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Analysis

Environmental Justice in India: Incidence of Air Pollution from Coal-Fired Power Plants

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ABSTRACT

Air pollution is a vexing problem for emerging countries that strike a delicate balance between environmental protection, health, and energy for growth. We examine these difficulties in a study of disparate levels of exposure to pollution from coal-fired power generation in India, a country with high levels of air pollution and large, marginalized populations. With data on coal plant locations, atmospheric conditions, and census demographics, we estimate exposure to coal plant emissions using models that predict emission transportation. We find that ethnic and poor populations are more likely to be exposed to coal pollution. However, this relationship is sometimes non-linear and follows an inverted u-shape similar to that of an Environmental Kuznets Curve. We theorize that this non-linear relationship is due to the exclusion of marginalized communities from both the negative and positive externalities of industrial development.

1. Introduction

Air pollution is a severe threat to public health around the world. *Global Burden of Disease* estimates that more than 5.5 million people died prematurely due to air pollution in 2013 alone, with China and India claiming more than half of the deaths (Brauer, 2016). Coal in particular is a significant contributor to air pollution in emerging markets such as India, which has the second largest planned expansion of coal burning capacity in the world (second only to China) (CGS, 2018). This expansion, if brought online, could significantly increase health risks in neighboring communities; in fiscal year 2010–2011 alone, India's coal-fired plants caused as many as 80–115 thousand premature deaths at an estimated cost of USD 3.2–4.6 billion (Guttikunda and Jawahar, 2014).

However, the burden of air pollution is not evenly distributed across humanity. Scholarship on environmental justice has documented potential gaps in pollution burden between the wealthy and the poor (Konisky, 2017), and between white and non-white populations in the United States (Mohai et al., 2009; Ringquist, 2005; Brooks and RajivSethi, 1997). However, this literature has paid limited attention to environmental justice outside of developed OECD countries (Hajat et al., 2015). This oversight is unfortunate, given that the world's most heavily polluting industries are increasingly concentrated in developing markets, and therefore the potential distributional consequences of this development for marginalized communities is enormous (Brauer et al., 2015; Rao et al., 2017; Rafaj et al., 2018).

Here we explore the distribution of air pollution from coal-fired power generation in India. Drawing on environmental justice literature, we hypothesize that pollution from coal plants is more likely to affect disadvantaged communities. However, we go beyond previous studies on environmental discrimination by looking at the possibility of non-linear relationships between socio-economic characteristics and exposure to pollution. We build off insights from studies examining the Environmental Kuznets Curve (EKC), which posit the existence of an inverted u-shaped relationship between economic development and pollution (Grossman and Krueger, 1995). Here, we examine whether the exposure of disadvantaged communities to pollutants in emerging markets follows similar trends. We argue that a non-linear relationship is likely, given that the same factors that increase the risk of pollution exposure for disadvantaged communities (namely, the lack of political influence in decision-making), will also decrease access to the rapidly industrializing sectors of the economy which produce that pollution.

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Therefore, extremely marginalized communities may be spared from negative externalities, but also excluded from the benefits of industrial development.

To test these hypotheses, we explore the incidence of coal plant pollution across nearly 600,000 different villages and towns in India. We examine associations between pollution exposure and literacy rates, asset ownership (wealth), and ethnic identity. For this final group, we focus specifically on scheduled tribes and castes, marginalized groups that have deep sociological and political roots in India's history. Combining data on India's coal-fired power generation from the Global Coal Plant Tracker (EndCoal, 2018) and the 2011 Indian Census, we applied Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) models (Draxler and Hess, 1998; Stein et al., 2015) to simulate the trajectories of emissions for all coal-fired power plants with at least 30 MW of capacity and which were active in 2013. We then estimate the pollution exposure each Indian village and town receives from coal emissions.

We find robust evidence for the same environmental justice problems that the literature has documented in the United States (Konisky, 2017; Mohai et al., 2009; Ringquist, 2005). However, we also find evidence that the relationship between socio-demographic composition and exposure to emissions is not linear, but follows an inverted u-shaped curve. Evidence for this trend is the strongest for marginalized ethnic groups (scheduled tribes and castes). As the concentration of ethnic groups increases, so does the exposure to coal plant emissions. This positive correlation attenuates and turns into a downward slope as the concentration of ethnic groups reaches higher levels, in a similar shape to the EKC. For scheduled tribes, this curve peaks for communities where approximately 56% of the local population belongs to a scheduled tribe. Our estimates indicate that these communities on average are exposed to 78% more coal emissions when compared to communities with no scheduled tribes. These trends also hold constant even when controlling for wealth and ethnic composition prior to power plant construction.

To evaluate actual levels of pollution burden, we compare estimates from the HYSPLIT simulations to data on ground-level NO_2 and $PM_{2.5}$, pollutants commonly produced in coal plants and consistently linked with negative health outcomes (Burnett et al., 2004; Samoli et al., 2006) and the presence of other toxic chemicals (Brunekreef and Holgate, 2002).[1] We find that exposure rates attributable to our coal pollution model raise average $PM_{2.5}$ exposure from 29.1 $\mu g/m^3$ to 30.3 $\mu g/m^3$ and NO_2 exposure from 0.38 ppb to 0.43 ppb for communities with no scheduled tribes versus those with 56% scheduled tribes (peak exposure). This latter shift corresponds to about 11% of the average regional NO_2 level of 0.5 ppb for South Asia.

We interpret this non-linear relationship as the the interaction between political access and economic access. The most marginalized communities are completely excluded from the benefits of industrialization, which may also "spare" them from exposure to negative externalities. As disadvantaged communities begin to gain economic access to the industrializing sectors, their political access is still very weak. Therefore, they are still unlikely to influence the decision-making process regarding the siting of harmful activities. This interaction creates an inverted u-shape relation between ethnic composition and exposure to coal pollution. However, it is important to note that our study focuses on one source of pollution, coal plant emissions, and that extremely marginalized communities are likely exposed to other sources of contamination.

Our study makes several contributions to existing literature on the distributional consequences of pollution. First, we are among the very few studies examining environmental discrimination outside the developed world, (Rooney et al., 2012), and the first to do so in India. Second, we merge two related, but separate literatures on environmental justice and the EKC. While several scholars have examined the distributional consequences of the EKC for poor communities (Dasgupta et al., 2006; Liu, 2012), fewer have actually examined the possible existence of an EKC for ethnic groups (Germani et al., 2014). Finally, this paper draws upon atmospheric modeling and new geocoded data on coal plants. This approach allows us to circumvent the conventional problem associated with subpar quantity and quality of data on developing markets, which partially explains the dearth of environmental justice studies there (Hajat et al., 2015). More importantly, this approach pinpoints with high-level precision the source and impact of a critical contributor to air pollution—coal plants.

2. Coal and Air Pollution in India

Coal plays an important role in India's energy sector. In 2006, the installed generation capacity for coal was around 68,000 MW accounting for about 55% of the country's total installed capacity (Ministry of Power, Government of India, 2006). This increased to around 122,000 MW in 2013 and shot up to 197,000 MW in 2018 (Ministry of Power, Government of India, 2013, 2018). This huge increase in capacity in the past decade signifies the importance that coal plays in the country's industrial and electricity sectors. Though competition with renewables has also increased in the same period, renewable capacity is still around 66,000 MW (Ministry of Power, Government of India, 2018), less than coal's capacity a decade ago.

While the coal industry has had some positive impacts economically, it also has significant environmental costs. Chief among these is air pollution (Ghose and Majee, 2001; Ghose and Banerjee, 1995). The Health Effects Institute recently published a study concluding that air pollution was responsible for some 1.1 million deaths in the country in 2015 (HEI, 2018). The report also found coal combustion was responsible for about 15% of these deaths.

Central and State Pollution Control Boards (CPCB) are responsible for the creation, monitoring and enforcement of regulation related to air pollution. However, the judiciary, through the Supreme Court Action Plans, has led recent efforts directing cities to develop plans to reduce air pollution.[2] Importantly, these new plans have focused largely on urban areas and "pollution standards only exist for ambient air quality and not for individual power plants" (Guttikunda et al., 2015: 64).

Several studies have documented the negative effects of air pollution worldwide with a recent study concluding that its contribution to premature mortality could double by 2050 (Lelieveld et al., 2015). Indeed, air pollution is a major problem across India. In Delhi, exposure to air pollutants has been linked with an average reduction in life expectancy of 6.3 years (Ghude et al., 2016). A recent study estimates that 32% of the total global burden for chronic respiratory disease occurs in India and that the majority of this (53.7%) is attributable to air pollution (Salvi et al., 2018). The negative health impact of air pollution extends beyond the capital: Patankar and Trivedi (2011) and Guttikunda and Kopakka (2014) document the dismal outcomes of air pollution in Mumbai and Hyderabad respectively, and Mukhopadhyay and Forssell (2005) do likewise for the whole country.

Some recent studies have examined the role of pollution from coal-fired power plants in India. Guttikunda and Jawahar (2014) model emissions from coal plants and show that environmental regulations for coal burning are critical for improving health outcomes. While their focus on emissions from coal plants is helpful, they do not examine the socio-economic characteristics that can explain the spatial variation in pollution. Another attempt to model coal pollution in India uses

[1] We use NO_2 and $PM_{2.5}$ due to data availability, although many additional pollutants are associated with coal emissions.

[2] "Supreme Court asks Centre to notify pollution plan for Delhi-NCR" *India Today*. (Dec. 14 2017). https://www.indiatoday.in/story/supreme-court-centre-notify-pollution-plan-delhi-ncr-1106910-2017-12-14.

principal component analysis in the area around one coal field in the state of Jharkand (Pandey et al., 2014). Bhanarkar et al. (2008) measures the emissions from a coal plant in India and identifies the presence of metals such as magnesium, iron, lead, chromium and zinc. Lu et al. (2013) report increases in sulfur emissions from coal plants during the period 2005–2012, and in a similar vein, Raghuvanshi et al. (2006) examine carbon-dioxide emissions from coal plants nationally. While these studies are useful for understanding how coal contributes to air pollution, none have investigated the relationship between socio-economic characteristics and disparate exposure to pollution.

3. Environmental Justice

A rich literature has shown that in developed countries, poor and disadvantaged racial minorities are systematically exposed to greater levels of environmental hazards (Konisky, 2017).[3] Meta-analyses and literature reviews have concluded that race or ethnicity is an important predictor of inequalities in exposure to pollutants, even when controlling for other factors related to socioeconomic status (Mohai et al., 2009; Ringquist, 2005). This evidence is also robust for decisions related to the siting of environmentally hazardous activities (Anderton et al., 1994; Mohai and Saha, 2007), for exposure to a variety of air pollutants (Hajat et al., 2015; Pastor et al., 2006; Brooks and RajivSethi, 1997), and when controlling for input costs relevant for siting decisions (Wolverton, 2009), all of which are important factors related to siting new coal plants.

Our main focus is on the disparate impact of pollution for marginalized ethnic groups, specifically India's scheduled tribes and castes. Caste has a deep sociological history in Indian society. A key element of the Hindu religion, caste revolves around group membership based on heredity. At the upper end of the spectrum are the Brahmins and the Kshatriyas who typically controlled access to land and economic power. At the lower end are the Ati Sudras (who are now called the scheduled castes) who have historically been denied access to important public services. Similar to the lower castes, tribal populations of the country have been grouped as scheduled tribes. There is still strong evidence of discrimination against these groups in both the education sector and the labor market (Banerjee and Knight, 1985; Munshi and Rosenzweig, 2006; Kijima, 2006).

Though these marginalized groups live throughout India, scheduled tribes are generally located in more hilly areas. This makes accessibility an issue and there is some evidence that geography plays a role in the disparities between these groups (Corbridge, 2000; Kijima, 2006). Social exclusion primarily affects access to schools and economic opportunities (Thorat and Newman, 2007), but also limits access to health services (Baru et al., 2010). Since independence, a central government policy has been to reserve places for scheduled castes and tribes in educational institutions and public employment, but these initiatives are yet to bear fruit.

The literature on environmental justice has posited two broad sets of theoretical mechanisms that explain disparities in exposure to pollution across socio-economic groups: (i) inequalities in access to political power; and (ii) market mechanisms. The first mechanism assumes that the siting of environmentally harmful activities is a function of a community's capacity to resist having a plant located in its backyard. This variation in capacity could result from a community's potential to organize political opposition (Bullard, 1990; Hamilton, 1995), poor access to decision-makers, or even intentional discrimination (Konisky, 2017: 212–13).

The second mechanism is agnostic to potential disparities in political or organizational capacity, and instead posits that disparate exposure is a function of pricing mechanisms (Oakes et al., 1996; Pastor et al., 2001). Harmful activities tend to depreciate property values in the surrounding area. Therefore self-sorting may occur as lower income households migrate to polluted areas attracted by low property values, while higher income households move away.

Under either mechanism, we should expect a positive correlation between disadvantaged communities and exposure to coal pollution. However, the two mechanisms offer different predictions regarding trends in exposure over time. While the political inequality mechanism predicts that more politically powerful communities should avoid siting of harmful activities at all time periods, the market mechanism predicts that poorer households will migrate to polluted areas over time.

Could the relationship between disparate exposure to pollutions and disadvantaged populations be non-linear? A few studies have found a non-linear relationship between socio-economic characteristics and pollution exposure, although to our knowledge none have explored the theoretical mechanisms as applied to disadvantaged ethnic communities. An extensive literature on the EKC debates the existence of a non-monotonic relation between income and pollution (Grossman and Krueger, 1995). The EKC theory draws upon the work of the economist Kuznets (1955) who posited an inverted u-shape relationship between economic development and inequality. Later researchers then adapted this idea to explain the relationship between economic development and pollution-levels within an economy, with mixed results (see, e.g. Selden and Song, 1994; Arrow et al., 1995; List and Gallet, 1999; Dinda, 2004; Liao and Cao, 2013; Liddle, 2015).

We describe this theoretical relationship more in the Appendix Section A2. The key to our theory is that access to political power will influence both levels of economic development and exposure to environmental harms. Disadvantaged communities with weak political access, particularly in highly-unequal emerging markets, will be systematically excluded from the modernizing sectors of the economy. Therefore, these communities cannot access even the early (and dirtier) parts of the industrializing economy. An example would be a rural village with subsistence-level agriculture located far from industrial centers that could provide both economic opportunity and environmental harms.

As a community moves upward along the spectrum of political access, they will also increasingly access the benefits of the economy, but at first only to highly polluting industry. This will reach an inflection point at higher levels of political influence, at which point communities will both have greater access to the benefits of a modern economy, and also greater ability to avoid or "dump" (Cole, 2004; Liu, 2012) dirtier activities onto areas with relatively weaker political influence. Combined, these two tendencies should create an inverted u-shape very similar to the EKC.

4. Data and Methods

Our research design first models the emission trajectories of India's coal-fired power plants and then examines how those trajectories are distributed across communities using data from the 2011 Census of India. We aggregate both rural and urban census data into a master frame of 595,378 villages and 7816 towns across all states and Union Territories of India. We examine rural-urban, economic, literate-illiterate, and ethnic differences in exposure to coal emissions. As the census has no direct question on income, we use asset ownership (television, back account, and any major asset) as a proxy for wealth. We first present our data on coal plants and then characterize our air pollution modeling approach. Details on demographic variables and summary statistics are provided in the Appendix Section A3.1.

4.1. Coal Plant Data

Our data on coal plants is drawn from the Global Coal Plant Tracker (EndCoal, 2018), which provides global information on coal plant units larger than 30 MW. This data includes the location, size, and CO_2

[3] We include a full discussion on literature and theoretical mechanisms in Appendix Section A2.

emissions of a total of 618 coal-fired energy units comprising 244 unique power plants operating in India during 2013. The average capacity of a coal-fired unit in our dataset is 639 MW.[4]

Despite the high reliance on coal in India, plants are not evenly distributed within the country. Fig. 1 provides a map of the distribution of coal plants in our dataset. As the figure shows, plants are heavily concentrated in the eastern parts of the country with Chattisgarh and Orissa accounting for the large bulk of the units. The establishment of a coal plant depends on its proximity to mines, transportation facilities, and load centers. The state-owned Coal India Limited (CIL) is currently planning for more pithead thermal power plants (Press Trust of India, 2017), especially in the states of Jharkand and Orissa. In sum, the distribution of coal-plants is uneven across the country, and we therefore expect to find a high degree of geographic variation in exposure to coal pollution.

4.2. Air Pollution Transport Model

To identify the regions affected by coal plant emissions, we utilize the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model developed by the National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory (ARL) (Draxler and Hess, 1998; Stein et al., 2015). The HYSPLIT model has been used for a range of projects over the past 30 years, including the transport of allergens, volcanic ash, radionuclides, and air pollutants, among others (Stein et al., 2015). The HYSPLIT model utilizes meteorological information about wind speed and direction to estimate the trajectory of a particle or gas plume in three dimensions over time.

In this case, we start the forward trajectory model for each computational point starting at the latitude/longitude point for all of the 618 unique coal-fired units in our data set. Coal plants produce a range of pollutants, including mercury, sulfur dioxide (SO_2), nitrogen oxides (NO_x) and particulate matter. These pollutants have been linked to a range of maladies. Mercury can damage the nervous, digestive and immune systems. SO_2, NO_x, and fine particular matter (soot) are linked to asthma and aggravation of respiratory diseases like bronchitis, pneumonia and influenza. They can also increase cardiovascular health issues and cause premature death (Cohen et al., 2017a; Hu et al., 2017).

To estimate the geographic distribution of pollution burden, we created a 0.1° grid, counting the number of computational points that passed through each square of the grid. The result is a map similar to that in Fig. 2. To construct the village-level measure of exposure to pollution from coal plants, we first weight each point by the likely amount of pollution of the source coal plant. We then sum the weighted points passing through the grid square in which the centroid (center) of the village is located. This process has the advantage of not being confounded with village size.

Comprehensive atmospheric fate and transport modeling of power plant impacts in India has been carried out in previous studies (e.g. Guttikunda and Jawahar, 2014), but this type of analysis is beyond the scope of this paper. Instead, we have used a relatively simple trajectory-based approach to estimate the spatial distribution of downwind impacts from power plants. While this approach is admittedly an oversimplification of the complex downwind behavior of emitted pollutants, we believe that it captures the essential elements of the source-receptor relationships involved and is useful to analyze the distributional consequences of plant siting. We have used the HYSPLIT model in trajectory mode to carry out this analysis. To accommodate the large number of coal plants and time periods estimated, we leveraged the *PySPLIT* package for Python to produce the trajectories (Warner, 2018).[5] Appendix Section A4 provides further details on the use of the model and includes supplementary analyses showing that conclusions are robust regardless of the parameters chosen (see Section A7).

Unfortunately, we cannot use direct observations of plant emissions to test the validity of our measurements, given that monitoring data is unavailable for the vast majority of plants (Guttikunda and Jawahar, 2014: 423). Therefore, to test the construct validity of our HYSPLIT measure, we compared the estimated annual pollution burden due to power plants from the HYSPLIT model against satellite-derived annual average nitrogen dioxide (Geddes et al., 2016) near the surface for 2013.[6] We used the gridded concentration of these pollutants at the village centroid and compared them to the estimates from our HYSPLIT model. The results were in line with what we expected. Weighted model points have a pearson correlation of $r = 0.580$ with satellite NO_2 measurements in rural areas and $r = 0.540$ in urban areas. These results give us some confidence that the HYSPLIT model is correctly picking up on pollution increases related to the location of coal-fired power plants.

We adopt a cross-sectional rather than longitudinal approach, using pollution estimates based on active plants as our primary outcome. Though panel data would allow us to examine temporal variation, we lack detailed historical data on coal plant locations and census. In this setting, however, we expect that our cross-sectional approach captures the majority of variation in this context. Though air quality in India has, of course, varied over time, the change has largely been in the direction of increasing air pollution everywhere; we therefore do not expect much annual sub-national variation. Additionally, research on planned new coal plant construction suggests that many recent constructions are additions to existing plants and the resulting pollution should thus vary in magnitude but not pattern.[7] Nonetheless, we use prior census data in Section 5.4 below as a check of post-siting economic migration.

4.3. Estimation Strategy

Our procedure for estimating the relationship between exposure to coal emissions and socio-demographic composition of communities is an OLS model with non-linear terms. Following prior studies on the EKC (Grossman and Krueger, 1995; Dinda, 2004), we include both linear and quadratic transformations of the main independent variable of interest. The inclusion of the quadratic term is to capture a possible non-monotonic trend in exposure to pollution. The functional form of our model is specified below:

$$Y_i = \alpha_i + \gamma_s + \beta_1 D_i + \beta_2 D_i^2 + \sum_k \beta_k X_i^k + \varepsilon_i \tag{1}$$

here, *i* indexes for a census tract as the unit of analysis (village or town), *s* indexes the state, and *D* represents the primary demographic variable of interest in the model—either a proportion of ethnic group or economic indicators as a proxy for income. *X* is a series of controls for other demographic characteristics of the village that are not the primary interest of the regression model. We also control for state fixed effects in all models. Due to the likelihood of spatial correlation in the census data, we also estimate robust standard errors clustered at the district level.

Interpreting the slope coefficients for the quadratic terms in our model is crucial for finding evidence of a non-linear relationship. For

[4] We provide more information on plant data in the Appendix Section A3.2

[5] One limitation to the *PySPLIT* package is that it currently only supports 1° GDAS meterological data, with horizontal resolution of about 100 km., which limits its capacity to capture the effect of complex terrain.

[6] NO_2 data available at http://fizz.phys.dal.ca/ atmos/martin/?page_id = 232. We supplement the NO_2 estimates with estimates for $PM_{2.5}$ exposure, obtained through Van Donkelaar et al. (2016), though we urge greater caution in interpreting the latter as a large part of the $PM_{2.5}$ is formed from complex chemical reactions in the air and therefore require greater assumptions regarding atmospheric conditions to model. Additionally, $PM_{2.5}$ is more likely to come from sources other than coal, as evidenced by other studies estimating that the relative contribution of thermal plants to atmospheric NO_2 levels is nearly twice that of $PM_{2.5}$ (Guttikunda and Jawahar, 2014).

[7] See Kopas et al. (2019).

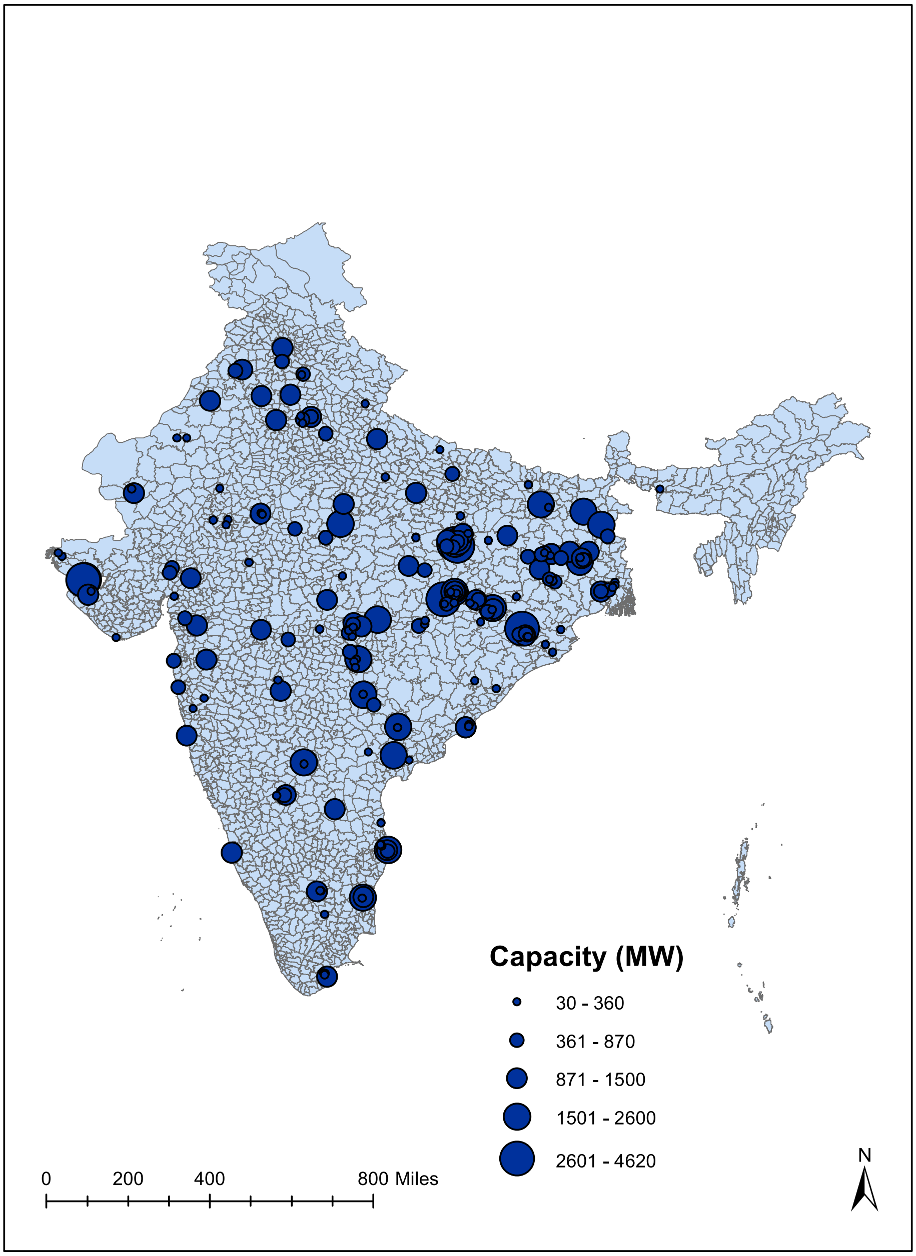

Fig. 1. Distribution of coal-fired power plants in India. Coal-fired power plants in India operating in 2013 and grouped by capacity.

ease of interpretation, we include Table 1 below that examines the different combinations of sign (negative or positive) and statistical significance (distinguishable from zero or not). All socio-demographic variables are coded from 0 to 1 with 0 representing no presence of marginalized ethnic groups or low-income households. A simple linear relationship as predicted by the environmental justice theory corresponds to the first row below, while an inverted u-shape as predicted by the EKC theory corresponds to row 4.

As a robustness check, we also test for a more complex model that uses a cubic term for the demographic variables, following some studies on the EKC (List and Gallet, 1999; Dinda, 2004; Özokcu and Özdemir, 2017). A cubic term could capture, for example, a particularly severe level of exposure for areas that are extremely impoverished or have an exceptionally high concentration of ethnic minorities (for an N-shaped relationship, row 5). We discuss here only the results for the linear and quadratic models, and include full results of all models in the Appendix.

5. Results

5.1. Bivariate Relationships: Rural, Ethnicity, Income, and Education

We first examine the distribution of pollution across rural and urban areas, shown in Fig. 3. This box plot reveals that, at a national level, the distribution of pollution is very similar within these categories. The distribution of pollution among rural populations is only slightly higher than for urban populations. This result suggests that infrastructure investments are not located so as to protect concentrated urban populations from pollution.

We do find, however, that when comparing rural and urban areas within each state—controlling for state-specific effects—rural areas experience somewhat less pollution on average (Tables A2 and A3 in the Appendix).[8] We also consider the relationship between population

[8] To facilitate visualization, we drop 1792 observations (0.3% of the total

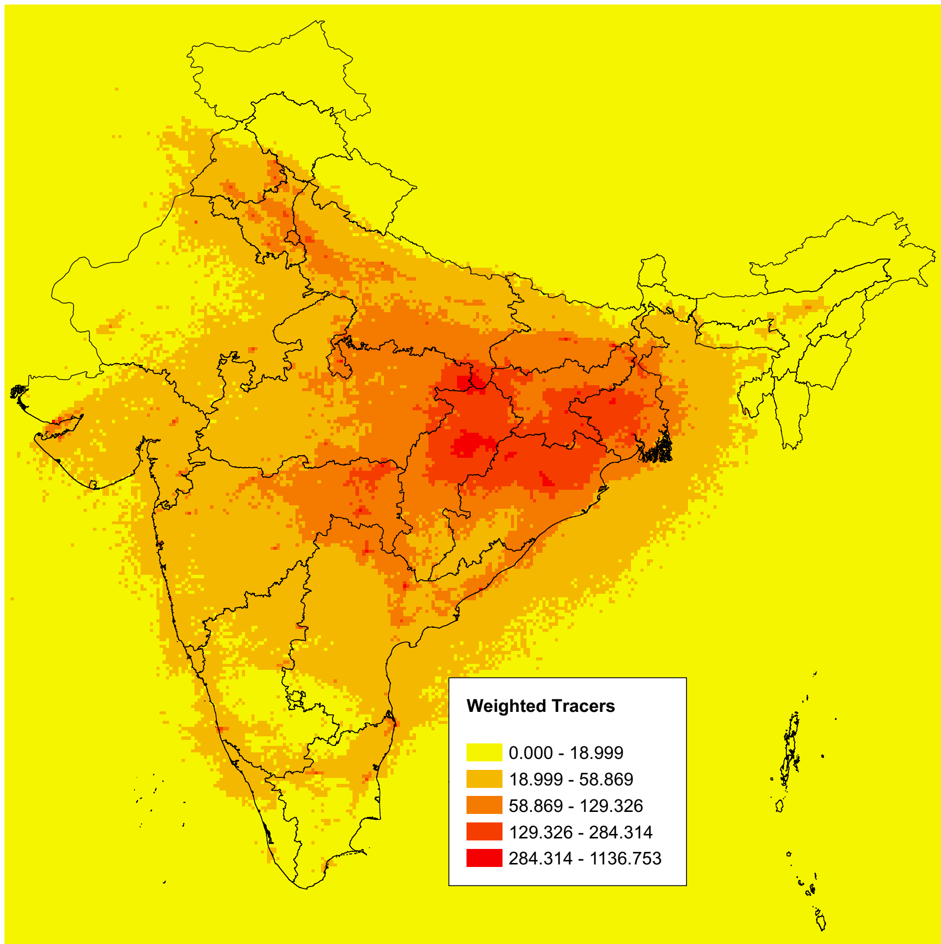

Fig. 2. HYSPLIT model of air pollution from coal-fired power plants in India. Concentration of emissions from coal plants based on a HYSPLIT model for 2013. Emission tracers represent trajectories of particles or gas plumes and may reflect multiple air pollutants.

Table 1
Interpretation of coefficient estimates for the linear and quadratic terms for the primary independent variables.

Curve shape	Linear ($\beta_1 D_i$)	Quadratic ($\beta_2 D_i^2$)	Cubic ($\beta_3 D_i^3$)
Monotonic downward	Negative, significant	Not significant	Not significant
Monotonic upward	Positive, significant	Not significant	Not significant
U-shaped	Negative, significant	Positive, significant	Not significant
Inverted U-shape	Positive, significant	Negative, significant	Not significant
N-shaped	Positive, significant	Negative, significant	Positive, significant
Inverted N-shape	Negative, significant	Positive, significant	Negative, significant

size and pollution. We do not find an obvious linear relationship between population and air pollution (see Appendix Fig. A3), though on average, larger units experience somewhat lower levels of pollution.

We next examine the relationships between pollution and socioeconomic characteristics including asset ownership, membership in scheduled caste or scheduled tribe, and the prevalence of illiteracy within the community. The analysis here is, again, purely descriptive and presented without controls for state effects or other variables. Fig. 4 summarizes the relationship between each socioeconomic characteristic and the coal-weighted pollution estimate, binning village-level observations by half-percentage point increments of each attribute and examining the mean pollution level by bin. Note that the size of the bubbles indicates the number of observations included in each bin, illustrating the underlying distribution of each predictor.

The top left panel in Fig. 4 addresses the relationship between the rate of illiteracy within communities and pollution. We find a complex relationship, with pollution rates peaking in places with close to the median illiteracy rate of 41%. Areas with extremely high or extremely low rates of literacy tend to experience lower amounts of pollution. For this measure of low social status, we do not see conclusive evidence in favor of the simple environmental justice hypothesis. However, the inverted u-shape does suggest there may be a more complex, non-linear

(*footnote continued*)
dataset) with exceptionally high pollution (greater than 300 pollution trajectories).

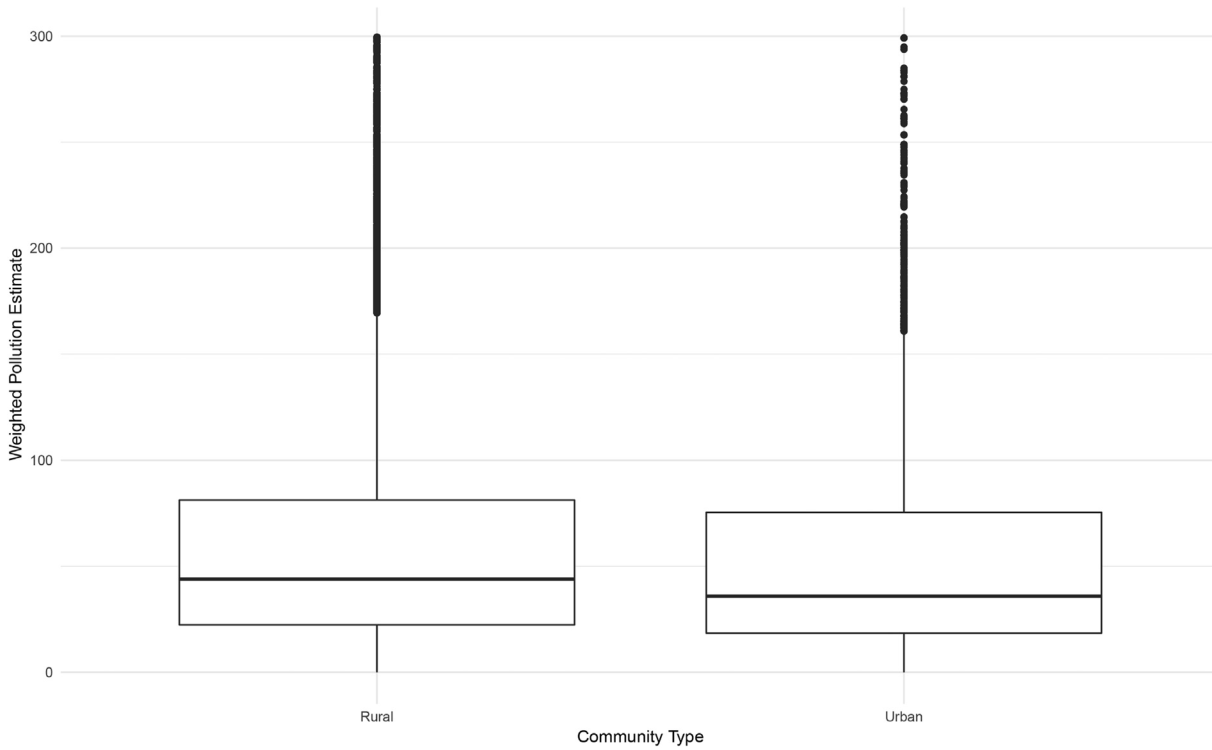

Fig. 3. Rural-Urban Distribution of Air Pollution. Boxplots indicate distribution of pollution measures among rural versus urban communities.

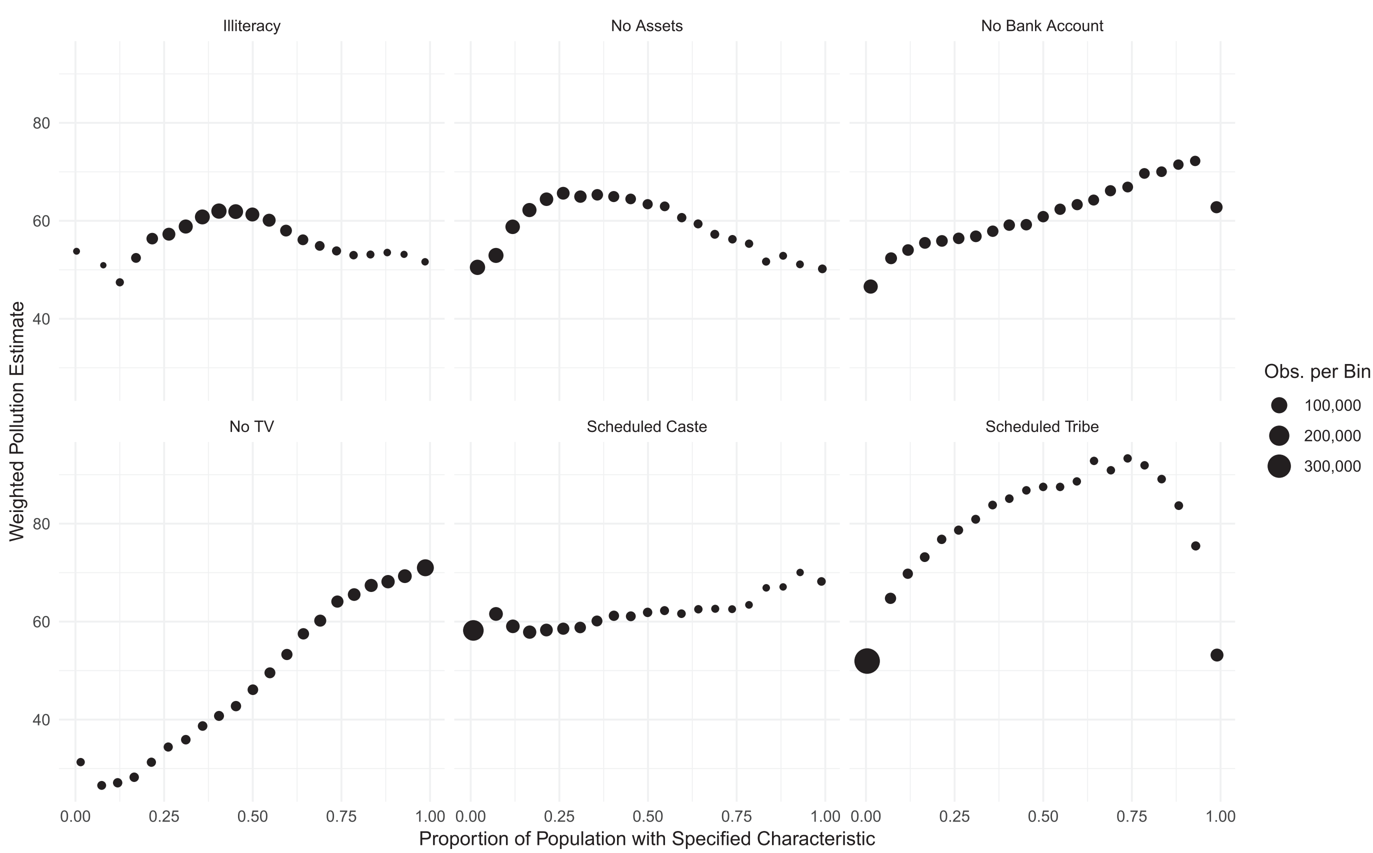

Fig. 4. Pollution Outcomes by Socioeconomic Characteristics. Plot shows average pollution measures within groups binned by proportion of the population with the characteristic indicated by the panel label.

relationship that is consistent with the theory that extremely illiterate populations are being excluded from the main industrial sector that is simultaneously providing economic opportunity and electricity while also exposing populations to air pollution.

Economic wealth shows mixed evidence, supporting both a monotonic relationship and an inverted u-shape. We use asset ownership as an approximation of societal wealth: proportion of census respondents with no major assets, no bank account, or no TV. Fig. 4 reveals the relationship between ownership of two such assets–televisions and bank accounts–and measures of air pollution. In both cases, there appears to be a strong, negative, and linear relationship between asset ownership and pollution; areas with more assets and, relatedly, more wealth experience lower rates of pollution on average. Here we see strong evidence of the kind of inequality that the environmental justice hypothesis predict: communities with less poverty also suffer from less pollution.

We also consider a possible measure for extreme poverty: the proportion of the population that lacks *all* of the assets included in the census battery. Fig. 4 suggests that there is indeed a positive relationship between extreme poverty and pollution levels, though this changes for communities in which more than 50% of the population lives in extreme poverty. This again is consistent with our theory that certain populations may not be exposed to extreme pollution simply because they are completely excluded from the developing sectors of the economy, as those communities reporting no major assets would likely be the most excluded from the benefits of development.

We next consider social status and marginalized ethnicities, as evidence by SC or ST status. The bottom right two panels in Fig. 4 plot the proportion of a community that is from a scheduled caste or tribe and measures of air pollution. These data suggest a consistent, positive relationship between the variables: areas with a majority scheduled caste or scheduled tribe population experience more pollution. Here, the environmental justice hypothesis is supported by the data, as disadvantaged minorities in particular suffer from pollution. The ST population also seems to follow the more complex, non-monotonic trend we find with prior variables, as pollution levels decline for communities with 75% or more ST population.[9]

SC and ST communities are historically marginalized in India, so we might expect a correlation between these social attributes and poverty indicators. The nature of our data (collected at the community rather than individual level) makes it challenging to disentangle the relationship between these ethnic metrics and measures of economic disadvantage. However, we note that while there is a strong positive correlation (0.43) between the proportion of scheduled tribe residents and the proportion of the community that is economically disadvantaged (those with no census assets), the correlation with scheduled caste is small and negative (−0.12). This may be a feature of scheduled caste members being more integrated into larger communities and the aforementioned ecological inference issue.

5.2. Non-linear Models: Evidence of an Environmental Kuznets Curve?

In this section, we estimate multivariate regressions with state fixed effects to allow multiple explanatory variables and remove any variation caused by state-to-state differences. For these regression models we also include linear and quadratic transformations of the main demographic variables of interest to test if the relationship between pollution and these factors is monotonic or more complex. If the simple environmental justice hypothesis is correct, we would expect a positive coefficient for demographic variables, as higher scores indicate greater proportion of marginalized communities (ethnic groups, poor, and nonliterate). However, if there is a non-monotonic relationship similar to an EKC, then the quadratic term should also be significant and negative.

To better illustrate these effects, Fig. 5 plots predicted values of pollution exposure for different levels of demographics using the quadratic specification of each model. Other socioeconomic variables for illiteracy, scheduled castes and tribes, and no assets were also included in the models. We include full regression results in the Appendix Tables A2 and A3. The strongest results are for both Scheduled Tribes and Scheduled Castes, which show large estimates in a consistent and positive direction when included in all models. In contrast, both the economic and illiteracy variables switch direction when used as a control variable in Models (1)–(6) in Table A3. This indicates that these measures of poverty and lack of access to formal education could be picking up the effect of ethnicity, as scheduled tribes and castes also tend to be the most economically disadvantaged in India.

Interestingly, the models which include the quadratic term for all variables show statistically significant estimates in the direction consistent with an inverted u-shape relationship between pollution exposure and disadvantaged communities. This shows support for the more complex hypothesis of a non-monotonic relationship similar to the EKC. However, given that there are a large number of observations in our data set, higher ordered polynomials may be significant while not substantively changing the overall relationship between pollution exposure and demographics.

Overall, the strongest evidence for a non-monotonic relationship concerns the scheduled tribes and castes and the proportion of illiterate population. The scheduled tribes and castes models show a clear trend of increasing exposure to pollution as the proportion of ethnic groups increases. This reaches a high point near the middle range of both figures, and the decreases slightly for areas with very high concentration of ethnic groups, while never returning to the lower levels enjoyed by areas with no ethnic groups. The relationship is most pronounced for scheduled tribes, for which the model predicts a roughly 78% increase in exposure to pollution at the peak of the curve for areas in which 56% of the population is from a scheduled tribe, relative to communities with no tribes.[10] Considering that India's scheduled tribe population is heavily concentrated in specific districts and mostly rural areas—90 out of 640 districts had over 50% scheduled tribe population and 337 had fewer than 5% in the 2011 Census—it is not surprising that these patterns are very strong for the scheduled tribe population in particular. The curve for illiteracy rates shows a similar dramatic drop, with extremely illiterate areas showing less exposure to pollution on average. However, this extreme effect may be from confounding variables given the inconsistent direction of estimates in other models.

The economic variables show mixed support for a linear or monotonic relationship, although they all are consistent with a hypothesis that more economically disadvantaged communities suffer from relatively greater levels of exposure to pollution. The no-TV variable tends toward a simple, monotonic relationship between wealth and coal pollution exposure. Not owning a bank account shows a slightly inverted u-shape similar to the effect of scheduled caste population on pollution exposure. The measure of no major assets, however, shows a downward relationship between poverty and air pollution, with extremely impoverished areas suffering less exposure to coal pollution. These inconsistent results are likely due to the different economic variables capturing different levels of economic impoverishment. No-assets likely shows extreme poverty, while no-bank accounts or no-TV may proxy for poor communities that are above the extreme poverty line. Together, however, they support the conclusion that the

[9] Note that the scheduled tribe population is distributed somewhat bimodally such that most communities have a very high or very low proportion of ST inhabitants. In contrast, few communities have a majority scheduled caste population.

[10] Note that these predicted values are calculated based on mean values for continuous indicators (e.g. assets, literacy), median values for binary indicators (e.g. rural/urban), and the state-level intercept for Puducherry. Percent change in predicted exposure will vary for different subsets of the data.

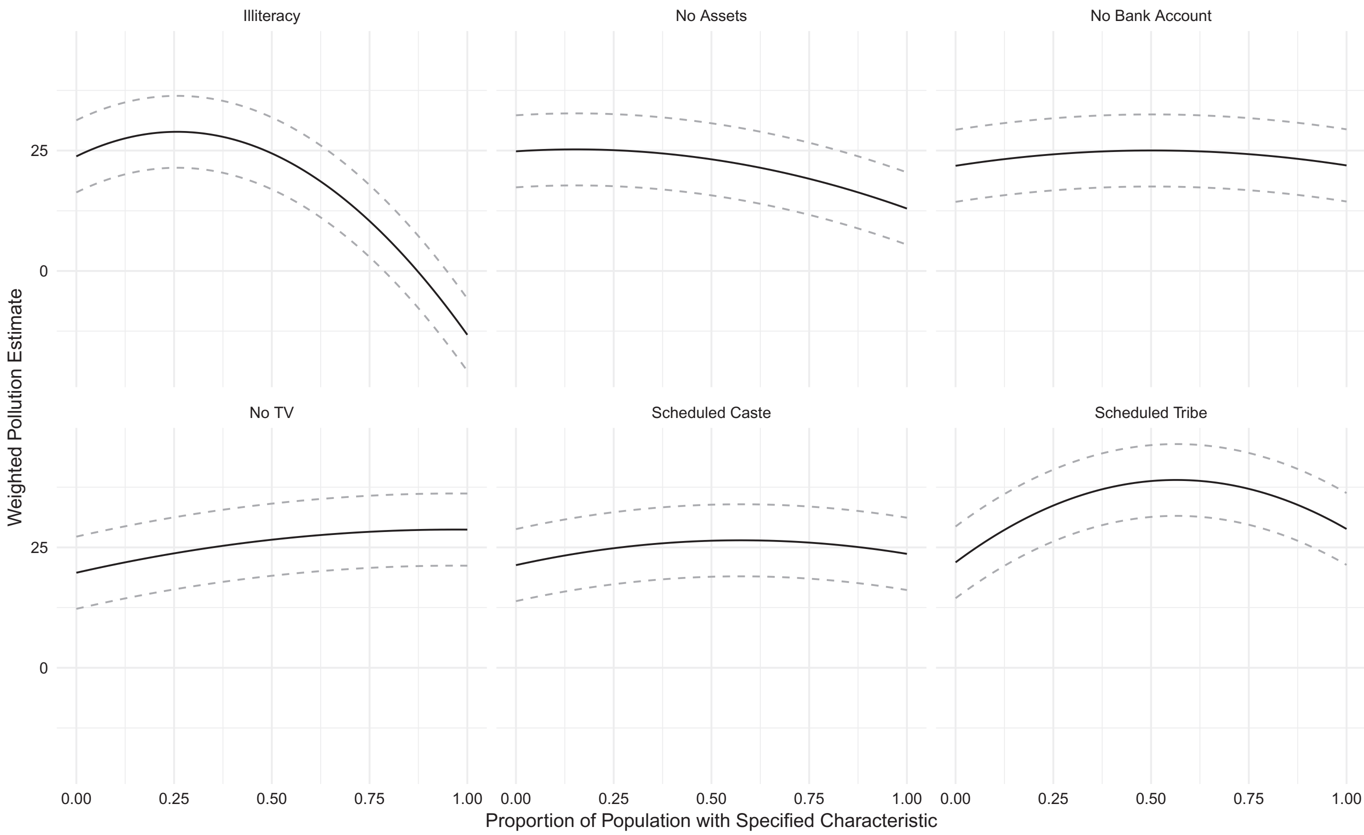

Fig. 5. Predicted values from OLS regression of coal emissions on socioeconomic factors. Models also include controls for other socioeconomic variables and state fixed effects.

relationship between poverty and exposure to pollution may not be as straight forward in the context of developing and emerging markets.

We also test more complex models that include cubic terms of the demographic variables. This might pick up more complex relationships than an inverted u-shape, that shows different effects for areas with very high concentrations of disadvantaged groups. We include full regression results and figures of predicted values in the Appendix Section A5. While the regression results produce statistically significant coefficient estimates on the cubic term, these effects are small and do not substantively alter the predicted values of exposure relative to the quadratic model.

5.3. Estimated Exposure to Pollutants

While the above results show the relative exposure to emission trajectories from coal-fired power plants for different demographic characteristics, the values of our dependent variable can be difficult to interpret in terms of exposure to actual pollutants. To provide a more realistic picture of what these estimated disparities in exposure mean when translated into a measure of actual pollutants, we use our model to predict exposure to nitrogen dioxide (NO_2), a common pollutant produced from coal combustion and which can indicate concentrations of coal plant emissions, as well as $PM_{2.5}$, also associated with coal-fired power plants. NO_2 and $PM_{2.5}$ are also informative pollutants to examine because their presence is often strongly correlated with negative health outcomes (Burnett et al., 2004; Samoli et al., 2006) and the presence of other chemicals hazardous to human health (Brunekreef and Holgate, 2002).[11]

We obtained NO_2 data from a global survey utilizing satellite imagery to measure tropospheric levels of nitrogen dioxide and convert these into estimates of ground-level exposure (Geddes et al., 2016). We also used satellite imagery to estimate ground-level exposure to $PM_{2.5}$ (Van Donkelaar et al., 2016). We estimated the contribution of our coal plant emissions transmission measure to remote sensing measures of NO_2 and $PM_{2.5}$ using a simple linear regression model that estimates the amount of variation in atmospheric NO_2 and $PM_{2.5}$ explained by variation in our emissions model.[12] We then used the resulting coefficient estimates to scale the estimated exposure rates in our main regression models. We show a plot of predicted levels of exposure to the two pollutants in Fig. 6 below.

The graphs map output from our coal pollution models onto estimated exposure to NO_2 and $PM_{2.5}$. NO_2 levels are expressed as a measure of parts per billion and $PM_{2.5}$ is measured in micrograms per cubic meter.[13] For the most extreme inequality in our dataset,

[11] A primary complication with estimating actual levels of exposure to different pollutants is the lack of reliable, ground-level air quality measurements

(*footnote continued*)
for India. Ground-level NO_2 and $PM_{2.5}$ measurements derived from satellite imagery, however, are available for all geographic regions in India (Geddes et al., 2016). Unfortunately, similar estimates at the ground-level are not available for other common coal pollutants, such as SO_2.

[12] Note that while the HYSPLIT estimates are positively correlated with both pollutants, the correlation is stronger for NO_2 estimates; we suspect that this is the result of two factors: first, that there are many potential sources of $PM_{2.5}$ pollution other than coal-fired power plants, and second, that a limitation of the version of the HYSPLIT model we use is that it does not incorporate information on complex atmospheric interactions. As a result, we have greater confidence in the predicted estimates for NO_2, though we include both pollutants for completeness.

[13] In comparing the charts, it is clear that the curves are similar in shape though not in magnitude. This is a result of both particulates being modeled as a

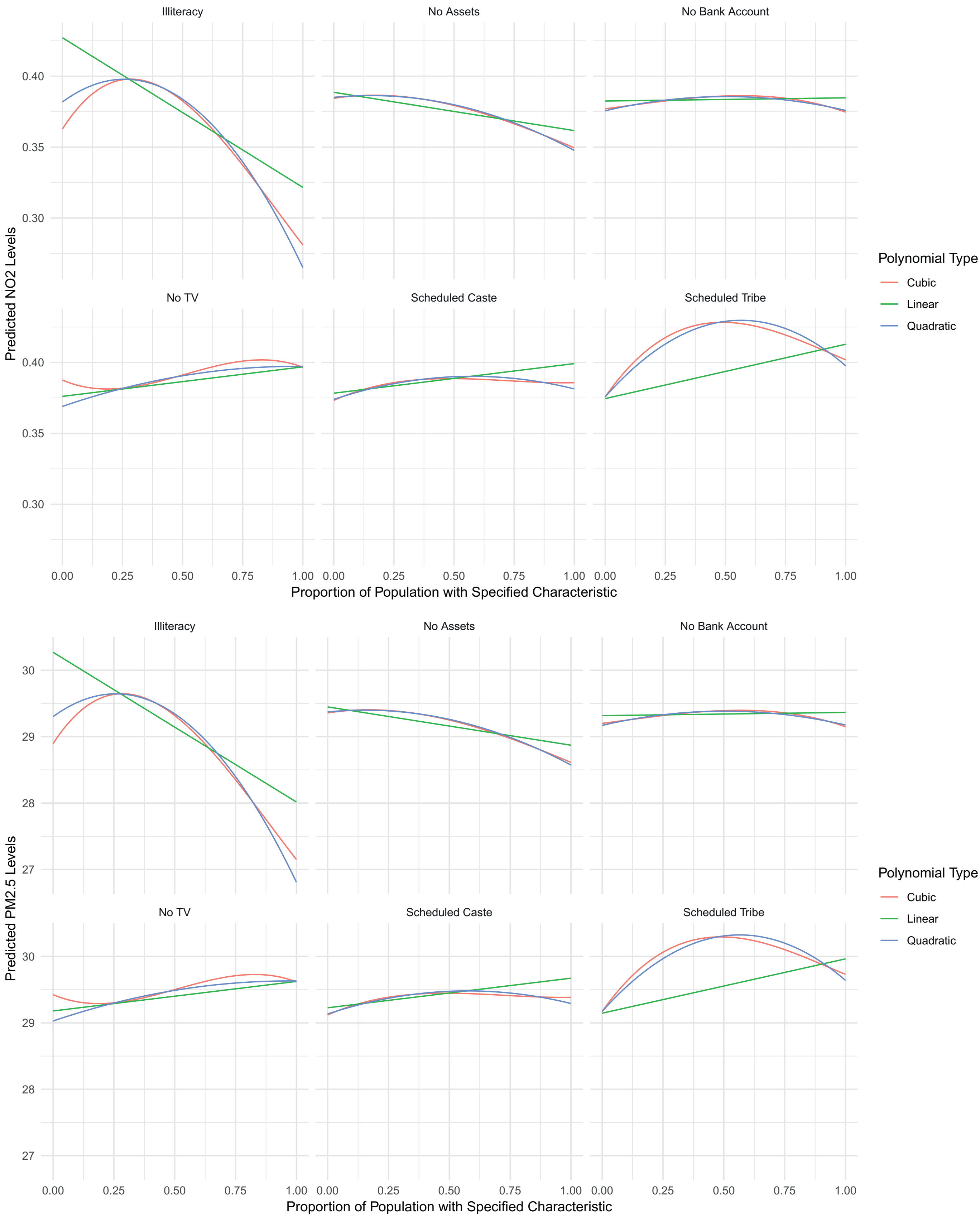

Fig. 6. Predicted changes in NO_2 exposure (top panel) in ppb and $PM_{2.5}$ (bottom panel) in micrograms per cubic meter as a function of socioeconomic characteristics and coal pollution. Figure shows predicted values based on fully specified models with linear, quadratic, and cubic terms for socioeconomic characteristics.

scheduled tribes, moving from the peak exposure at 56% of a community belonging to a scheduled tribe to no scheduled tribes increases the estimated average exposure from 0.38 ppb to 0.43 ppb. Although this difference is a proportionally smaller increase than for the emission transportation estimate (approx. 14% increase), it is nonetheless a relatively large change in exposure when compared to the average level of ground-level NO_2 for the region of South, which are estimated at 0.5 ppb during the period from 2001 to 2010 (Geddes et al., 2016). This shift, which represents 11% of the average regional level, is attributable to one source of emissions—coal plants—and therefore represents a significantly disproportional share of the burden of coal plant emissions borne by these communities.[14] Likewise, the model estimated variation in $PM_{2.5}$ exposure ranges from 29.1 $\mu g/m^3$ in a locale with no scheduled tribes to 30.3 $\mu g/m^3$ in a community with 56% of residents belonging to a scheduled tribe.[15] $PM_{2.5}$ is associated with major health issues[16]; Cohen et al. (2017b) attribute 1.09 million deaths in India to ambient particulate matter pollution in 2015. The authors of that study define the theoretical minimum risk exposure level for $PM_{2.5}$ between 2.4 and 5.9 $\mu g/m^3$, suggesting that even a small amount of increased exposure can be detrimental.[17]

It is important to note that we utilize these two pollutants as an illustrative analysis to demonstrate the relative pollution burden on scheduled tribes due to coal plant emissions. As mentioned previously, NO_2 is a convenient pollution measure for our HYSPLIT model and due to data availability. $PM_{2.5}$ is, likewise, a pollutant with serious health implications that is also associated with coal production. Where concentrations of NO_2 and $PM_{2.5}$ are higher, other harmful pollutants related to coal emissions such as SO_2 are also likely to be present, thereby increasing the pollution burden.

5.4. Robustness Using Historical Data

Is it possible that the patterns identified above are explained by migration subsequent to the presence of pollution? Several scholars have hypothesized that poorer or disadvantaged households move to an area with pre-existing polluting industries following lower property values (Oakes et al., 1996; Pastor et al., 2001). Non-seasonal migration in India is relatively limited: according to the 2001 Indian census, roughly 70% of Indians live in the place of their birth; 90% live in the same district in which they were born. Nevertheless, it is possible that migration subsequent to coal plant construction explains a part of the demographic relationships we identify.

We first test the possibility of reverse-causality by estimating the relationship between our present-day coal plant pollution and social indicators from the 2001 Indian national census. If estimates are consistent between the 2001 and the 2013 census demographics, this would provide some (although not conclusive) support against the post-siting migration hypothesis. Unfortunately, the 2001 census only includes measures for illiteracy, scheduled tribe, and scheduled caste populations, and not for economic variables. Therefore we limit our analysis to these factors.

Table 2
OLS regression output for pollution exposure on socioeconomic factors from the 2001 census. All models incorporate state fixed effects and estimate robust standard errors clustered at the district-level.

	Dependent variable:			
	Weighted pollution estimate			
	(1)	(2)	(3)	(4)
2001 Illiteracy	−15.629***			−21.373***
	(0.332)			(0.350)
2001 Scheduled caste		4.262***		7.255***
		(0.253)		(0.263)
2001 Scheduled tribe			3.030***	10.636***
			(0.178)	(0.202)
Rural	−3.847***	−6.469***	−6.633***	−4.379***
	(0.434)	(0.439)	(0.440)	(0.433)
State FE	Yes	Yes	Yes	Yes
Observations	546,180	579,864	579,864	546,180

Note: *$p < .1$; **$p < .05$; ***$p < .01$.

Table 2 reveals similar relationships for Scheduled Castes and Tribes as those found with the more recent census data; all relationships are significant and in the same direction as those found in Table A2. This is suggestive evidence that the effects we have found are not the result of recent population movement in which disadvantaged ethnic groups migrate to more polluted areas. However, illiteracy is negative and in the opposite direction as the more recent census data. This result is consistent with a hypothesis of post-siting migration, and may reveal that poorer families are moving to areas closer to coal plants, either driven by low cost housing, or more-likely in the context of India, drawn by economic opportunities. However, the same is not true for the scheduled tribes and castes, which show more consistency between the two censuses. The correlation between the scheduled castes and tribes in the two census is also very high, with correlations of 0.887 for scheduled castes and 0.927 for tribes. Such high correlations are inconsistent with significant migration patterns. Indeed, much of Indian migration is seasonal in nature, with individuals leaving their home village to work in a town and later returning to the family, which remains in the village throughout (Coffey et al., 2015). Such migration would not generate post-siting shifts based on living conditions.

We also conduct an additional robustness check using different subsets of our coal plant database over time, and report full results in Appendix Section A7.5. Specifically, we re-estimate our HYSPLIT model on four subsets of coal plants: plants in operation before and after 2001 (the date of the earlier census), and plants in operation before and after 2009 (following a large boom in coal plant construction). We then re-estimate our fully-specified quadratic models using these new HYSPLIT estimates as the main outcome measure, and compare results to our initial results in Section 5.2. If the reverse-causality migration hypothesis is true, then the relationship between 2011 demographics and pollution should be driven by older coal plants, and not recent construction. However we find that across different subsets, the sign and significance of our coefficient estimates are largely unchanged, particularly for the social predictors of illiteracy, scheduled caste, and scheduled tribe. The curve of predicted values are also highly similar between the different subsets. Although we cannot conclusively reject the possibility that migration of disadvantaged individuals to polluted areas occurs, this evidence supports our conclusion that migration itself does not appear to drive our main results.

6. Conclusion

Our above findings demonstrate that concern with environmental

(*footnote continued*)
linear function of the HYSPLIT particle concentrations. As noted above, this is a data limitation, stemming from our lack of reliable data about the makeup of different pollutants from each plant.

[14] However, we should note that a 0.5 ppb level is not very high relative to health standards. This is a result of many of our units being located relatively far away from coal plants, making their total exposure relatively low.

[15] We expect that this estimated variation is conservative due to the relatively low correlation between the HYSPLIT estimated pollution and the total particulate matter.

[16] Bowe et al. (2019) link exposure not only to cardiovascular disease, diabetes, lung cancer, and pneumonia, but also chronic kidney disease, hypertension, and dementia.

[17] It is also notable that the predicted exposure across all demographics exceeds the national ambient air quality primary standards of 12 $\mu g/m^3$ established by the US Environmental Protection Agency.

justice is also applicable to emerging and developing markets such as India. By combining data from the 2011 Census of India with emission trajectory models for India's operating coal-fired power generation fleet, we have found that air pollution from coal-fired power plants is more heavily concentrated in poor, low-caste communities than in their wealthier, high-caste counterparts. Similar to uneven exposure to pollution among minorities and poor households in the United States, India's coal-fired power plants are located such that they exacerbate inequality in the country.

However, we also show that this relationship is likely more complex in the context of the developing world than previous work on the differential impacts of pollution has considered. Specifically, we find evidence for a non-monotonic, inverted u-shape relationship between disadvantaged communities and exposure to coal pollution. This relationship is particularly pronounced for scheduled tribes and castes, two broad categories of ethnic groups in India which have suffered historical patterns of discrimination. While areas with a majority share of scheduled tribes or castes tend to be exposed to more coal plant pollution, this trend is abated somewhat for communities which are overwhelmingly from either type of ethnic group. We argue that this is evidence that in the developing context, some disadvantaged groups will be “spared” from exposure to pollution from heavy industry because they are also systematically excluded from the benefits of these early stages of development.

However, it is important to note that our analysis only focuses on pollution from coal-fired power generation—a concrete source of pollution that is associated with heavy industry and industrial development. While communities with high levels of ethnic groups in India might be excluded from both the benefits and the negative externalities of this type of industrialization, this is not to say that these same groups are similarly spared from exposure to other forms of pollution, such as agricultural chemicals. Further analysis and studies must be done to understand the full degree of exposure to multiple sources of pollution.

To be sure, our work has several limitations that future research should address. For one, our dataset does not allow us to consider the impacts of potential differences in emission controls. Environmental justice scholarship would lead us to expect that our estimates of the unequal pollution burden are underestimated, as wealthy and high-caste communities presumably have greater means to influence environmental regulations in nearby coal-fired power plants. Similarly, the lack of data on the type of coal and the emission control technologies used limits the reliability of our pollution impact estimates. While they are useful for illustration, the estimates are likely to become more precise as better data becomes available. Investigating the implementation and enforcement of environmental regulations and improving the data on coal plant characteristics across India's coal-fired power plants would be a natural next step for environmental justice research in India.

Additionally, we refrain from analyzing the policy and business decisions that lead to this unequal pollution exposure. While the associations between poverty, low status, and exposure are robust, we cannot attribute them to government policy, private sector investment, or collective mobilization by different communities. Theoretical and empirical examination into the causes of this unequal exposure would not only be inherently interesting, but also create an opportunity for policy change, as identifying the root cause of the problem would make solving the problem more tractable.

These limitations notwithstanding, our results also have implications for the emerging environmental justice concerns in India. By documenting unequal exposure to pollution from coal-fired power plants, we provide a solid, evidentiary basis for questioning the way investments in polluting infrastructure are currently made in India. Our results draw attention to the need to consider unequal exposure in regulatory processes such as the environmental impact assessment, and use these considerations to protect the most vulnerable from damaging pollution exposure.

Environmental justice is a pressing concern at a time when environmental degradation threatens the very foundations of human societies, but past research has focused on a narrow range of geographies. We hope that our work inspires future studies of environmental justice in diverse human societies across the Americas, Europe, Asia, Africa, and Oceania. As emerging economies look for ways to stop environmental degradation and minimize the negative externalities of economic growth, focusing on the fair and equal treatment of all people, regardless of their background and social status, is a powerful normative frame for advocacy and action.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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