

Annual PM2.5	Category	# of districts	% of districts	# of exposed population	% of exposed population	Exposed % > Indian standard	Comments
< 15.2	low	1	0.35	441956	0.06	18.97	WHO IT-III
15.2-25	moderate	9	3.17	9059676	1.28		WHO IT-II, EU AQS
25-35	high	31	10.92	56973744	8.07		WHO IT-I
35-40	high	35	12.32	67430456	9.55		Indian standard
40-70	very high	139	48.94	318200000	45.08	81.03	2*WHO IT-I
70-90	severe	56	19.72	212000000	30.04		>2*Indian standard
>90	extreme	13	4.58	41676652	5.92		>9*WHO AQG

Notes: The table accompanies Appendix Fig. A3 by providing summary statistics corresponding to changes in PM2.5 and population exposure to PM2.5 pollution across districts for 2008, 2012 and 2015, representing pre-crisis, crisis and post-crisis cut-off points. Panel A documents changes in PM2.5 concentrations, while Panel B relates these changes to population exposure. Categorization of districts due to PM2.5 concentrations corresponds to those explained in the notes to Appendix Fig. A3. Taken together, Fig. A3 and Panel A of this table support the hypothesis that districts with high pre-crisis levels of air pollution likely experienced a more significant improvement in air quality than districts with initially low pollution concentrations. Fig. A3 and Panel B of this table provide suggestive evidence that improvements in infant mortality could be more pronounced in districts with high pre-crisis levels of air pollution.

Table A2 – Structural trend break analysis

Panel A: sup Wald and LR tests, unknown breaks, study area's aggregated time series

a) Sup Wald				b) Sup LR			
Test window	Trimming, %	Year of break	W-statistic	Test window	Trimming, %	Year of break	F-statistic
2004-2011	25	2010***	16.63	2004-2011	25	2009	4.63
2005-2010	30-35	2010***	16.63	2005-2010	30-35	2009	4.63
2006-2009	40	2009***	12.92	2006-2009	40	2009	4.63
2007-2008	45	2007	1.76	2007-2008	45	2007	1.89

Panel B: Wald and LR tests, known year of break, study area's aggregated time series

a) Wald			b) LR		
Tested Year	W-statistic	Significance	Tested Year	F-statistic	Significance
2004	1.29	-	2004	1.47	-
2005	2.09	-	2005	2.56	-
2006	0.98	-	2006	1.46	-
2007	1.76	-	2007	1.89	-
2008	0.42	-	2008	0.63	-
2009	12.92	***	2009	4.63	*
2010	16.63	***	2010	3.95	-
2011	6.1	***	2011	2.49	-

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table shows the results of the time-series econometric test for structural trend break, supremum Wald and likelihood-ratio (LR) tests, designed for cases when the breakpoints are unknown (Andrews, 1993, 2003; Hansen, 1997). Both supremum tests identify structural breaks within the 2009-2012 air quality improvement episode, thus associating them with the respective reversal of the upward trend in PM2.5. Panel A shows that whenever the year 2010 is included in the test window, the maximal W-statistics are concentrated at this year, and the null hypothesis of no trend break can be rejected at the 1 percent level. When tested by the sup LR, the same is relevant for the year 2009 except that neither of the F-statistics is significant. Panel B uses analogous tests for structural trend break but designed for cases when it is pretended that the year of trend break is known. It shows that neither of the years within the 2005-2006 interval, the years of the largest pre-crisis drop in PM2.5, are trend break years. This relaxes a concern about the possible confounding role of these years in the results.

Table A3 – Descriptive statistics for treated and control districts for pre- and post-crisis

	Pre-crisis (2007-2009)		Post-crisis (2010-2011)	
	Control	**Treated**	**Control**	**Treated**
Panel A: District-specific characteristics				
Average year-level population	2021699	2486424	2131144	2604290
Total number of live births	558026	289891	366973	214173
Average year-level number of births	1240.06	1271.45	1287.625	1409.033
Total number of infant deaths (all causes):	48597	24297	25230	14158
Average year-level number of infant deaths	107.99	106.57	88.53	93.14
Infant Mortality Rate (all causes)	95.31	96.05	80.07	74.65
Mean district-level air pollution ($PM_{2.5}$)	41.69	68.75	39.62	61.87
Average age of mothers	27.36	27.20	26.38	26.18
% of Married mothers	98.87	99.24	99.29	99.47
Panel B: Deceased infants characteristics				
% of Male infants	50.56	50.56	51.23	50.20
% of Infant deaths in rural areas	88.28	83.61	88.37	84.64
Average birth order	2.61	2.85	2.36	2.56
Panel C: Head of the household characteristics				
% of Male Head of the household	89.77	93.01	85.62	88.75
% of Heads from Scheduled Castes	20.81	26.19	20.83	26.51
% of Heads from Scheduled Tribes	22.75	6.34	22.99	5.81
% of Illiterate Heads	37.78	35.89	37.27	35.15
% of Hindu Heads	89.44	83.57	89.41	83.80
% of Muslim Heads	8.14	15.23	7.98	15.02
% of Unemployed Heads	7.43	6.66	9.24	9.06
% of Smoking Heads	25.47	37.38	23.57	33.96
% of Alcohol-drinking Heads	29.50	17.98	26.81	15.93
Panel D: Deceased infants household characteristics				
% of Houses with filtered water	24.08	14.31	23.55	14.07
% of Houses with electrical lightning	47.92	51.49	45.07	51.55
% of Houses with kerosene lightning	50.47	46.67	53.39	46.68
% of Households cooking on firewood	69.03	49.35	69.85	50.23
% of Households cooking on cow dung cake	13.89	27.04	13.98	27.70
% of Households cooking on coal/charcoal	1.80	0.17	1.48	0.11
% of Households cooking on electricity	0.16	0.05	0.08	0.05
% of Households cooking inside	87.86	79.79	88.03	79.36
% of Households without toilet	80.49	67.40	81.36	66.93
Panel E: Medical services utilization				
% of Mothers with no ante natal care	13.00	17.31	2.29	0.59
% of Deliveries at government facilities	45.44	42.37	54.22	50.29
% of Newborns with no after births checkups	21.67	26.85	13.33	15.83
% of Vaccinated babies	94.54	93.53	94.18	94.99
Panel F: Meteorological covariates				
Mean district-level air temperature (p/a)	25.59	25.66	25.64	25.80
Mean district-level precipitation (p/a)	85.57	57.05	93.08	68.74

Notes: The table presents descriptive statistics separately for treated and control districts before and after the crisis. There is less room for the possibility that there is a selection or contamination of the control group. The table also provides evidence in favor of the hypothesis that the crisis-induced reductions in PM2.5 pollution led to a statistically significant decline in district-level infant mortality rates.

Table A4 – Results of the test suggested by Altonji, Elder, and Taber (2005)

Panel A. Districts with improved air quality

Dependent variable	% Boys	% Rural Deaths	avg. Order of Birth	% Male hh Heads	% Sch. Casts Heads	% Sch. Tribes Heads	% Hindu Heads	% Muslim Heads
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated · Post	-0.55	-0.10	0.02	-0.89	-0.03	-0.75	-0.17	0.27
	(1.50)	(1.33)	(0.10)	(1.12)	(1.83)	(0.82)	(1.08)	(1.03)
Dependent variable	% Christian Heads	% Sikh Heads	% Buddhist Heads	% Illiterate Heads	% Literate w/o Ed.	% Lit. w/ Mid. Ed.	% Lit. w/ Sec. Ed.	% Lit. w/ Grad. Ed.
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treated · Post	0.04	-0.09	0.11	1.34	1.34	-0.47	-1.40	-0.86
	(0.14)	(0.16)	(0.07)	(1.71)	(1.05)	(1.26)	(1.35)	(0.59)
Dependent variable	% Cultivator Heads	% Agri. Wage	% Non-Agri. Wage	% Self-Employed	% Reg. Salaried	% Did not work	% Pens. & Other	% Smoking Heads
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Treated · Post	2.02	-1.88	-4.60**	0.87	0.74	1.29	-0.26	-2.07
	(1.44)	(1.34)	(1.93)	(1.12)	(0.89)	(1.30)	(1.23)	(1.69)
Dependent variable	% Alcohol Drinkers	% HH w/ Filt. Water	% HH w/ Electricity	% HH w/ Kerosene	% HH w/ Solar	% HH w/ Oils	% HH w/ Any Other	% HH w/ Firewood
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
Treated · Post	-0.84	-0.47	1.45	-1.49	0.23	-0.08	-0.07	0.70
	(1.52)	(0.80)	(2.37)	(2.51)	(0.31)	(0.11)	(0.21)	(1.40)
Dependent variable	% HH w/ Cr. Residue	% HH w/ Cow Dung	% HH w/ Coal	% HH w/ Kerosene	% HH w/ LPG/PNG	% HH w/ Electricity	% HH No Cooking	% HH Cook Inside
	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Treated · Post	-0.33	0.73	0.37	0.05	-1.54	-0.07	0.06	1.50
	(0.67)	(1.30)	(0.27)	(0.19)	(1.26)	(0.05)	(0.24)	(1.14)
Dependent variable	% HH w/o Toilet	ln(GDP per capita)	Num. of Births	Num. Popuation	avg. Age of Mothers	% Married Mothers	% No ANC Received	% Gov. Deliveries
	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Treated · Post	-0.16	-0.03	110.03	32,257.84	-0.13	-0.05	-7.24***	1.93
	(1.43)	(0.07)	(86.60)	(31,695.21)	(0.17)	(0.11)	(1.91)	(2.14)
Dependent variable	% Babies No CheckUp	% Babies w/ Vaccine	avg. p/a Air Temp	avg. p/a Precipitation	avg. U-Wind Direct.	avg. V-Wind Direct.	avg. Wind Speed	
	(49)	(50)	(51)	(52)	(53)	(54)	(55)	
Treated · Post	-5.03*	2.58***	0.14***	1.82	-0.12***	0.11***	-0.16***	
	(2.62)	(0.80)	(0.02)	(3.70)	(0.02)	(0.03)	(0.03)	
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further validates the DID identifying assumption of the model in equation (4). The test suggested by Altonji, Elder, and Taber (2005) examines whether the impact of the crisis has any association with changes in observable characteristics. Although this is not a formal test for exclusion restrictions, the absence of a statistically significant association with observable characteristics would suggest that there should not be a correlation with unobservable variables either (Altonji et al., 2005). I first successively regress my empirical model with every observable characteristic as a dependent variable. Then, I check whether the coefficients on the interaction term, $\widehat{\delta_1}$, are statistically significant. Table A4 presents results for both types of treated districts in Panel A and Panel B, respectively. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Table A4 – Results of the test suggested by Altonji, Elder, and Taber (2005) (continued).

Panel B. Districts with worsened air quality

Dependent variable	% Boys	% Rural Deaths	avg. Order of Birth	% Male hh Heads	% Sch. Casts Heads	% Sch. Tribes Heads	% Hindu Heads	% Muslim Heads
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated · Post	-2.39	0.14	-0.21*	-2.05	1.72	-1.49	-3.39	-1.03
	(2.04)	(1.19)	(0.12)	(1.39)	(1.32)	(1.02)	(2.54)	(2.02)
Dependent variable	% Christian Heads	% Sikh Heads	% Buddhist Heads	% Illiterate Heads	% Literate w/o Ed.	% Lit. w/ Mid. Ed.	% Lit. w/ Sec. Ed.	% Lit. w/ Grad. Ed.
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treated · Post	4.70	-0.02	0.05	2.91	0.28	-1.34	-1.37	-0.53
	(3.93)	(0.08)	(0.06)	(2.37)	(1.13)	(1.92)	(1.28)	(0.68)
Dependent variable	% Cultivator Heads	% Agri. Wage	% Non-Agri. Wage	% Self-Employed	% Reg. Salaried	% Did not work	% Pens. & Other	% Smoking Heads
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Treated · Post	-0.20	1.96	-3.09	1.30	-0.55	0.95	1.63*	0.19
	(1.85)	(1.68)	(1.98)	(1.07)	(0.89)	(1.36)	(0.88)	(1.87)
Dependent variable	% Alcohol Drinkers	% HH w/ Filt. Water	% HH w/ Electricity	% HH w/ Kerosene	% HH w/ Solar	% HH w/ Oils	% HH w/ Any Other	% HH w/ Firewood
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
Treated · Post	-2.04	0.52	1.17	-1.17	0.32	0.03	-0.29	0.80
	(1.66)	(1.11)	(2.02)	(2.06)	(0.33)	(0.16)	(0.47)	(1.73)
Dependent variable	% HH w/ Cr. Residue	% HH w/ Cow Dung	% HH w/ Coal	% HH w/ Kerosene	% HH w/ LPG/PNG	% HH w/ Electricity	% HH No Cooking	% HH Cook Inside
	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Treated · Post	-1.05	0.43	-0.21	-0.06	0.32	-0.08	-0.24	0.16
	(1.44)	(1.22)	(0.48)	(0.18)	(0.83)	(0.07)	(0.31)	(1.46)
Dependent variable	% HH w/o Toilet	ln(GDP per capita)	Num. of Births	Num. Popuation	avg. Age of Mothers	% Married Mothers	% No ANC Received	% Gov. Deliveries
	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Treated · Post	-1.70	0.02	-54.86	-209.69*	0.02	-0.02	-4.10***	0.81
	(1.55)	(0.09)	(187.42)	(119.82)	(0.11)	(0.10)	(1.50)	(1.31)
Dependent variable	% Babies No CheckUp	% Babies w/ Vaccine	avg. p/a Air Temp	avg. p/a Precipitation	avg. U-Wind Direct.	avg. V-Wind Direct.	avg. Wind Speed	
	(49)	(50)	(51)	(52)	(53)	(54)	(55)	
Treated · Post	-0.12	-0.49	0.11***	32.66***	0.30***	-0.01	0.13***	
	(1.84)	(1.12)	(0.02)	(5.25)	(0.02)	(0.03)	(0.03)	
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further validates the DID identifying assumption of the model in equation (4). The test suggested by Altonji, Elder, and Taber (2005) examines whether the impact of the crisis has any association with changes in observable characteristics. Although this is not a formal test for exclusion restrictions, the absence of a statistically significant association with observable characteristics would suggest that there should not be a correlation with unobservable variables either (Altonji et al., 2005). I first successively regress my empirical model with every observable characteristic as a dependent variable. Then, I check whether the coefficients on the interaction term, $\widehat{\delta_1}$, are statistically significant. Table A4 presents results for both types of treated districts in Panel A and Panel B, respectively. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Table A5 - Estimated effects of the crisis-induced economic slowdown on PM2.5 pollution

Dependent variable = PM2.5	Districts with improved air quality		Districts with worsened air quality	
	(1)	(2)	(1)	(2)
Treated · Post	-11.89***	-7.54***	2.75***	2.68***
	(0.94)	(0.71)	(0.27)	(0.36)
Treated · Post · t		-3.02***		0.04
		(0.26)		(0.17)
Observations	4,086	4,086	3,744	3,744
R-squared	0.96	0.97	0.97	0.97
District FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
District-specific trends	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the results of the regression analysis by reporting the estimates from fitting equations (A1) and (A2), which are similar to equations (4) and (5) in the chapter, but with PM2.5 concentrations (PM_{dt}) as a dependent variable and without additional control variables.

$$PM_{dt} = \alpha + \delta_1 (Treated_d \cdot Post_t) + \mu_d + \gamma_t + \lambda_d t + \varepsilon_{dt} \tag{A1}$$

$$PM_{dt} = \alpha + \delta_1 (Treated_d \cdot Post_t) + \delta_2 (Treated_d \cdot Post_t \cdot t) + \mu_d + \gamma_t + \lambda_d t + \varepsilon_{dt} \tag{A2}$$

The description of the variables is the same as provided in the chapter. The equations (A1) and (A2) test in the DiD framework if the crisis-induced economic slowdown reduced PM2.5 air pollution in the treatment districts relative to control districts after adjustment for district fixed effects, year fixed effects and differential trends. Equation (A2) additionally allows for both level and slope changes during the post-crisis period. For both types of treated districts, columns (1) report the estimate of the coefficient δ_1 and columns (2) report the estimates δ_1 and δ_2 after the estimation of equation (A1) and equation (A2), respectively. Standard errors clustered at the district level are shown in parentheses.

The coefficients in both columns for the treated districts with the reduction in PM2.5 pollution suggest that these districts experienced a statistically significant decline in PM2.5 concentration after 2010. Moreover, column (2) provides evidence of a negative and statistically significant change in the slope of PM2.5 pollution after 2010. Therefore, regression analysis confirms the visual impression that air pollution reduction occurred during the post-crisis period. The regression coefficients for the treated districts with the increase in PM2.5 pollution captured by the variable Treated · Post are positive, much smaller, and significant. In contrast to the districts with a decline in air pollution, PM2.5 concentration in districts with worsened air quality does not demonstrate a sign of a statistically significant change in slope after 2010. Thus, there is little evidence of the trend-break impact of the crisis on air pollution in these districts.

For the treated districts with improved air quality, the coefficient in column (1) implies PM2.5 in this group of treated districts decreased 11.89 μg/m3 relative to the control districts between the pre- and post-crisis period. Coefficients in column (2) from the model that allows for changes in the level and slope show a somewhat smaller decrease of 9.05 μg/m3 ($\hat{\delta}_1 + 0.5 \cdot \hat{\delta}_2$, where the factor of 0.5 is equal to the average value of the continuous year variable t for two post 2010 years ((0+1)/2; t is set to be equal to zero in 2010).

Overall, regression analysis confirms the visual impression that air pollution reduction occurred during the post-crisis period.

Table A6 – Sensitivity analysis

Dependent variable = ln(Infant Mortality Rate)	Districts with improved air quality											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated · Post	-0.26***	-0.25***	-0.31***	-0.30***	-0.31***	-0.30***	-0.32***	-0.32***	-0.31***	-0.31***	-0.28***	-0.29***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)
Treated · Post · t		-0.17**		-0.04		-0.04		-0.04		-0.03		0.02
		(0.07)		(0.07)		(0.07)		(0.07)		(0.07)		(0.05)
ln(GDP per capita)	-0.03	-0.03	0.06	0.06	0.06	0.06	0.04	0.04	0.03	0.03	-0.02	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
Observations	1,115	1,115	1,115	1,115	1,115	1,115	1,110	1,110	1,110	1,110	1,110	1,110
R-squared	0.37	0.38	0.43	0.43	0.43	0.43	0.47	0.47	0.48	0.48	0.73	0.73
Dependent variable = ln(Infant Mortality Rate)	**Districts with worsened air quality**											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated · Post	0.08	0.09	-0.07	-0.03	-0.08	-0.03	-0.14	-0.10	-0.16	-0.12	0.03	0.03
	(0.13)	(0.13)	(0.15)	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)	(0.08)	(0.08)
Treated · Post · t		-0.23***		-0.32***		-0.34***		-0.30***		-0.29***		-0.03
		(0.08)		(0.09)		(0.10)		(0.10)		(0.10)		(0.08)
ln(GDP per capita)	0.09	0.07	0.15**	0.13**	0.15**	0.13**	0.11*	0.10*	0.11*	0.10	0.01	0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
Observations	1,007	1,007	1,007	1,007	1,005	1,005	1,001	1,001	1,001	1,001	1,001	1,001
R-squared	0.27	0.29	0.31	0.32	0.31	0.32	0.36	0.38	0.38	0.39	0.68	0.68
Income per capita	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Meteorology	-	-	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Infant	-	-	-	-	Y	Y	Y	Y	Y	Y	Y	Y
Head of household	-	-	-	-	-	-	Y	Y	Y	Y	Y	Y
Household	-	-	-	-	-	-	-	-	Y	Y	Y	Y
District & Med. System	-	-	-	-	-	-	-	-	-	-	Y	Y

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table addresses concern that changes in the dependent variable may be explained by changes in the observable time-varying characteristics that potentially correlated with the impact of PM2.5 pollution changes attributable to the effect of the crisis. For that purpose, I perform a sensitivity analysis. The table reports results for both types of districts. Every pair of columns represents estimates from fitting equations (4) and (5). All regressions include district FE, year FE, district-specific trends. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Table A7 – Falsification tests: Pre-crisis data sample, placebo $Post_t$= 2008

Dependent variable = ln(Infant Mortality Rate)	(1) Group 1	(2) Group 2	(3) Group 1	(4) Group 2	(5) Group 1	(6) Group 2	(7) Group 1	(8) Group 2	(9) Group 1	(10) Group 2	(11) Group 1	(12) Group 2
Treated · Post	0.03	0.03	0.11	-0.12	0.10	-0.13	0.07	-0.09	0.08	-0.11	0.08	-0.11
	(0.06)	(0.09)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)	(0.11)	(0.09)	(0.10)	(0.08)	(0.08)
ln(GDP per capita)	-0.00	-0.11	0.00	-0.16	-0.00	-0.17	-0.01	-0.16	0.01	-0.18	-0.03	-0.13
	(0.12)	(0.15)	(0.13)	(0.16)	(0.12)	(0.15)	(0.13)	(0.16)	(0.13)	(0.15)	(0.12)	(0.12)
Observations	452	414	452	414	452	414	450	412	450	412	450	412
R-squared	0.41	0.37	0.47	0.44	0.48	0.48	0.56	0.54	0.62	0.60	0.73	0.74
District FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
District-specific trends	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls:	.	.	.	.	.	.	.	.	.	.	.	.
Income per capita	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Meteorology	-	-	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Infant	-	-	-	-	Y	Y	Y	Y	Y	Y	Y	Y
Head of household	-	-	-	-	-	-	Y	Y	Y	Y	Y	Y
Household	-	-	-	-	-	-	-	-	Y	Y	Y	Y
District & Med. System	-	-	-	-	-	-	-	-	-	-	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of another falsification test. I re-estimate the model using observations only from the pre-crisis period when the effects of the crisis-induced reduction in air pollution could not exist. I assign 2008 as a placebo trend break point and thus consider 2007 as the pre-crisis period, and 2008 as the post-crisis period. The table reports point estimates after fitting equation (4) with different combinations of W_{dt} and X_{dt} vectors for the districts from both treated groups with improved (Group 1) and worsened (Group 2) air quality. As expected, the regressions return statistically insignificant coefficients. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Table A8 – Additional falsification and robustness checks

Specifications	Coeff. on *Treated · Post*
Falsification Tests	
Not detrended pre-crisis observations	0.09
	(0.07)
Common support alternative control	-0.28***
	(0.07)
Robustness Checks	
NSS regions*year FE	-0.28***
	(0.07)
State*year FE	-0.28***
	(0.07)
No weighting	-0.28***
	(0.06)
Weighting by number of births	-0.25***
	(0.06)
Cluster at NSS regions level	-0.28***
	(0.06)
Controls:	.
Income per capita	Y
Meteorology	Y
Infant	Y
Head of household	Y
Household	Y
District & Med. System	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table provides results of the additional falsification and robustness checks. See the text for explanations.

Table A9 - Alternative sorting of districts into treatment and control groups (T&C)

Dependent variable = ln(Infant Mortality Rate)	Hot Spot Analysis Reported results	Chay&Greenstone Simple change	Chay&Greenstone % change	Hot Spot Analysis Balanced panel	Hot Spot Analysis Adjacent T&C dist.	Hot Spot Analysis 10% drop 1	Hot Spot Analysis 10% drop 2	Hot Spot Analysis Drop adjasent T&C
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated · Post	-0.283***	-0.305***	-0.287***	-0.270***	-0.323**	-0.293***	-0.282***	-0.257***
	(0.068)	(0.099)	(0.093)	(0.070)	(0.125)	(0.068)	(0.069)	(0.078)
Observations	1,110	550	553	1,040	257	1,095	1,095	853
R-squared	0.728	0.794	0.779	0.737	0.859	0.727	0.727	0.722
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
District-specific trends	Y	Y	Y	Y	Y	Y	Y	Y
Controls:	.	.	.	.	.	.	.	.
Income per capita	Y	Y	Y	Y	Y	Y	Y	Y
Meteorology	Y	Y	Y	Y	Y	Y	Y	Y
Infant	Y	Y	Y	Y	Y	Y	Y	Y
Head of household	Y	Y	Y	Y	Y	Y	Y	Y
Household	Y	Y	Y	Y	Y	Y	Y	Y
District & Med. System	Y	Y	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table compares resulting estimates based on the model in equation (4) from the robustness checks that focus on alternative options for sorting districts into treatment and control groups. Each column of the table corresponds to one of the eight regressions, which are intuitively illustrated by the graphs in Fig. A4. The sign, magnitude and order of statistical significance of the coefficients on Treated · Post remain similar between each other and to the coefficient estimated using my preferable specification. T&C refers to the treated and control districts. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Table A10 - Alternative estimation strategies

Dependent variable = ln(Infant Mortality Rate)	De-trended	Conditioning on Xs & districts' trends	Matching & DiD on pre-crisis Xs & districts' trends	Matching & DiD on pre-crisis Xs & districts' trends
	(1)	(2)	(3)	(4)
Treated · Post	-0.283***	-0.267***	-0.309***	-0.318***
	(0.068)	(0.092)	(0.114)	(0.086)
Observations	1,110	1,110	877	877
R-squared	0.728	0.891	0.887	0.701
District FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
District-specific trends	Y	Y	Y	Y
Controls:	.	.	.	.
Income per capita	Y	Y	Y	Y
Meteorology	Y	Y	Y	Y
Infant	Y	Y	Y	Y
Head of household	Y	Y	Y	Y
Household	Y	Y	Y	Y
District & Med. System	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table compares resulting estimates based on the model in equation (4) from another set of robustness checks that focus on alternative estimation strategies. The test checks whether the main finding would remain robust to different estimation strategies, namely detrending, conditioning on the explanatory variables and district-specific trends, and the method combining matching on pre-crisis explanatory variables and trends with subsequent difference-in-differences. Column (1) shows the coefficient on Treated · Post estimated using my preferable specification based on detrending. Column (2) shows the same coefficient estimated using my preferable specification but based on the conditioning on explanatory variables and district-specific trends. Columns (3) and (4) show the results from the regressions that combine matching on pre-crisis explanatory variables and district-specific trends with specifications in columns (2) and (1), respectively. Matching is performed as a 1-to-1, nearest-neighbor, without replacement and with common support. In other words, the results in columns (3) and (4) are the estimated coefficients on Treated · Post obtained from the regressions like in columns (2) and (1) but on matched sample. The results indicate that all specifications return estimated coefficients of interest that are not substantially different from each other, thus confirming the credibility of the main analysis. Heteroskedasticity-robust standard errors clustered at the district level are shown in parentheses.

Appendix A1 – Details Getis-Ord Hot Spot Analysis

Getis-Ord Hot Spot Analysis (HSA) is, in essence, a test for spatial dependence (autocorrelation or association) and is designed to assess the extent of clustering between units based on their attributes and make inferences about its statistical significance. In spatial statistics, the notion of spatial dependence, reflecting the tighter relationship between near than distant units, means that the similar values of some attribute or characteristic for one unit will likely occur in neighboring units also, leading to the formation of spatial clusters (Anselin, 1992).

HSA is designed to answer several types of research questions. Specifically, a researcher might apply HSA to a particular characteristic of the unit of analysis to identify the spatial concentration of its incidents or to locate units with high or low values of the particular attribute. Alternatively, a researcher may be interested in locating units with unexpectedly, compared to the purely random occurrence, high/low attribute values in relation to some other variable. The latter is of special interest to my study. Applying HSA, I am interested in identifying spatial clusters of districts with unusually large and statistically significant changes in the concentrations of fine particulate matter during the 2009-2012 improvement episode in relation to pre-crisis 2008 air pollution levels. I already established the fact that pollution in 2008 could be a predictor for the magnitude of changes in air pollution, implying that heavily polluted districts in 2008 likely experienced more substantial and significant changes by 2012 than districts with initially low or moderate levels of air pollution.

In turn, the type of question that I ask determines the construction of the districts' attribute, an input variable analyzing which HSA assesses whether districts with high/low attribute values are spatially clustered or associated. Addressing my type of questions, it is not appropriate to run HSA on raw values of the attribute. Instead, I construct my input variable as a ratio by dividing the magnitude of the 2008-2012 changes in air pollution by the level of fine particulate pollution in 2008. In this form, the HSA input attribute allows to obtain a correct answer to my question.

Technically, in the framework of the HSA, answering my question boils down to testing the null hypothesis of "no spatial dependence." The null implies that the assignment of the input attribute values to the particular districts does not depend on spatial location; the value of the attribute itself matters. The alternative hypothesis instead focuses on cases districts with large and small attribute values are systematically surrounded by other districts with large and small values. Rejection of the null hypothesis would imply the presence of statistically significant spatial clusters of similar values (Anselin, 1992). Statistically significant spatial clusters of high values are referred to as hot spots, while clusters of low values as cold spots.

The researchers have offered a number of statistics to test the hypotheses of interest effectively. In ArcGIS software, the Hot Spot Analysis tool calculates the Getis-Ord G_i^* statistic presented in Getis and Ord (1992):

$$G_i^{\text{¿}}=\frac{\sum_{j=1}^{n}\omega_{i,j}x_j-\overline{X}\sum_{j=1}^{n}\omega_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n}\omega_{i,j}^2-\left(\sum_{j=1}^{n}\omega_{i,j}\right)^2\right]}{n-1}}} \qquad \text{(A3)}$$

where x_j is the attribute value for feature (district, in my case) j; $\omega_{i,j}$ is the spatial weight between feature i and j; n is the total number of features; $\overline{X}$and S are respectively average and standard deviation of the attribute value. Spatial weight is an element of a binary spatial weights matrix that represents a theoretical understanding of spatial interdependence between the selected features.

ArcGIS implements Hot Spot Analysis in several steps. G_i^* statistic, a z-score in essence, is calculated for each district separately and measures the extent to which this spatial unit is surrounded by other neighboring districts with high or low values of the input attribute, i.e. spatial clustering. G_i^* statistic defines neighbors for each district as those that fall within a critical distance. Measured by G_i^*, local spatial clustering for a particular district and its neighbors is compared to the global measure of clustering of all districts in the data layer together. When the local measure is different from the expected one as suggested by its distribution under the null hypothesis and too large to be the result of random chance, a conclusion about statistical significance can be made. As the output, ArcGIS HSA tool returns z-scores and p-values for every district and creates a new output data layer.

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