Master's in International Trade, Finance, and Development

"Pollution and Premature Deindustrialization: Examining the Effects of Black Carbon on Manufacturing Employment in Developing Countries"

Adam Vilio, Emmett Sexton, Tania Chaar, Jan Bester

Supervising Professors:
Fernando Broner and Geert Mesters

8 June 2024

ABSTRACT:

This study investigates the impact of pollution on manufacturing employment shares in developing countries, contributing to previous literature on the potential causes of premature deindustrialization. Analyzing data from 112 low- and low-middle-income countries between 1998 and 2021, we employ wind speed as an instrumental variable to address endogeneity concerns. Our findings reveal that higher pollution levels significantly reduce manufacturing employment shares, with a pronounced effect in regions such as India, South America, and Africa. At the state level in India, a 10% increase in pollution is associated with a 0.87 percentage point decrease in manufacturing employment shares. However, this effect is less evident at the district level, suggesting that the relationship may be more influenced by policy making at national and state levels. We explore the role of international climate policies, such as the Clean Development Mechanism (CDM), in shaping these outcomes. We find that CDM projects do not significantly alter the pollution-employment relationship, opening avenues for future research to explore other potential mechanisms, such as the productivity impacts of pollution on workers and the subsequent effect this has on firms' location decisions.

KEYWORDS:

Premature Deindustrialization, Pollution, Manufacturing

Acknowledgements: We would like to thank our supervising professors Fernando Broner and Geert Mesters, as well as our supervising TA, Ayah Bohsali, for their advice and guidance. We additionally thank the other master's students of the BSE ITFD program and Albrecht Glitz.

1 Introduction

Structural transformation of the economy involves a transition from low productivity, labour-intensive activities in agriculture to higher productivity and skill-intensive activities in manufacturing and services. Whereas it used to be standard in the process of development for an economy to exhibit declining employment in agriculture, a humped-shaped share of employment in industry, and an increasing share of employment in services, present-day developing countries seem to be deviating from this path. (Rodrik, 2016; Sen, 2019; Kruse et al., 2023). Specifically, over the past three decades, low- and low-middle income countries have depicted a premature decline of manufacturing, reaching peaks of manufacturing employment that are much lower and occur earlier on than their early industrialised counterparts (Rodrik, 2016). Some have expressed concerns over this pattern, arguing that in jumping directly from employment concentration in agriculture to services, labour subsequently becomes concentrated in low-skill, non-business services, which often exhibit less productivity gains than manufacturing (Rodrik, 2013, 2016; Sen, 2019). Consequently, the developing countries of today may miss out on the significant productivity and human capital gains that historically developed under industrialisation. It is therefore valuable to identify the potential causes of this shift.

This is difficult since the phenomenon has coincided with major societal and economic changes such as the ICT Revolution and a new wave of globalisation. In fact, Rodrik (2016) poses these mechanisms as two potential drivers of this change, although he does not provide causal evidence. This creates a gap in the literature that we seek to fill. In particular, we aim to explore another potential mechanism for this change: the impact of pollution levels on manufacturing employment. This topic is of interest given the increasing local and global concerns regarding pollution, its role in policy making, and the unintended consequences this may have on developing countries. Our hypothesis is that higher pollution levels have had a negative effect on employment shares in manufacturing in developing countries, owing to the increased demand for pollution reduction which has occurred alongside the climate revolution over the past three decades. This can contribute to better understanding the potential causes of premature deindustrialisation in developing countries.

To study the effect of pollution on manufacturing employment shares, we first perform an analysis at the macro level. We consider 112 countries categorised as low- and low-middle income by the World Bank over the period from 1998 to 2021. Due to endogeneity issues, we instrument pollution levels using wind speed, a reasonably exogenous variable. It is highly predictive, as areas with higher wind speeds have significantly lower concentrations of pollution. We gather data on pollution, wind speed, and other geographic controls from NASA satellite data and data on employment shares in manufacturing is taken from the World Bank. We find that across the 112 developing economies, pollution levels have a significant and negative effect on employment shares in manufacturing. This effect is disproportionately observed in India, South America, and Africa.

To address concerns that we are capturing unobserved confounders that vary across national borders, we proceed to analyse this effect at more micro-levels. We choose to focus on India, which contributes significantly to the effect observed in our cross-country analysis. Moreover, India is a large country with high variation in wind speeds and pollution levels. We carry out the analysis at the state and district level. At the state level, we find that a 10% increase in pollution levels is associated with a decrease of approximately 0.87 percentage points in manufacturing employment shares. At the district level, no significant effect is observed across our Full Sample, although there does seem to be some heterogeneity across broader regions, with districts in Western India demonstrating a significant, negative effect similar to that observed in the state and country level regressions. The lack of general significance at the district level may reflect that outcomes related to emissions and structural concentration are more influenced by policy making at the national and state levels in India.

To discuss potential mechanisms driving this relationship, we posit that it is possible that international climate treaties have discouraged foreign direct investment into the relatively more emission intensive manufacturing sector, having a negative impact on manufacturing employment shares in more polluted areas. As a first major landmark treaty committing state parties to reduce greenhouse gas emissions, the Kyoto Protocol coincides with the timeline of our analysis (Oberthür and Ott, 1999). While most developing nations signed on as parties with non-binding targets, some would take part in Kyoto emission reduction mechanisms, one of which is the Clean Development Mechanism (CDM). This program allowed developed countries to meet their emissions reduction targets by funding projects in developing countries that reduced greenhouse gas emissions. We explore CDM financing as a potential mechanism for the negative effect of pollution levels on manufacturing employment shares in developing countries, but find no differential effect for areas that received CDM projects. We present productivity concerns as another mechanism for future research.

The remainder of the paper is structured as follows. In Section 2 we review the existing literature on the topic. Sections 3 and 4 present the data and empirical specification, respectively. Section 5 includes the results and Section 6 discusses potential mechanisms. Finally, Section 7 concludes.

2 Literature Review

To the best of our knowledge, this is the first paper to study the direct effect of pollution on employment shares in manufacturing. The available papers on the topic have mostly focused on identifying the existence of premature deindustrialisation and its impact on productivity and equality, while other strands of the literature have assessed the effects of pollution on economic outcomes and the effects of environmental regulation on firm displacement.

Taguchi (2023) notes that developing economies under globalisation witnessed earlier-than-before deindustrialisation in the post-1990 era, with the effect being the strongest in Latin America and some regions of Africa. Similarly, Sen (2019) argues that present-day developing countries depict a different path when it comes to the structure of their economies. As labour moves directly from agriculture to services, economic growth suffers because non-business services typically exhibit lower levels of productivity relative to manufacturing. He also highlights the need for the identification of causal mechanisms to explain the cause of these new structural transformation paths, which our paper aims to identify. Furthermore, the relationship between premature deindustrialisation and growth slowdowns in middle-income countries is addressed by Rekha and Suresh Babu (2022). Their findings indicate that premature deindustrialisation raises the probability of economic deceleration for developing economies. They also underlined the trade-off between economic growth and income inequality. Similar to Rodrik (2016), the authors find that the trend of premature deindustrialisation was more prevalent in Latin America and Sub-Saharan Africa.

Extensive research has demonstrated that pollution can negatively affect workers' health, resulting in higher absenteeism and diminished productivity. Leroutier and Ollivier (2023) observe that a 10% increase in black carbon exposure increased absenteeism among workers by 1%, coupled with reduced sales in manufacturing. Air pollution significantly reduces labour productivity, rendering polluted areas less attractive for manufacturing operations (Zivin and Neidell, 2012). In Mexico, environmental degradation led to decreased hours worked and earnings for labourers, underscoring the pollution's direct impact on labour markets in a developing country (Hanna and Oliva, 2015). Additionally, Zhou and Zhang (2023) examine the impact of air pollution on firm-level labour income share in China. Their results show that contaminated air has a significant negative impact on firm-level labour share. A 1 $\mu g/m^3$ increase in PM2.5 concentration led to a 0.17 percentage point drop in firms' labour income share, based on data spanning 1998 to 2007. Air pollution was shown to affect labour income share by decreasing average wages and productivity. In the extensive margin, air pollution was found to possibly increase the number of employees required at the lower-tech firms in order to offset the losses in production. Similarly, an increase of PM2.5 concentration of the same magnitude was found to decrease the productivity of Chinese manufacturers by an equivalent of 0.039% of China's GDP, reaffirming the air pollution's impact on productivity (Fu et al., 2021).[1]

While environmental regulations are imperative for improving air quality and public health, they can also impose substantial costs on manufacturing firms, potentially resulting in job losses. Greenstone et al. (2012) illustrate that stringent air quality regulations in the United States pre-

[1] We view productivity concerns due to pollution as a very plausible mechanism for the negative effect of pollution on manufacturing that we identify later in our analysis. However, due to data availability at the firm level, we were unable to study this mechanism. Future research into this field would be valuable.

cipitated significant employment declines in regulated industries, suggesting that similar dynamics could be at play in developing countries. Previous empirical studies have touched upon related issues. The literature on the relationship between environmental regulations and industrial intensity is mixed (Keller and Levinson, 2002; Eskeland and Harrison, 2003). Some scholars support the pollution haven hypothesis, suggesting that lax environmental standards correlate with increased industrial activity, as heavily polluting industries and foreign investment move to areas where the cost of emissions is lower (Cole, 2004). However, the pollution haven hypothesis appears to only hold in specific contexts, and it is not observed at all when only considering foreign direct investment in manufacturing from highly developed countries (Cole, 2004; Dean et al., 2009).

Taken as a whole, previous literature has shown that pollution has significant negative effects on productivity, health outcomes, worker earnings, and firm costs. Despite these findings, the direct link between pollution and manufacturing employment shares remains largely unexplored. Our study aims to fill this gap by examining pollution as a key mechanism affecting manufacturing employment shares and offers a novel view on the multifaceted relationship between the environment and economic structure in developing countries. We hypothesise that higher levels of pollution in a host region negatively impact employment shares in manufacturing, contrary to the pollution haven hypothesis. This is based on the rationale that while manufacturing industries may be attracted to regions with higher pollution levels due to more lax environmental regulations, in the last few decades the rising costs of emissions, potential sanctions from international climate treaties, and resulting productivity losses have had a prevailing negative effect on manufacturing growth in highly polluted areas. We combine cross country and within country analyses to test this hypothesis, and use India as our country of focus for the latter.

We investigate the link between pollution and manufacturing shares of employment at the state and district level in India. As one of the world's most populous and fast-growing countries, India's manufacturing employment decisions will have outsized importance on the country's productivity. Moreover, efforts to promote manufacturing as means to development for India have been studied extensively as a part of the discussion surrounding India's future (Taguchi and Tsukada, 2022). In the following section, we present the data employed in our analysis.

3 Data

To test the impact of pollution levels on manufacturing employment shares, we construct several novel datasets at the country, Indian state, and Indian district levels.

3.1 Dependent variable: Manufacturing share of employment

We use three different sources for our main outcome variable, manufacturing share of employment, depending on the unit of analysis in our regressions. Unfortunately, we are not aware of manufacturing share of employment estimates that are consistent from the country level down to the district level within India. At the country level, we gather data from the World Bank on the annual employment shares in industry, modelled on the International Labour Organization's estimates of the percent of total employment in the industrial sector. We do this for all countries categorised as low- or low-middle income countries by the World Bank in 1991, the first year of data availability. Indian state level manufacturing shares of employment were not available, so we constructed industrial employment as a share of state population as a proxy from 1998–2020. Industrial employment figures are from the Annual Survey of Industry and state level population data was pulled from various sources.[2]

Indian district level manufacturing shares of employment are constructed using the Development Data Lab's Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). SHRUG stores data from several of India's population and economic censuses. Crucially, they summarise data at the village or town level[3] and maintain consistent borders across census years. In the SHRUG dataset each of these village or towns is called a SHRID (short for SHRUG Id), We utilise the two most recently released Indian Economic Census years (2005 and 2013) and aggregate the number of manufacturing employees and the total number of non-agricultural employees within a district across years.[4] We construct a balanced panel consisting only of SHRIDs where data is available for both years of the regression. We then define our Full Sample as those districts where the balanced panel of SHRIDs covers at least 50% of the area of an Indian district, i.e. each regression consists of districts that are at least 50% covered by SHRIDs which are present across each regression year. This reduces the measurement error that would be introduced from the districts with very sparse data coverage.[5]

3.2 Geospatial variables

The remaining independent, instrumental and control variables have the same sources across regression specifications. We utilise NASA's Giovanni Portal, which compiles NASA's gridded data from various satellite and surface observations, for our main independent variable, black carbon, as well as for several control variables including wind speed, vegetation, and precipitation. We

[2] Because state level population figures were only available for 1991, 2001, 2011 and 2023, we linearly interpolated between these years.

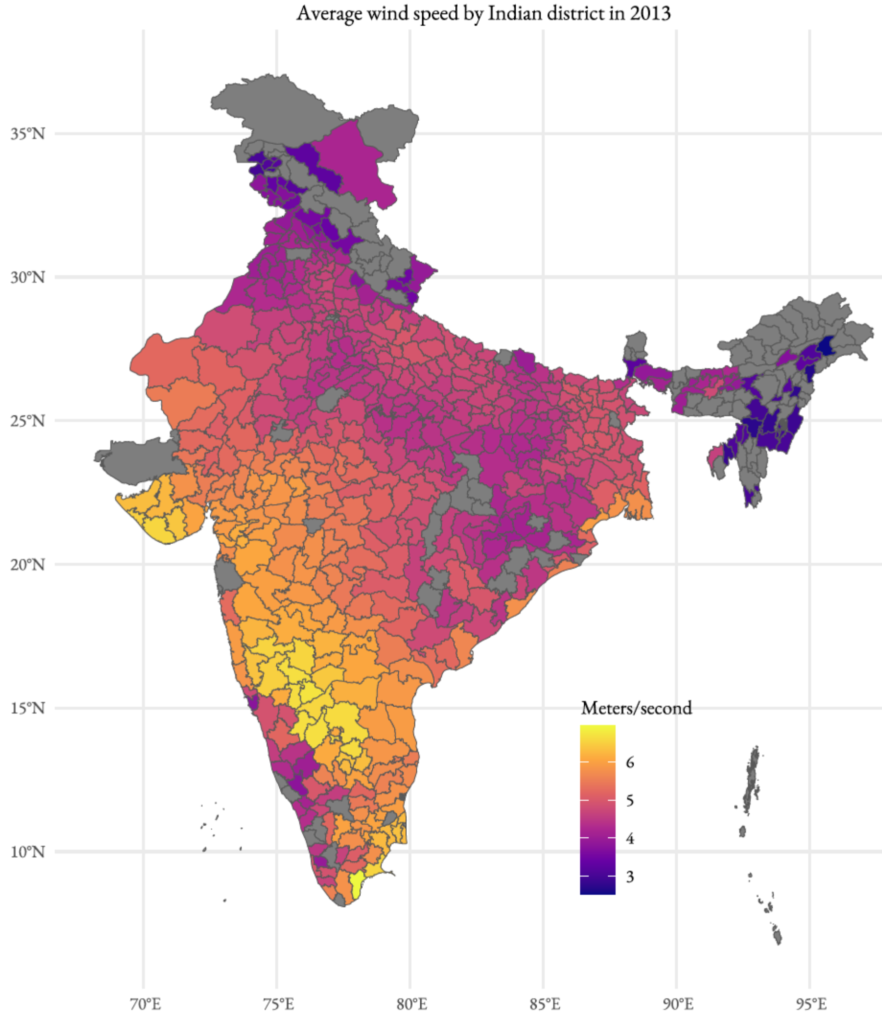
[3] This is only approximate and the cofnsistent boundaries they identify can sometimes be slightly smaller or larger than the size of a village or town.

[4] We aggregate to the district level because the size of a district typically better matches the resolution of our instrument and control variables relative to the smaller unit of observation in the SHRUG.

[5] We also test a more inclusive sample with all districts that have underlying village data and our results remain unchanged.

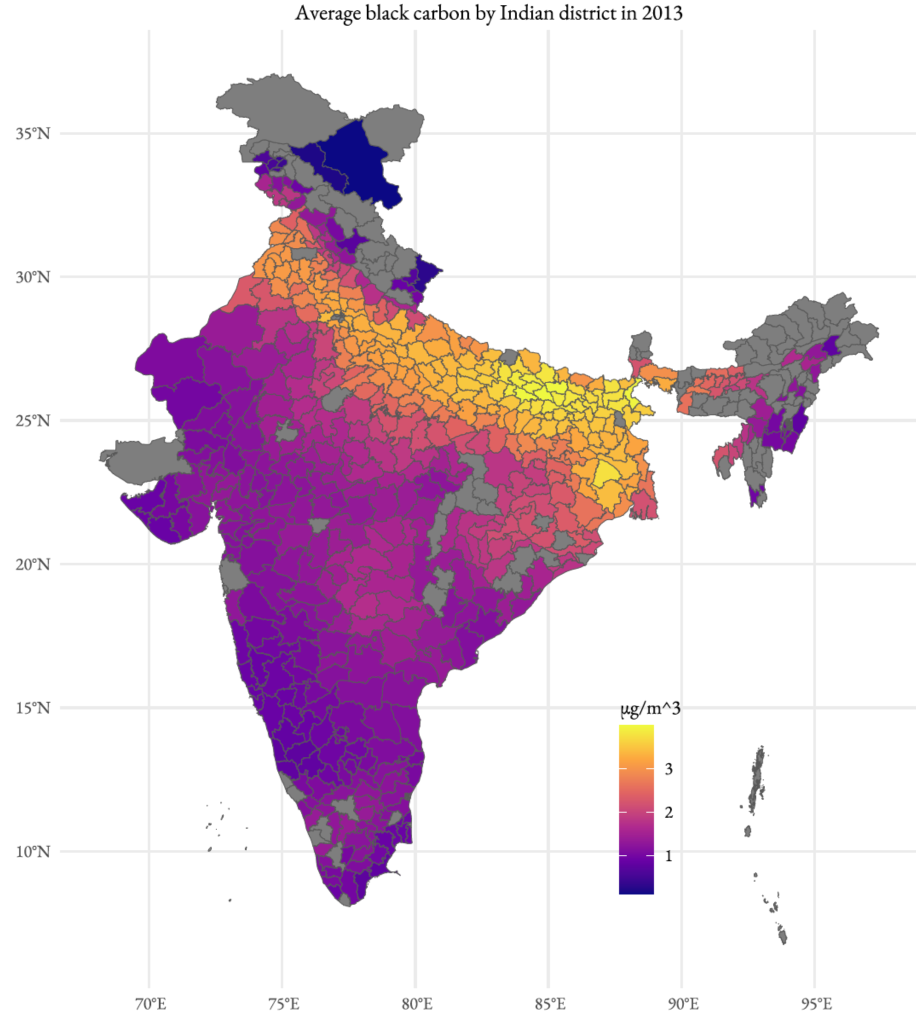
choose black carbon as our variable of interest as it is highly associated with industrial production and a significant component of both PM2.5 air pollution and global carbon levels (US Environmental Protection Agency, 2011). Thus, its effect on manufacturing employment shares may come through mechanisms regarding local pollution and global carbon emission concerns. Each of the four variables accessed through Giovanni are averages for each year of interest and are available at the 0.5° x 0.5° resolution, which is approximately 55 km x 55 km at the equator. We calculate the area-weighted average value of these pixels across states or districts depending on the regression. Indian elevation data at the 1km x 1km resolution was accessed through the 'elevatr' R package. Figures I and II present average wind speeds and black carbon concentrations across Indian districts in 2013. Districts in grey have sparse manufacturing employment data and are excluded from the Full Sample. Examining these maps, one can see an immediate correlation between higher wind speeds and lower pollution levels.

FIGURE I.
Average wind speed by Indian district in 2013



Note:
Data only shown for districts in the Full Sample.

FIGURE II.
Average black carbon by Indian district in 2013



Note:
Data only shown for districts in the Full Sample.

In Tables I and II we summarise our main variables of interest: manufacturing employment and pollution. Directly comparing the manufacturing employment summary statistics across the three datasets is challenging due to the slightly different variable definitions. The outcome variable for the Indian state regression, manufacturing employment as a share of population, is consistently lower than the employment share outcome variables for the country and Indian district regressions. This is intuitive based on the variable definitions as total population is always greater than labour employment. Additionally, both tables show that the district data for India has larger variance in both manufacturing share and pollution across districts relative to the country and state samples. Lastly, India is significantly more polluted than the average country from our country dataset. The average Indian state and district have levels of black carbon surface concentration that are 300% as high as the average low-to-middle income country.

TABLE I.

Manufacturing Employment

Unit of observation	Variable	Time period	25%	50%	Mean	75%	Std. Dev
Country	Manufacturing share of employment	1998–2022	10.0%	17.5%	17.2%	22.5%	8.0%
Indian state	Manufacturing employees as share of population	1998–2020	3.2%	6.2%	9.0%	13.0%	7.8%
Indian district	Manufacturing share of non-agricultural employment	2005 & 2013	17.5%	22.1%	24.1%	28.0%	9.9%

TABLE II.

Black Carbon Surface Concentration ($\mu g/m^3$)

Unit of observation	Time period	25%	50%	Mean	75%	Std. Dev
Country	1998–2022	0.15	0.30	0.41	0.56	0.37
Indian state	1998–2020	0.93	1.19	1.54	1.95	0.88
Indian district	2005 & 2013	1.15	1.61	1.95	2.87	0.97

4 Empirical Specification

Given that the relationship between pollution and employment in manufacturing is likely influenced by dual-direction causality and endogeneity, a simple OLS regression would be significantly biased, capturing the fact that higher levels of manufacturing employment are associated with more industrial activity and thus higher pollution levels. To account for this, we propose using an Instrumental Variable (IV) strategy, allowing us to generate exogenous variation in pollution levels and arrive at a causal interpretation. We identify surface wind speed (measured in metres per second) as a suitable instrument for pollution levels. The use of wind speeds as an instrument for pollution levels has been used in a number of past studies (e.g. Anderson, 2020; Bondy et al., 2020).

4.1 Identification Strategy

We look at the effects of pollution on employment in manufacturing at three levels: cross-country, cross-state, and cross-district. This allows us to first generate an understanding of the macroeconomic relationship between pollution and employment in manufacturing. This is valuable, given that outcomes related to carbon emissions and structural concentration are often heavily influenced by national government policy (Deb and Kohli, 2022). The subsequent disadvantage is that there is concern that unobservables can vary significantly over time when looking across national borders. Moreover, taking the average pollution levels and wind speeds across the entire area of particularly large and geographically heterogeneous countries may be problematic.

To address these concerns and extend our analysis, we also look at the relationship across Indian states. India was chosen because in previous literature, it is identified as being particularly affected by premature deindustrialisation (Amirapu and Subramanian, 2015; Rodrik, 2016). Moreover, a portion of the negative effect of pollution on manufacturing employment shares identified in our cross-country analysis is driven by India. The large size of India also provides suitable variation in wind speeds and pollution levels across sub-national borders and employment data in manufacturing is available at both the state and district level. As a result, zooming in on Indian states allows us to reduce unidentified confounders that vary across countries and identify more precise measures of wind speeds, pollution levels, and employment shares in manufacturing. To further increase this precision, we finally repeat this analysis at the most granular district level in India.

We introduce the principal regression form used to estimate the effect of pollution levels on employment shares in manufacturing. The first stage is defined as follows:

$$logP_{a,t} = \alpha_0 + \alpha_1 \log W_{a,t} + X^{'}_{a,t}\gamma + \phi_a + \phi_t + \varepsilon_{a,t} \tag{1}$$

Where $P_{a,t}$ is the concentration of black carbon (kg/m3) in area a (country, state, or district) in year t; $W_{a,t}$ is the average surface wind speed (m/s) in area a in year t; $X^{'}_{a,t}$ is a vector of control variables including log GDP (country and state regressions only) and geographic controls (state and district regressions only), ϕ_a are area fixed effects (country and district regressions only); ϕ_t are year fixed effects; and $\varepsilon_{a,t}$ is the error term. We use robust standard errors at the country level and Conley standard errors at the state and district levels to account for correlations of the error term across space (Conley, 1999). The second stage is defined as follows:

$$M_{a,t} = \alpha_0 + \alpha_1 \log \hat{P}_{a,t} + X^{'}_{a,t}\gamma + \phi_a + \phi_t + \varepsilon_{a,t} \tag{2}$$

Where $M_{a,t}$ is the manufacturing employment share in area a in year t.

4.2 Validity of Instrument

First, to establish wind as a valid instrument for pollution, it is necessary that wind speeds are significantly predictive of pollution levels. Conceptually, this mechanism is plausible, as higher wind speeds disperse particulate components of black carbon over a larger area, reducing pollution concentration levels. This mechanism is also confirmed in the data. Across all levels of our analysis, wind speeds have a significant, and negative effect on pollution levels at the 5% level. For example, in Panel A of Table III, detailing the regression results for the cross-country analysis, it is seen in the full sample that increasing wind speeds by 1 metre per second, is associated with an approximately 9.5% decrease in black carbon concentrations. This effect is similar when looking at the specific Africa, America, and India subsample where the corresponding decrease in pollution levels is approximately 10.6%. The presence of this relationship is similarly confirmed at the state and district level analyses shown in Tables IV and V. We also report the first-stage F-statistics in all regression tables which confirm the significant relationship between wind speeds and pollution levels, indicating that a strong first-stage is present in our chosen identification strategy.

Next, it is necessary to establish the exclusion restriction of our instrument, that is, that wind speeds are not directly related to the error term in the regression of employment shares in manufacturing on pollution levels. At first glance, this seems to be a plausible assumption, given that it is difficult to think of a mechanism through which wind speeds would have a measurable effect on manufacturing employment shares other than through pollution levels. However, it is conceivable that wind speeds are correlated with other weather patterns that may have a more direct effect on employment shares. We posit elevation, precipitation, and vegetation as potential confounders. This is because higher elevations are associated with higher wind speeds as well as differences in geography, like access to the coast, that may impact manufacturing concentrations. Additionally, very high levels of precipitation may make it difficult to establish large manufacturing centres. Similarly, areas with higher levels of vegetation are less dense and more rural and as a result, are likely to have lower levels of manufacturing employment. We include these variables in our state and district level analyses, allowing us to control for geographic differences that may correlate with wind speeds and employment shares in manufacturing. In Table IV, we see that including these controls greatly increases the precision of our estimates. At the country level, we instead use country fixed effects to control for time-invariant geographical differences.

Finally, we recognise that it may be possible that wind speeds are correlated with non-geographic variables that affect employment shares in manufacturing. To account for this, we run a robustness check at the macro level across our specified samples, regressing GDP on wind speeds. The concern that we aim to pre-emptively disprove is that wind speeds may have some relation to GDP and economic development, which in turn, will have an effect on employment shares in manufacturing. Shown in Table A.I of the Appendix, it is seen that wind speeds have no significant relationship to GDP for our cross-country sample. We repeat this exercise at the state level for India and again find no measurable effect.

Taken as a whole, we believe including these geographic controls and the results of these robustness checks provides reasonably sufficient evidence that wind speeds are exogenous of employment shares in manufacturing, confirming the validity of our identification strategy. Following from this, we present and discuss our empirical results.

5 Results

5.1 Country-Level Analysis

Table III presents the results of our country-level analysis. Panel A details the first-stage regression of the log of black carbon surface concentration on surface wind speed across the full sample of developing countries; the Africa-America and India (AAI) subsample; and the Asia-Europe (excluding India) subsample controlling for GDP and year and country fixed effects. We divide the samples as such to correspond with the research of Rodrik (2016) who finds that premature deindustrialisation is most pronounced in Africa, the Americas, and India, while developing countries in Europe and Asia have been relatively immune to this phenomenon. Here we see that wind speeds have a significant, negative effect on pollution levels in the full and AAI subsample. The large F-stats further confirm the strength of the first stage. We are unsure why this relationship does not hold for the Asia-Europe subsample, although we posit that it may be due to a lack of variation in the European observations, which come almost entirely from Eastern European countries. Nonetheless, this is not a major concern, as this sample is not the focus of our analysis.

TABLE III.
Country-Level Regression Results

	Full Sample	Africa & Americas + India	Asia & Europe
	Panel A: First Stage, Outcome Variable is Log Pollution (Black Carbon kg/m³)		
Wind Speed (m/s)	-0.106 (0.030)	-0.125 (0.026)	-0.034 (0.041)
R^2	0.978	0.970	0.970
First Stage F-Stat	12.632	22.967	0.677
	Panel B: Second Stage Least Squares, Outcome Variable is Employment Shares in Manufacturing		
Log Black Carbon Surface Concentration	-6.979 (2.957)	-10.014 (3.019)	-14.631 (22.267)
Log GDP	2.011 (0.160)	0.517 (0.244)	2.931 (0.250)
Year and Country F.E.s	Yes	Yes	Yes
Obs.	2,605	1,484	1,001

*First Stage and Second Stage Least Squares Coefficient Estimates. Panel A presents the first stage results of the regressions of log black carbon concentration on annual average wind speed across the outlined samples, controlling for all variables specified in the corresponding columns of Panel B. Panel B presents the second stage least squares coefficient estimates of the regressions of a country's employment share in manufacturing on the log of a country's pollution levels instrumented using wind speed, controlling for log GDP and year and country fixed effects. Robust standard errors are presented in parentheses.

Panel B presents the coefficient estimates of the second stage least squares regressions of employment shares in manufacturing on instrumented black carbon concentrations. Here we see that in both the full and AAI sample, pollution levels have a significant, and negative effect on manufacturing employment shares, in line with our initial hypothesis. For the full sample, an increase in a country's average yearly pollution level of about 10% sees a fall in manufacturing employment shares of about 0.7 percentage points. For the AAI sample, this effect is even stronger, where the same increase in yearly pollution levels results in a fall of manufacturing employment shares of about one percentage point. This effect is both significant at the 5% level and economically meaningful, given that the average percent share in manufacturing is 17.2% in our sample. Additionally, a simple OLS regression of GDP on manufacturing employment share shows that a decrease in one percentage point in the manufacturing employment share is associated with a fall in GDP of approximately 4.5%.

These results are informative of a general negative relationship between pollution and employment shares in manufacturing. However, we are concerned that a cross-country macro sample might introduce many time-varying, country-specific unobservables into our identification strategy and that taking the average pollution levels and wind speeds across large and geographically heterogeneous countries may fail to account for the diversity of these variables across regions within a country. To address this and get more precise estimates of wind speeds, pollution levels, and employment shares in manufacturing, we repeat this analysis at the Indian state level.

5.2 State-Level Analysis

Table IV presents the results of our state-level analysis. Panel A again details the first-stage regression of the log of black carbon surface concentration on surface wind speed. Column 1 controls for GDP, column 2 controls for geographic characteristics, and column 3 controls for both. Here we see that wind speeds have a significant and negative effect on pollution levels in all specifications. The large F-stats again confirm the strength of the first stage.

Panel B presents the coefficient estimates of the second stage least squares regressions of employment shares in manufacturing on instrumented black carbon concentrations. Column 1 reports the specification controlling for GDP but not geography. Here we see that the effect is negative but not significant. When we look at the results in column 2 that include geographic controls, we see that the effect becomes significant at the 5% level. Finally, looking at our preferred specification in column 3 which includes controls for both GDP and geography, we find that an increase in pollution levels of 10% is associated with a decrease in approximately 0.87 percentage points in manufacturing employment as a share of population. We believe this result is more robust than that found in our country-level analysis since we are no longer concerned that unobservables that vary across countries and time are influencing our results, our values of wind speed and black carbon are averaged over smaller areas meaning they are more representative of the areas of observation, and we are able to use Conley standard errors which account for spatial correlations among the error term. Although the manufacturing employment share of the population used in the state

TABLE IV.
State-Level Regression Results

	Panel A: First Stage, Outcome Variable is Log Pollution (Black Carbon kg/m³)		
Wind Speed (m/s)	-0.269 (0.075)	-0.543 (0.124)	-0.627 (0.087)
R^2	0.321	0.532	0.633
First Stage F-Stat	92.6	236.3	378.6
	Panel B: Second Stage Least Squares, Outcome Variable is Manufacturing Employment as Share of Population		
Log Black Carbon Surface Concentration	-5.243 (6.392)	-10.984 (3.738)	-8.787 (2.792)
Log GDP	1.970 (0.846)		2.331 (0.962)
Geographic Controls	No	Yes	Yes
Year F.E.s	Yes	Yes	Yes
Obs.	457	457	457

*First Stage and Second Stage Least Squares Coefficient Estimates. Panel A presents the first stage results of the regressions of log black carbon concentration on annual average wind speed across the outlined specifications, controlling for all variables specified in the corresponding columns of Panel B. Panel B presents the second stage least squares coefficient estimates of the regressions of a state's manufacturing employment as share of population on the log of a state's pollution levels instrumented using wind speed across the outlined specifications. Geographic controls include precipitation, vegetation intensity, and elevation. Conley standard errors are presented in parentheses.

level regression is a proxy for manufacturing employment share, this estimate is very similar to the one we found in the country-level analysis, providing support for the general magnitude of the effect.

Given the results of the country and state level analyses, we contend pollution levels have had a significant and negative effect on employment shares in manufacturing at national and state levels over the past two decades. Next, we present our district level analysis to examine if the effect is consistent at the micro level.

5.3 District-Level Analysis

To further disaggregate our analysis, we repeat the exercise at the district level in India. Table V shows the results of this district level regression. In column 1, we use our Full Sample and in columns 2 through 7, we group districts by their administrative zones which correspond to larger geographic regions.

Panel A displays the first stage of the regression seen in the last two sections with geographic controls and both year and zone fixed effects. The results show a similar significant negative relationship between wind speed and pollution across most regions, with the exception of North and

TABLE V.
District-Level Regression Results

	Full Sample	North	North East	East	Central	South	West
	Panel A: First Stage, Outcome Variable is Log Pollution (Black Carbon kg/m^3)						
Wind Speed (m/s)	-0.257	-0.112	0.300	-0.341	-0.489	-0.167	-0.361
	(0.076)	(0.164)	(0.163)	(0.083)	(0.106)	(0.029)	(0.060)
R^2	0.765	0.790	0.857	0.711	0.823	0.545	0.667
First Stage F-Stat	158.4	3.9	31.5	81.3	165.1	50.9	192.9
	Panel B: Second Stage Least Squares, Outcome Variable is Manufacturing Share of Non-Agricultural Employment						
Log Black Carbon Surface Concentration	-3.944	-3.880	-14.964	1.158	3.338	1.333	-13.306
	(4.004)	(20.920)	(3.887)	(1.087)	(4.769)	(17.241)	(3.490)
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Zone F.E.s	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,052	198	72	208	266	184	124

*First Stage and Second Stage Least Squares Coefficient Estimates. Panel A presents the first stage results of the regressions of log black carbon concentration on annual average wind speed across the outlined specifications, controlling for all variables specified in the corresponding columns of Panel B. Panel B presents the second stage least squares coefficient estimates of the regressions of a districts's manufacturing share of non-agricultural employment on the log of a district's pollution levels instrumented using wind speed across the outlined samples. Geographic controls include precipitation, vegetation intensity, and elevation. Conley standard errors are presented in parentheses. "Full Sample" corresponds to all districts with more than 50% area coverage in the SHRUG database. Data are from the 2005 and 2013 Economic Censuses.

North East. In particular, the North East seems to display a non-significant positive relationship. We believe the Northern regions' close proximity to the Himalayas may inhibit the process of wind speeds dispersing black carbon concentrations and thus lowering pollution levels. Therefore, we have reason to believe the first-stage is not met for these districts and we do not apply causal interpretations to these results.

Panel B displays the second stage estimation, regressing the employment shares in non-agricultural manufacturing on the instrumented black carbon concentration with the same controls as in the first stage. The first column displays the results using the Full Sample, while there is a reported negative effect of pollution on employment shares, this is not significant. The coefficient estimates across the different zones are varied, with only the West region displaying a significant negative relationship of black carbon concentration on employment shares. There, we see that a 10% increase in pollution levels is associated with an approximately 1.3 percentage point decrease in manufacturing employment as a share of total non-agricultural employment, which aligns with the direction of the estimates found in the country and state level analyses. It is unclear why the West is the only one to display a significant relationship. To investigate this, we look at the values of various district characteristics related to poverty, structural composition, and geography and present these values in Appendix Table A.II. While there is no obvious differences between the West and the other zones, it is worth noting that the West has the highest average wind speeds as well as one of the lowest levels of pollution across the zones. Thus, the significance could be related to the particular strength of the instrument for Western districts.[6]

The varying effects across zones and the lack of significance may reflect that outcomes related to carbon emissions and structural concentration are more influenced by policy making at the national and state levels in India (Atteridge et al., 2012). While some decision making could be done at the district level through individual business and project decisions, these effects do not seem to be persistent enough to create a significant and consistent effect across India at the micro level.

Furthermore, these results are obtained using only districts with at least 50% coverage in the underlying village level data, as previously explained. We repeated the exercise for different levels of data coverage, which would either increase or reduce the number of observations used in our analysis, while shifting the amount of measurement error. When we repeat the analysis to include any district with underlying data, we get similar results to those discussed.

Overall, our results support the hypothesis that over the last two decades, pollution levels have had a significant negative effect on employment shares in manufacturing in developing countries. Specifically, our estimates indicate that increasing pollution levels in an administrative area by 10% on average, will decrease manufacturing employment shares by approximately 1 percentage point. This effect seems to be observed for both national and regional administrative areas, while for smaller district-level areas, it is only observed for districts in the West region. We posit that this is because decisions pertaining to emissions reductions that may influence manufacturing employment shares are made at higher levels of government, such as at the national and state levels, rather than at the municipal level. In the following section, we explore this argument and also examine foreign investment as a potential mechanism for the observed effect.

6 Mechanisms

One potential mechanism for the negative relationship between pollution levels and manufacturing employment is international climate policies affecting the composition of foreign capital flows. We posit that new foreign capital flows in green finance may have had a negative effect on industrial intensity, thus decreasing manufacturing employment in areas that may have been targeted due to high pollution levels. To test this hypothesis we examine the interaction between pollution

[6] It would be beneficial in the future to look specifically at differences in political outcomes, demographics, and heterogeneity across Western districts to gain a better understanding of why the relationship seems particularly strong here.

concentration and the number of United Nations Clean Development Mechanism (CDM) projects. As part of the Kyoto Protocol, the UN established the CDM as a way for more developed countries to meet their emissions reduction targets by funding projects in developing countries that would reduce greenhouse gas emissions. Each project had to verify the amount of greenhouse gases that would be avoided relative to a counterfactual without the foreign capital. These projects were diverse and implemented across sectors (e.g. methane recovery from manure, hydroelectric power installations, and switching fuels away from charcoal in food processing factories). Relevant for our investigation, more than 20% of the total number of CDM projects were established in India.

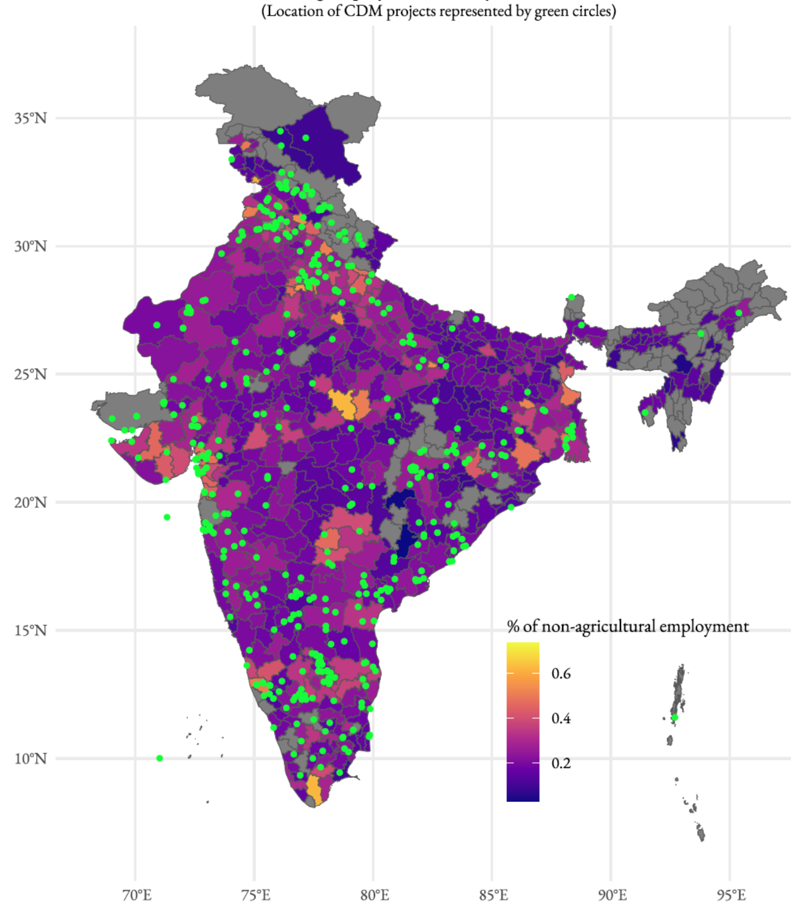
Precise location data for each CDM project is not readily available so we manually collect project location data using project description source documents. We first generate a list of CDM projects that were registered in India and had a positive number of validated emission reduction credits using the UN CDM Pipeline dataset. We then exclude all wind-based projects to avoid biassing our results when using wind speed as an instrument for pollution. Next, we find the project documentation for each of these projects on the CDM website and look for either latitude-longitude for each project. When the exact coordinates are not present, we use the coordinates from Google Maps for the village where the project is located. When village level project location specificity is not provided in the documentation, we drop those projects. This leaves 460 non-wind based CDM projects across India. We then count the cumulative number of CDM projects in each state or district for each year.[7] Figure III presents a map detailing the location of these CDM projects in India as well as the manufacturing employment shares of non-agricultural employment for the corresponding district. As one can see, these projects were relatively dispersed across India in districts with varying levels of manufacturing employment.

Building on our past empirical exercise, we continue to focus on India and add an interaction term between the cumulative number of non-wind CDM projects and pollution levels. While the first stages were still highly significant, for conciseness, we only present the second stage results in Table VI.

The point estimate for the impact of predicted black carbon on manufacturing employment in the state and district regressions are essentially unchanged when adding the interaction term that includes the number of CDM projects. While the standard error of the state pollution coefficient increases slightly when adding the interaction term, the estimate remains significant. Similarly, the district level pollution coefficient for the Full Sample remains insignificant. Additionally, we tested the joint significance of the predicted pollution coefficient and the interaction term and found that there was no statistically significant difference between the coefficients on black carbon concentration for the districts and states with and without CDM projects. This holds true when

[7] Further research on the impact of CDM projects may factor in the relative size of each project, but due to the current ambiguity in the CDM data it's not possible to accurately obtain the number of validated emission reduction credits over time.

FIGURE III.
Manufacturing employment share by Indian district in 2013
(Location of CDM projects represented by green circles)



Note:
Data only shown for districts in the Full Sample.

looking across the Full Sample and the various zonal samples.

It does not appear that CDM projects were a significant mechanism in establishing the negative relationship between pollution and manufacturing employment in India. This may be due to the relatively small total number of CDM projects within India relative to the total number of businesses or it may be that the CDM projects did not have a consistent non-manufacturing employment bias in more polluted areas. This leaves open the question of why we see a negative relationship between pollution and manufacturing after 1998, especially at the country and Indian state levels. As discussed in the literature review, one other remaining potential mechanism may lie in the negative health and production externalities posed to workers if they were to set up shop in already heavily polluted areas. Future research should try to investigate if the negative productivity impacts of high pollution levels influence firms when they are deciding where to locate operations. Providing empirical evidence that firms choose to locate new operations in cleaner areas due to productivity concerns may help explain why pollution seems to have a negative effect on manufacturing employment.

TABLE VI.
CDM Regression Results: Second Stage Least Squares

	States		Districts	
	Outcome Variable is Manufacturing Employment as Share of Population		Outcome Variable is Manufacturing Share of Non-Agricultural Employment	
Log Black Carbon Surface Concentration	-8.787	-9.143	-3.944	-3.865
	(2.792)	(4.425)	(4.004)	(3.839)
Cumulative # of CDM projects * Log Black Carbon		0.002		-0.020
		(0.004)		(0.013)
GDP Controls	Yes	Yes	No	No
Geographic Controls	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes
Zone F.E.s	No	No	Yes	Yes
Obs.	457	457	1,052	1,052

*Second Stage Least Squares Coefficient Estimates. This panel presents the second stage least squares coefficient estimates of the regressions of manufacturing employment on the log of an state/district's pollution levels instrumented using wind speed. Geographic controls include precipitation, vegetation intensity, and elevation. Conley standard errors are presented in parentheses. In the districts regressions, all districts with more than 50% area coverage in the SHRUG database were used. District data are from the 2005 and 2013 Economic Censuses and state data cover 1998–2020.

7 Conclusion

Our study contributes to the understanding of premature deindustrialisation by exploring the impact of pollution on manufacturing employment shares. Our analysis provides evidence that higher pollution levels have a significant negative effect on manufacturing employment shares in developing countries. This effect is particularly pronounced in India, where a 10% increase in pollution levels is associated with a 0.87 percentage point decrease in manufacturing employment shares at the state level. However, the effect is less clear at the district level, suggesting that national and state policies may play a more significant role in shaping these outcomes.

Our findings suggest that the premature deindustrialisation observed in many developing countries may be partially driven by increased pollution levels, which discourage manufacturing activities. We posited that this may be driven by the broader narrative of global environmental policies and their unintended economic consequences on developing economies. While international climate treaties aim to reduce global emissions, they may inadvertently contribute to the decline in manufacturing employment in more polluted regions. This may occur through mechanisms like the Clean Development Mechanism (CDM) which potentially incentivise investment in projects that are less manufacturing intensive.

However, the lack of a significant differential effect of pollution on manufacturing employment shares in districts that received CDM projects indicates that these initiatives alone likely do not explain the observed relationship. This opens avenues for future research to explore other potential mechanisms, such as the productivity impacts of pollution on workers and the subsequent effect this has on firms' location decisions. Understanding these dynamics is crucial for designing policies that balance environmental sustainability with economic development, ensuring that developing countries do not disproportionately bear the costs of global emission reduction efforts.

References

[1] Amirapu, A., & Subramanian, A.(2015). Manufacturing or services? An Indian illustration of a development dilemma. *Washington, DC: Center for Global Development and Peterson Institute.* https://www.cgdev.org/publication/manufacturing-or-services-indian-illustration-development-dilemma-working-paper-409

[2] Anderson, M. (2020). As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality. *Journal of the European Economic Association*, 18(4), 1886–1927 https://doi.org/10.1093/jeea/jvz051

[3] Asher, S., Lunt, T., Matsuura, R., & Novosad, P. (2021). Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in India using the shrug open data platform. *The World Bank Economic Review*, 35(4). https://docs.devdatalab.org/

[4] Atteridge, A., Shrivastava, M.K., Pahuja, N., and Upadhyay, H. (2012). Climate policy in India: what shapes international, national and state policy? *Ambio*, 41, 68–77. https://doi.org/10.1007/s13280-011-0242-5

[5] Bondy, M., et al. (2020). Crime is in the Air: The Contemporaneous Relationship Between Air Pollution and Crime. *Journal of the Association of Environmental and Resource Economists*, 7(3), 555–585. https://www.journals.uchicago.edu/doi/full/10.1086/707127?mobileUi=0

[6] Central Statistics Organisation, Ministry of Statistics and Programme Implementation, Government of India (2020). Annual Survey of Industry 1998–2020. Accessed: June 1, 2024. https://microdata.gov.in/nada43/index.php/catalog/ASI

[7] Central Statistics Organisation, Ministry of Statistics and Programme Implementation, Government of India (2013). Economic Censuses. Accessed: June 1, 2024. http://microdata.gov.in/nada43/index.php/catalog/ECO

[8] Cole, M. (2004) Trade, the pollution haven hypothesis and the environmental Kuznets curve: examining the linkages. *Ecological Economics*, 48(1), 71-81 https://doi.org/10.1016/j.ecolecon.2003.09.007

[9] Dean, J., et al. (2009) Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China. *Journal of Development Economics*, 90(1), 1-13 https://doi.org/10.1016/j.jdeveco.2008.11.007

[10] Deb, K., & Kohli, P. (2022). Assessing India's Ambitious Climate Commitments. *Columbia SIPA Center on Global Energy Policy* https://www.energypolicy.columbia.edu/publications/assessing-india-s-ambitious-climate-commitments/

[11] Eskeland, G., & Harrison, A. (2003) Moving to greener pastures? Multinationals and the pollution haven hypothesis. *Journal of Development Economics*, 70(1), 1-23 https://doi.org/10.1016/S0304-3878(02)00084-6

[12] Fu, S., Viard, B. & Zhang, P. (2021) Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China. *The Economic Journal*, 131 (640), 3241-3273 https://doi.org/10.1093/ej/ueab033

[13] Global Modeling and Assimilation Office (GMAO) (2015), MERRA-2 tavgM_2d_lnd_Nx: 2d, Monthly mean, Time-Averaged, Single-Level, Assimilation, Land Surface Diagnostics V5.12.4, Greenbelt, MD, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: June 1, 2024. 10.5067/8S35XF81C28F https://giovanni.gsfc.nasa.gov/giovanni/

[14] Greenstone, M., et al. (2012) The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing. *National Bureau of Economic Research* https://doi.org/10.3386/w18392

[15] Keller, W., & Levinson, A. (2002) Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States. *Review of Economics and Statistics*, 84(4), 691-703 https://doi.org/http://dx.doi.org/10.1162/003465302760556503

[16] Kruse, H., Mensah, E., Sen, K., & de Vries, G. (2023). A Manufacturing (Re)Naissance? Industrialization in the Developing World. *IMF Economic Review*, 71. https://doi.org/10.1057/s41308-022-00183-7

[17] Leroutier, M. & Ollivier, H. (2023) The Cost of Air Pollution for Workers and Firms. *Mistra Centre for Sustainable Markets* https://marionleroutier.github.io/files/LeroutierOllivier_2022_cost_pollution_jmp.pdf

[18] Oberthür, S., & Ott, H. E. (1999). *The Kyoto Protocol*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-03925-0

[19] Rekha, R. & Suresh Babu (2022) Premature deindustrialisation and growth slowdowns in middle-income countries. *Structural Change and Economic Dynamics*, 62, 377-389 https://doi.org/10.1016/j.strueco.2022.04.001

[20] Rema, H. & Oliva, P. (2015) The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics*, 122, 68-79 https://doi.org/10.1016/j.jpubeco.2014.10.004

[21] Reserve Bank of India (2020). State Domestic Product 1998–2020. Accessed: June 1, 2024. https://rbi.org.in/Scripts/PublicationsView.aspx?id=21812

[22] Rodrik, D. (2013). Unconditional Convergence in Manufacturing. *The Quarterly Journal of Economics*, 128(1), 165–204. https://doi.org/10.1093/qje/qjs047

[23] Rodrik, D. (2016). Premature Deindustrialization. *Journal of Economic Growth*, 21(1), 1–33. https://doi.org/10.1007/s10887-015-9122-3

[24] Sen, K. (2019). Structural Transformation around the World: Patterns and Drivers. *Asian Development Review*, 36(2), 1–31. https://doi.org/10.1162/adev_a_00130

[25] Taguchi, H. (2023) Premature deindustrialization: an empirical analysis in latecomer developing countries. *Munich Personal RePEc Archive* https://mpra.ub.uni-muenchen.de/118346/

[26] Taguchi, H. & Tsukada, Y. (2022) Premature Deindustrialization Risk in Asian Latecomer Developing Economies. *Asian Economic Papers*, 21(2), 61-77 https://doi.org/10.1162/asep_a_00851

[27] The World Bank (2024). World Development Indicators. Employment in Industry-SL.IND.EMPL.ZS. Accessed: June 1, 2024. https://data.worldbank.org/indicator/SL.IND.EMPL.ZS

[28] The World Bank (2024). World Development Indicators. GDP (Current US$)-NY.GDP.MKTP.CD. Accessed: June 1, 2024. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

[29] United Nations Environment Programme (2024). Clean Development Mechanism Pipeline. Accessed: June 1, 2024. https://unepccc.org/cdm-ji-pipeline/

[30] US Environmental Protection Agency. (2011). *Black Carbon Research and Future Strategies*. Retrieved from https://www.epa.gov/sites/default/files/2013-12/documents/black-carbon-fact-sheet_0.pdf

[31] Zhou, T., & Zhang N. (2023) Does air pollution decrease labor share? Evidence from China. *Global Environmental Change*, 82. https://doi.org/10.1016/j.gloenvcha.2023.102706

[32] Zivin, J. & Neidell, M. (2012) The Impact of Pollution on Worker Productivity. *American Economic Review*, 102 (7), 3652-73 https://doi.org/10.1257/aer.102.7.3652

8 Appendix

TABLE A.I.
Instrument Robustness Check

	Outcome Variable is Log GDP			
	Country Level			Indian State Level
Wind Speed (m/s)	0.015 (0.035)	-0.005 (0.045)	-0.034 (0.076)	0.511 (0.316)
Geographic Controls	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes
Obs.	2,605	1,484	1,001	457
Sample	Full	Africa & Americas + India	Asia & Europe	Full

*OLS regression results of log GDP on wind speeds for the cross-country sample (columns 1–3) and Indian states sample (column 4). Geographic controls at the country level include country fixed effects and at the state level include precipitation, vegetation intensity, and elevation. All regressions include year fixed effects. Robust standard errors for the country level and Conley standard errors for the Indian State Level are shown in parentheses.

TABLE A.II
Comparison of Average Summary Statistics Across Zones

Variable	Zone					
	Central	East	North	North East	South	West
Precipitation (g/m^3)	0.04	0.04	0.03	0.06	0.04	0.04
Leaf Area Index	1.02	1.06	0.98	2.55	1.14	0.86
Elevation (m)	322.85	177.63	639.67	350.77	383.56	270.15
Pollution ($\mu g/m^3$)	2.40	2.97	1.95	1.63	1.13	1.21
Wind Speed (m/s)	4.73	4.66	4.32	3.38	5.60	5.70
Manufacturing share	23.2%	20.6%	25.7%	13.9%	24.1%	25.4%
Services share	74.4%	75.6%	73.5%	82.2%	72.8%	72.0%
Industry share	3.8%	2.6%	5.4%	2.0%	3.7%	4.6%
Rural poverty	39.0%	43.2%	23.4%	40.7%	15.3%	31.7%
Urban poverty	13.1%	18.8%	8.3%	14.0%	5.4%	10.9%