Does Air Pollution Lower Productivity? Evidence from Manufacturing in India

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October 11, 2018

Abstract

Environmental policy aims to ensure the economic benefits of pollution abatement justify the costs. This calculation is especially challenging when considering how to account for common minor tolls of air pollution that may vary widely in their cumulative impact across the population. In particular, industries risk incurring costs from unhealthy workers and polluted workplaces, yet they differ substantially in their workplace conditions and operating processes. This paper evaluates the extent and variation of these costs across manufacturing industries in India, a setting where air pollution exceeds international guidelines with near ubiquity. I estimate the effect of air pollution on industrial productivity using wind velocity as an instrument for pollution. With firm panel and satellite-derived pollution data, I find air pollution substantially lowered productivity among industries with labor intensive technology, yet I find pollution had little average effect. To understand the sources of variance, I estimate a model of profit maximization that incorporates pollution into production. The model implies that differences in technology contribute to heterogeneity. I estimate that a one standard deviation increase in the labor intensity of production technology leads to a 0.6 percentage point fall in the impact of pollution on productivity. I show that excess pollution results in costly profit reductions among adversely affected industries but little reduction overall.

I would like to thank Andrew Foster, Jesse Shapiro, Matt Turner, Ken Chay, Emily Oster, Lint Barrage, Daniel Björkegren, David Glick, Stefano Polloni, Will Violette, and participants of the Brown Development Economics Breakfast and Applied Microeconomics Lunch for helpful feedback. All mistakes are my own. Contact: `jamie_hansen-lewis@brown.edu`.

1 Introduction

Counteracting negative externalities is a primary rationale for government regulation. It is often the case that the burden of an externality is not shared equally and regulators must determine policy without full knowledge of the distribution of damages. When unobservable damages vary widely, limited knowledge of damages may lead to inaccurate assessments that overstate the cost or fail to find any cost. Moreover, the social costs of correcting such externalities could be substantially lower under policies that target groups with the greatest marginal social benefit relative to policies that ignore the distribution of marginal social benefits.

Air pollution is an important externality with these features. Although some industries may benefit from foregoing abatement investments, many face losses from sick workers and damaged materials. Even with evidence establishing the presence of meaningful occupational health risks, these damages are largely unobserved as they accrue from widespread minor health detriments that would not result in recorded illness, hospitalization, or death.[1] If minor health tolls accumulate across a large economy, air pollution may cause substantial economic losses beyond recorded illnesses. Alternatively, air pollution may present little economic cost beyond recorded illnesses if industries adapt to the presence of minor tolls to prevent cumulative losses. Evaluating the cumulative impact of air pollution on industries is even more difficult if industries vary widely in their ability to adapt or their inherent risk. Thus, it is important to consider the diverse effects across industries over time to understand the economic costs of air pollution.

In this paper, I ask whether air pollution affects manufacturing productivity in India and how much industries vary in their sensitivity to air pollution. In this setting, exposure to air pollution above international guidelines is nearly universal, so a wide range of industries risk losses from unhealthy workers. Air pollution exceeds the World Health Organization (WHO) standards for 99.5 percent of the population and results in premature deaths totaling 2.1 billion life years (Greenstone et al., 2015). The health toll of air pollution in India is estimated to be around 8 percent of GDP (World Bank, 2016). Further, public and political attention to improving air quality is considerable.[2] Existing regulations are weak (Duflo et al., 2013, 2014) and industries stand to benefit from productivity improvements because it lags behind developed countries (Bloom et al., 2010; Hsieh and Klenow, 2009).

While it is plausible the economic implications of air pollution in India are meaningful, a challenge of assessing the costs is defining a reasonable measure of sensitivity. I present a

[1]See Graff Zivin and Neidell (2018) for a review.

[2]Economic Times Bureau (2014); Moham (2015)

model of production with pollution to illustrate how damages from pollution are reflected in manufacturing production and to determine an appropriate benchmark. In the model, the contribution of each input to output is a function of air pollution. The model shows that candidate metrics, such as the effect of pollution on value added per unit labor, conflate the impact of pollution on production with changes in labor intensity and input prices. By contrast, the effect of air pollution on total factor productivity reflects the net impact of pollution on production without the additional input adjustment and price effects present in the effect of air pollution on the average product of labor. A key prediction of the model is that the overall effect of pollution on productivity is a function of both damages to inputs and the production technology. Thus, I expect variation in technology to generate heterogeneity in the impact of pollution on productivity.

To estimate the model, I use a panel survey of manufacturing firms in India. I observe firms annually from 2000/01 to 2009/10 in the Annual Survey of Industries (ASI). While the data report the value of inputs and output, productivity is not readily observable. I use methods developed in Ackerberg et al. (2015) to obtain estimates of the production technology parameters and calculate productivity. The approach relies on the assumptions that firms can readily hire labor and materials with full knowledge of productivity, whereas they determine capital inputs without full knowledge of future productivity.

Given an appropriate metric of sensitivity, the measurement of how air pollution affects productivity is not straightforward. Two challenges I address are poor measures of air quality and confounding factors. Comprehensive measures of air pollution are not generally available during the period of study. The network of public air pollution monitors in India is limited to 140 cities before 2008, leaving large geographic areas where pollution might take effect unobserved (Greenstone and Hanna, 2014; Greenstone et al., 2015). In lieu of monitor data, I use satellite derived measures of air quality from Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth (AOD). AOD is a strong proxy of particulate matter over India (Dey et al., 2012), and daily measurements at fine spatial resolution are available for the entire firm sample.

Moreover, even with perfect data, it is difficult to estimate the causal effect of pollution on productivity. Pollution and productivity both reflect underlying economic conditions. For example, decay of local infrastructure may inhibit connectivity, resulting in lower productivity, as well as add traffic, resulting in higher pollution. To accurately measure the impact of pollution, the econometrician requires a source of variation in air quality that is plausibly exogenous to productivity.

To address bias, I measure the impact of air quality on productivity with an instrumental variables estimation strategy. The strategy isolates variation in pollution unrelated to industrial productivity with annual distribution of wind speed. The wind data come from an atmospheric reanalysis model, the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim (Dee et al., 2011). The data show that wind velocity is strongly negatively correlated with aerosols because wind disperses emitted particulates. I perform additional tests to show that the wind velocity is plausibly not correlated with productivity except through its effect on pollution.

Following the research design, I examine the effect of pollution on manufacturing productivity in three parts. First, I assume the effect is constant and homogeneous and estimate the average impact of pollution on productivity. Second, I allow the impact of pollution to differ arbitrarily across industries. I estimate industry-level impacts of air pollution on productivity and perform an empirical Bayes shrinkage with the industry-specific sensitivity estimates to determine the underlying sensitivity distribution. Third, I measure how industries' technology contributes to heterogeneity using the industry-specific impacts of pollution on productivity. In particular, I examine the role of the labor intensity of production technology in generating sensitivity to air pollution.

The results indicate that air pollution has widely varied impacts that reflect industries' technology. To begin, I find air pollution had little effect on productivity overall. I fail to detect a significant average effect of air pollution on productivity. The confidence interval is precise enough to exclude previous estimates of the effect of air pollution on productivity. When I consider industry-specific impacts of pollution on productivity, I find air pollution negatively affects productivity in a substantial portion of industries. Estimation of industry-specific damages indicates that pollution has a negative toll in industries accounting for 61 percent of output. Further, estimation of the underlying damage distribution confirms significant variance in sensitivity across industries. Last, to identify sources of variation in the damages from air pollution, I find that production technology predicts industries that are sensitive to air pollution. I estimate that a one standard deviation increase in the labor intensity of production technology leads to a 0.6 percentage point more negative impact of pollution on productivity. As further confirmation, I detect a significant negative impact of pollution on productivity among industries with labor intensive technology. This result is consistent with the interpretation that air pollution is a risk to workers' health.

Given the impact of air pollution on productivity, it remains difficult to infer the economic costs of air pollution for the Indian manufacturing sector. To benchmark the welfare implications of air pollution in this setting, I simulate the impact of reducing air pollution to the level of international guidelines on average variable profits. I employ the industry-specific sensitivity estimates in the model of production with pollution to measure counterfactual profits. Across all manufacturing firms, reducing air pollution to the international standard would have led to a significant increase in profits of 0.26 percent, but among sensitive industries it would have led to increases as high as 1.07 percent.

This paper makes four primary advances from prior studies. First, it considers how pollution affects the production function and production function estimation. In contrast to previous research, the model permits firms to differ in their underlying risk and to adjust inputs in response to pollution. This distinction is necessary in a setting where firms are diverse and have time to adapt to the presence of pollution. Second, the evidence of manufacturing-wide impacts in this paper is an important improvement because the set of industries in an economy exhibits a broad range of production technologies, and each industry faces unique risks from air pollution. I show that results for a particular industry are not representative of the overall manufacturing sector. Third, rather than examining the instantaneous impact of pollution on output, this paper explores the effect of increasing the annual average pollution measured over a decade. Consistent with habituation abating the impact over time, the findings imply that the impact of increasing annual average pollution is notably smaller than the effect of day-to-day variation in pollution. Fourth, previous literature relies on the premise that short-term fluctuations in pollution are quasi-random; however, this does not address the possibility that firms sensitive to pollution anticipate and adapt. The instrumental variables approach in this paper addresses bias from firms' anticipation of damages.

While wind has been previously used as an instrumental variable, the formulation I employ is novel. Schlenker and Walker (2015) and Sullivan (2015) use the direction of wind at pollution sources as variation for pollutant concentration at downwind locations; by contrast, I rely on the wind velocity at each location for variation in pollutant concentration at the same location. Since winds affect atmospheric stability and the probability of highly stable conditions that trap pollutants near the surface, my instrumental variable approach relates closely to prior studies that employ atmospheric conditions, inversions, as an instrument for air quality (Arceo et al., 2016; Fu et al., 2017). My approach also draws on the same meteorological principles as Broner et al. (2012) with notable differences in the application. Broner et al. (2012) use a long-term average of meteorological factors as an instrument for cross-sectional variation in environmental regulation; however, I use higher frequency variation wind velocity as an instrument for panel-variation in air quality.

This paper joins two central questions in the study of development and environmental economics. In development economics, much concern has been placed on the causes for low productivity in Indian manufacturing (Sudarshan et al., 2015; Allcott et al., 2016; Hsieh and Klenow, 2009; Bloom et al., 2012). This paper adds to evidence of barriers to production in the developing country context. In environmental economics, a key concern has been measuring the costs of poor air quality. A substantial literature has documented major and minor health tolls of particulate matter pollution. Greenstone and Hanna (2014) and Cropper et al. (2015) collect evidence for India specifically. Previous research on worker productivity has further substantiated the premise that air pollution has meaningful impacts on workers in the United States (Chang et al., 2016; Graff Zivin and Neidell, 2014, 2012; Ostro, 1983), Germany (Lichter et al., 2017), China (Chang et al., 2016; Fu et al., 2017; Li et al., 2015), Mexico (Hanna and Oliva, 2015), Peru (Aragón et al., 2017), and India (Adhvaryu et al., 2014). While existing work has demonstrated a pollution productivity relationship in diverse settings, prior publications report the impact of pollution for individual workers with detailed data at a single plant or location and short term exposure to air pollutants. By contrast, this paper comprehensively estimates the effect of pollution on productivity across all manufacturing industries in a developing country.

2 Data and Background

2.1 Firm Survey

Data on firms are from the Annual Survey of Industries (ASI), a large administrative survey on firms in India. The ASI is a panel of registered firms for 1995-2011. I employ a 10 year sample from 2000-2001 to 2009-2010 inclusive. The ASI provides the most comprehensive source available on firm attributes in this context and time frame. The data have been used previously to study the productivity of Indian industry in Martin et al. (2017), Allcott et al. (2016), and Hsieh and Klenow (2009) among others.

While the ASI is the main source of industrial statistics for the setting, the sample coverage requires a few important qualifications. The survey does not include a few states and territories: Arunachal Pradesh, Mizoram, Sikkim, and Lakshadweep. The survey also does not include unregistered firms, the "unorganized" manufacturing sector. Although by number the ASI sample of registered firms covers only roughly 37 percent of industrial firms, its sample accounts for 94 percent of value added per worker by manufacturing industries while the unorganized sector accounted for 6 percent. The unorganized manufacturing sector is composed of mainly small firms with fewer than two workers. The ASI covers all establishments with over 50 workers. Further, its sample better represents heterogeneity in firms' number of employees, fixed capital, and output compared to the unorganized manufacturing sector. Manna (2010) provides these comparisons for 2005/06, the only year in the sample data was collected for unorganized manufacturing.

I made several important decisions in the preparation of the data. First, the data do not distinguish a plant from a firm so I assume they are equivalent. Second, I use survey weights so the sample is representative of the firm population. For the most part, firms with over 100 employees were surveyed every year and smaller firms were surveyed according to a random sample. However, the details of the sampling design changed from year to year. As a result, I weight firms by the average value of the weighting variable over the time periods. I report robustness checks to show that the results are not sensitive to the firm weights. Third, the classification of industries and industry codes changed twice during the sample so I aligned them manually. Fifteen industries did not include enough firms to estimate the capital factor share. After this procedure, my sample included 150 unique industries.

From the firm observations, I construct the location, inputs, and output of each firm for each year. The firm observations can be located geographically in one of 524 districts, the administrative division below a state. I map all observations to 2001 administrative districts via name and 2001 census code because the district boundaries changed during the period of study. After 2009-2010, the ASI no longer reports the district so I include only the prior periods in the analysis. The main variables are the gross revenue, capital stock, labor cost, input materials cost, investment, and number of workers. Since firms report the monetary values of inputs and outputs instead of quantities, I deflated monetary amounts to quantities with prices. Further, outliers were removed to correct irregularities.[3] I report firm descriptive statistics of firms in the sample in Table A1.

[3]This preparation replicates the preparation of Allcott et al. (2016). In particular, I repeat their procedures to align industrial codes to the classification of 1987 at the 3-digit level, deflate values to quantities, and remove outliers.

2.2 Air Quality

In lieu of ground monitor data, I obtained information on air quality from Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth Product (AOD). [4] Aerosols are measured from the MODIS sensor of the Terra satellite. MODIS features a 2330km wide swath, twice daily coverage, and high spectral resolution which enables it to detect clouds and aerosols better than previous instruments. The data have a spatial resolution of 10 km per pixel. MODIS reports AOD on a log scale of 0 to 5. AOD below 0.1 is considered to be clear and the maximum possible AOD of 5 indicates that sunlight cannot pass through the air. Prior research on the effects of air pollution has previously employed MODIS AOD (Foster et al., 2009; Greenstone et al., 2015; Gendron-Carrier et al., 2017).

There are several important differences between AOD and traditional air quality monitor data. First, while air quality monitors track a variety of pollutants, aerosols measure only suspended particulates. Thus, AOD proxies for fine and course particulate matter and does not represent of other pollutants such as ozone or sulfur and nitrogen oxides. Second, whereas ground monitors measure air quality on the surface, satellites measure air quality for the entire atmospheric column. A high measurement of AOD does not imply that there was high exposure to aerosols at the surface if the distribution of aerosols in the atmospheric column is not uniform. Last, monitors are available for only a limited set of locales in India; by contrast, AOD offers universal spatial coverage.

Despite the differences between AOD and traditional monitor data, AOD is a valid and well-established proxy for surface air quality. Research in atmospheric science has validated MODIS AOD as a measure of ground-level fine particulate matter globally as well as over India.[5] To supplement these studies, I conducted two validation exercises. First, I relate AOD to historical recordings from the Central Pollution Control Board (CPCB) ground monitors (CPCB data in Greenstone and Hanna (2014)). Figure 1a demonstrates a strong correlation between AOD and the level of suspended particulate matter (SPM) from ground monitors. Second, I relate AOD to estimated ground-level fine particulate matter (PM2.5) from Van Donkelaar et al. (2016). Van Donkelaar et al. (2016) produce estimates of ground-level PM2.5 concentrations for the entire globe at 0.01 degree resolution for each calendar year. Their method combines information from multiple satellites, ground monitors, and chemical transport models for atmospheric

[4] I employ the data collected in Gendron-Carrier et al. (2017).

[5] See Remer et al. (2005, 2006); Ten Hoeve et al. (2012); Guazzotti et al. (2003); Dey et al. (2012).

composition.[6] Figure 1b also demonstrates a strong correlation between AOD and the surface PM2.5 as estimated in Van Donkelaar et al. (2016). It shows that for a one unit increase in mean AOD the average change in mean PM2.5 was 108 micrograms per cubic meter (μgm^{-3}). The consistency of these findings indicates that AOD is a strong proxy for variation in air quality with the additional advantages of consistent measurement and universal spatial coverage over the period of study.[7]

I take several steps to further ensure the AOD data are a valid representation of ground-level fine particulate matter. I account for the strong seasonal patterns air pollution exhibits in India. Since precipitation removes particulates from the air, air quality is much higher during the summer monsoon than during the winter. July and August are the peak of the monsoon season in India and AOD is infrequently observed during this period. To address this, I calculate the district annual mean AOD excluding the months of July and August to ensure that missing data from precipitation do not bias the measurement of AOD. I further limit the sample to district-years were there at least one AOD observation for all other months to reduce bias from missing months. I include additional controls in the analysis for the atmospheric conditions, in particular the vapor pressure, that influence the concentration of aerosols at the surface.

Figure 2 presents the district mean AOD during the period of study. It demonstrates that the AOD data are consistent with the main descriptive features of air pollution in India. Across India, AOD exceeds the clear air level of 0.1. The mean AOD is 0.41 (Table 1). Due to inversions and inland accumulation, air pollution is much worse in the north. Urban centers also have poor air quality: the highest annual averages are consistently in Delhi.

2.3 Weather

The traditional approach to construct wind data would be to collect observational data from weather stations and interpolate the observations with a statistical procedure. However, like the network of air quality monitors, public weather station data for this setting is limited: wind is measured at least once per year at less than 150 stations in India in some years of the sample.[8] Interpolation across stations could yield substantial measurement error Dell et al. (2014).

I use atmospheric reanalysis data to measure annual mean wind velocity in lieu of weather station monitors. Atmospheric reanalysis data are gridded records of meteorological variables

[6] Since the Van Donkelaar et al. (2016) estimates correspond to the calendar year while the firm data correspond to the ASI year, it is not feasible to use only Van Donkelaar et al. (2016) for annual PM2.5 measurements.

[7] In A1.2, I provide addition background on satellite measurements of aerosols.

[8] Available at `http://www7.ncdc.noaa.gov/CDO/cdoselect.cmd`.

derived from both observational data and a meteorological model. Given the drawbacks to wind station data, there are two distinguishing advantages of reanalysis data. First, while traditional gridded data interpolate observations with a statistical procedure, reanalysis data interpolate observational data with a climate model (Dell et al., 2014). Second, reanalysis data integrate more observational sources than an individual researcher could possibly collect. The sources include radiosondes, satellites, buoys, aircraft and ship reports, and other sources from within the area of interest and elsewhere (Dee et al., 2016). Reanalysis data provide comparable measurements over the entire sample and are well-vetted in scientific research (Dee et al., 2016, 2011).

For the main analysis, I focus on the yearly distribution of wind velocity. Surface wind velocity was constructed from ECMWF ERA-Interim (Dee et al., 2011).[9] The dataset provides the monthly mean component vectors of wind at 10 meters above the surface in 0.75 degree girds. For each month, I calculate the magnitude of the wind vector, wind speed, in each grid cell and average over the geographic district. A potential concern is spatial dependence of observations for different districts within the same grid cell. Although this arrangement is uncommon in the sample, I repeat the main results with standard errors clustered at the state level to address potential dependence.[10]

Annual variation in the yearly distribution of wind speed is an important feature of wind in this setting. As with unseasonably warm or cold years, annual periods exhibit substantial variation in wind velocity. Figure 4 reports the average annual deviation from the mean wind velocity in the sample. The data indicate that annual average wind velocity is fairly variable. The average annual percent change in wind velocity was 3.6%. The annual wind velocity often deviated by over 10 percent of the overall mean for many districts in the sample. Wind varies even more at higher temporal frequencies. Figure 3 depicts a histogram of the mean wind velocity for each district-month observation. The median district-month had mean wind velocity of 1.26 meters per second (m/s). Throughout the analysis, I use the mean temperature, precipitation, and vapor pressure; squared mean temperature, precipitation, and vapor pressure; and interactions of mean temperature and vapor pressure with mean precipitation for each season as the meteorological controls.

To improve the analysis of wind and air quality, I also employ data on temperature, precipitation, and vapor pressure. Temperature and precipitation were obtained as monthly mean and

[9] I obtain the ERA-Interim monthly mean surface-wind from Wentz and J. Scott (2015).

[10] To summarize the count of grid centroids per district: 39 percent of districts do not contain grid centroid, 46 percent have one, and 15 percent have more than one. Clustering at the state level is a more conservative approach than clustering at the grid point as it also allows for spatial correlation within a state Bester et al. (2016).

monthly total respectively in 0.5 degree grids from Willmott and Matsuura (2015). Monthly vapor pressure was also obtained in 0.5 degree grids from CRU TS Harris et al. (2014). Since the impact of meteorology on air quality and firms in India varies seasonally, I computed the district mean of each meteorological control variable for each of seasons January-March, April-June, July-September, October-December. Table 1 reports descriptive statistics of wind and weather controls.

3 Production Model

To illustrate how air pollution affects productivity and production, I model a firm with Cobb-Douglas production facing pollution. The model allows unstructured heterogeneity across industries in the impact of air pollution on total factor productivity. The impact of air pollution on total factor productivity differs from the impact on labor productivity because firms may change input intensities in response to air pollution.

3.1 Production with Pollution

Each firm f is a member of industry i, located in district d, and observed in year t. Firms produce output that is sold on a perfectly competitive market to obtain revenue Y. The inputs to production are labor L, capital K, and materials M. Air pollution, A, and total factor revenue productivity (TFPR) absent pollution, $\tilde{\Omega}$, also contribute to revenue. The annual revenue Y is a Cobb-Douglas function of inputs, TFPR, and air pollution:

$$Y_{fidt} = A_{dt}^{\lambda_{it}} \tilde{\Omega}_{fidt} L_{fidt}^{\beta_{Lit}} K_{fidt}^{\beta_{Kit}} M_{fidt}^{\beta_{Mit}}. \tag{1}$$

I assume firms cannot control their average ambient air quality A_{dt}.[11] Since I observe neither the indoor pollution for each firm nor the production on each day, I focus on the role of the annual average outdoor air quality in the broad vicinity d of the firms. This formulation is appropriate for considering the effect of an externality.

The key distinction in this model is the inclusion of air quality as an additional factor in production. Air pollution affects revenue though the sensitivity λ_{it}. The sensitivity to air pol-

[11] This assumption is consistent with studies of pollution source apportionment in India. Industry contributes around 10% to particulate matter pollution and weather plays a large role in average concentration of particulates (Chowdhury et al., 2007). Further, this assumption is appropriate for measuring the impacts of air pollution externalities. Firms may make production decisions that determine their indoor air quality; however, the air pollution within the firms' control is not an externality.

lution varies arbitrarily across industries and time. The inclusion of air quality as a factor in a Cobb-Douglas function supports several interpretations of how air quality affects firms. For example, if air pollution made hired workers less productive, as would be the case if workers took additional breaks or were slower as a result of pollution, λ_{it} would be negative. Likewise, if air pollution caused contamination of materials or output prior to sale, then λ_{it} would be negative.[12] If air quality has no effect, λ_{it} is zero.

Firms' objective is to maximize profits. They select the level of inputs $\{L_{fidt}, K_{fidt}, M_{fidt}\}$ to optimize:

$$\Pi_{fidt} = Y_{fidt} - p^L_{fidt} L_{fidt} - p^K_t K_{fidt} - p^M_{fidt} M_{fidt} \tag{2}$$

where $p^L_{fidt}, p^K_t, p^M_{fidt}$ represent prices for labor, capital, and materials respectively. For given parameters and sensitivity, firms' optimal production and input decisions are functions of prices and air pollution: $L^*_{fidt}(A_{dt})$, $M^*_{fidt}(A_{dt})$, $K^*_{fidt}(A_{dt})$, and Y^*_{fidt}.[13]

3.2 Impact of Pollution on Production

An increase in air pollution affects firms revenue along several dimensions. First, akin to an intensive margin, air pollution affects the TFPR. Define the TFPR in logs with lowercase variables to denote the log of each quantity:[14]

$$\omega_{fidt} = \lambda_{it} a_{dt} + \tilde{\omega}_{fidt}. \tag{3}$$

The impact of air pollution on log TFPR is the sensitivity λ_{it}:

$$\frac{d\omega_{fidt}}{da_{dt}} = \lambda_{it}. \tag{4}$$

Second, akin to an extensive margin, air pollution affects revenue because it changes the optimal level of the inputs:

$$\frac{dy_{fidt}}{da_{dt}} = \lambda_{it} + \beta_{Lit} \frac{\partial \ell_{fidt}}{\partial a_{dt}} + \beta_{Mit} \frac{\partial m_{fidt}}{\partial a_{dt}} + \beta_{Kit} \frac{\partial k_{fidt}}{\partial a_{dt}}. \tag{5}$$

Adjustments in inputs to maximize profits imply that an increase air pollution need not have the same effect on TFPR and labor productivity. For example, given a decline in productivity

[12] This has been documented in the Indian salt industry (Praveen, 2015).

[13] I excluded $\{p^L_{fidt}, p^K_t, p^M_{fidt}\}$ to simplify the notation.

[14] In levels, the definition of TFPR is: $\Omega_{fidt} = \frac{Y_{fidt}}{L^{\beta_{Lit}}_{fidt} K^{\beta_{Kit}}_{fidt} M^{\beta_{Mit}}_{fidt}} = A^{\lambda_{it}}_{dt} \tilde{\Omega}_{fidt}$.

and no change in input prices, the firm lowers all inputs, and the effect of pollution on labor productivity is greater than the effect on TFPR. Similarly, pollution may have no effect for firms in a particular industry and time period, $\lambda_{it} = 0$, yet lead to an increase in revenue if input prices fall. The extent to which inputs and output adjust to air pollution may depend on many conditions that are not explicitly modeled, such as the structure of the input markets, firms' costs to adjusting inputs, and the time horizon. In the short run limit, input adjustments are not feasible, so the impact of pollution on TFPR, labor productivity, and output are equivalent.

4 Estimation

4.1 Production Function Estimation

The impact of pollution on log TPFR ω_{fidt} is of interest, yet the production function parameters $\{\beta_{Lit}, \beta_{Kit}, \beta_{Mit}\}$ must be estimated to compute the TFPR. I use the method developed in Ackerberg et al. (2015) to estimate the production function parameters. Firms face constraints on their information set and input choice set when determining the optimal level for each input. As with other research with this dataset, I assume throughout that the firm observations are plants.

Static Inputs

Labor and materials are static inputs. I assume the plant can hire labor and materials from perfectly competitive factor markets without any adjustment cost. At time t, plants select their optimal level of labor and materials knowing their TFPR Ω_{fidt}, sensitivity λ_{it}, and air pollution A_{dt}.

At the optimal levels of labor and materials, the profit maximization first order conditions imply:

$$\beta_{Lfidt} = \frac{p^L_{fidt} L_{fidt}}{Y_{fidt}}$$

$$\beta_{Mfidt} = \frac{p^M_{fidt} M_{fidt}}{Y_{fidt}}.$$

Since I observe cost of labor and materials for every firm, I compute the parameters β_{Lfidt} and β_{Mfidt} directly from the formula for each firm. In the analysis that follows, I assign each firm the industry median factor share with a time trend β_{Lit} and β_{Mit} to smooth over idiosyncratic constraints to static profit maximization.[15]

Non-Static Inputs

The static input approach is both infeasible and inappropriate to measure β_{Kit}.[16] To begin, the dataset does not include firm-level interest rates so the first-order condition approach would introduce noisy proxies of investment costs. Relatedly, any exit of unproductive firms would imply selection bias. In addition to data limitations, the assumption that firms create and destroy capital instantaneously is implausible: it requires time to accumulate. It is also implausible to assume under profit maximization that capital inputs and productivity are exogenous. Under these conditions, neither the first-order condition approach nor a regression of log output on log capital would produce consistent estimates of the capital factor share.

In lieu of the static inputs approach, I estimate β_{Kit} with GMM following Olley and Pakes (1996) and Ackerberg et al. (2015). At time t, plants select their optimal capital stock for time $t+1$ without full information of their future TFPR Ω_{fidt+1} and air pollution A_{dt+1}. I assume that the returns to capital do not change over time, $\beta_{Kit} = \beta_{Ki}$ and I leverage unanticipated productivity shocks and past capital and investment to identify β_{Ki}.

Specifically, I impose three assumptions on the joint evolution of productivity and capital accumulation. First, capital takes one year to build. Current capital is a function, κ, of the previous period's capital and investment, $\mathcal{I}$, in logs.

$$k_{fidt} = \kappa(k_{fidt-1}, \mathcal{I}_{fidt-1}). \tag{A1}$$

(A1) is similar to the first-stage of an instrumental variables approach. Past investment predicts future capital. Second, productivity follows an AR(1) process, with unanticipated shocks ξ_{fidt}:

$$\omega_{fidt} = \rho_i \omega_{fidt-1} + \xi_{fidt}. \tag{A2}$$

(A2) isolates the shocks to productivity ξ_{fidt} that firms are not aware of when they set capital investment. While the AR(1) assumption deviates from Ackerberg et al. (2015) in that it is less flexible than assuming capital follows a generic non-linear process, it is common in previous

[15] This steps aligns with previous estimation of the production function in this setting and others (Allcott et al., 2016; Syverson, 2011).

[16] The concerns and solutions outlined here are well-established in the literature of production function estimation. In particular, Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015).

estimation with the ASI (see Collard-Wexler and De Loecker (2016); Allcott et al. (2016)). Last, firms set past capital without full knowledge of transitory productivity shocks:

$$E(\xi_{fidt}k_{fidt-1}) = 0. \tag{A3}$$

(A3) follows the approach of Olley and Pakes (1996); Ackerberg et al. (2015) to address the endogeneity of input choices to productivity. As an alternative to (A3), in robustness exercises I employ the assumption that firms set past investment without full knowledge of productivity shocks $E(\xi_{fidt}\mathcal{I}_{fidt-1}) = 0$ (Collard-Wexler and De Loecker, 2016). (A3) is akin to the exclusion restriction of an instrumental variables approach. It implies that productivity shocks ξ_{fidt} are not the deterministic and not related to prior capital investment decisions. Since air pollution is a component of productivity, an important implication of (A2) and (A3) for the research design is some variation in air pollution is also not deterministic and not related to prior capital investment decisions.

Under these conditions, I estimate β_{Ki} for each industry i with Generalized Method of Moments (GMM). I first rewrite production net the contributions of labor and materials:

$$\hat{y}_{fidt} = y_{fidt} - \beta_{Lit}\ell_{fidt} - \beta_{Mit}m_{fidt}$$

and I substitute so that for a given $\hat{\beta}_{Ki}$

$$\hat{\omega}_{fidt} = \hat{y}_{fidt} - \hat{\beta}_{Ki}k_{fidt}.$$

Second, I estimate the AR(1) coefficient of productivity with ordinary least squares

$$\hat{\omega}_{fidt} = \alpha_i + \rho_i\hat{\omega}_{fidt-1} + \xi_{fidt},$$

and compute the residuals ξ_{fidt}. Finally, drawing from the moment condition (A3), I select β_{Ki} to minimize the criterion

$$Q(\beta_{Ki}) = (\iota'\xi)'(\iota'\iota)^{-1}(\iota'\xi)$$

with ι = matrix of constant and k_{fidt-1} and ξ = vector of ξ_{fidt}.[17]

[17] The estimation is completed separately for each three digit industry. For example, for garment making, NIC = 265, there are 6573 firm-years of which 3639 have lagged capital, investment, and predicted productivity $\hat{\omega}$. Thus ι_{fidt-1} is 3639×2 and ξ_{fidt} is 3639×1.

Production Function Estimates

Table 2 reports summary statistics of the estimated production function parameters. The median labor share β_{Lit} is 0.07. The median capital share β_{Ki} is 0.18. The median materials share β_{Mit} is 0.68. The average log total factor revenue productivity, ω_{fidt}, is 2.55. These estimates closely replicate prior estimates in this sample (Allcott et al., 2016; Collard-Wexler and De Loecker, 2016). I cannot reject constant returns to scale.

4.2 Identification Using Wind Velocity

I wish to test whether $\lambda_{it} < 0$; however, a measurement problem arises. Specifically, were I to estimate λ_{it} from a regression of Equation 3, I would expect the residuals to be correlated with pollution: $E(\tilde{\omega}_{fidt} a_{dt}) \neq 0$. For example, the addition of nearby transportation infrastructure could raise productivity and pollution from traffic, so the resulting estimates would understate the impact of pollution on productivity. Besides the concern that pollution is endogenous, pollution measured with AOD includes measurement error. In turn, measurement error leads to attenuation bias. To address these concerns, I use the distribution of wind velocity as an instrument for air pollution.

First Stage

There is a strong scientific rationale that wind velocity is a key factor in the atmospheric concentration of particulates. Wind speed and direction are fundamental to determine how pollutants are spatially disbursed once emitted.[18] First, winds disburse pollutants over a wider horizontal area than weak winds. Second, winds increase vertical circulation of the air. More vertical mixing of the air allows pollutants to disburse to higher altitudes and lowers the concentration of pollution at the surface. Relatedly, air mixing evens the temperature in the atmospheric column and prevents the formation inversions, a condition where steep temperature gradients keep pollutants trapped near the surface. The impact of wind velocity on reducing pollution concentration is greater at higher wind velocities. Previous studies of air quality and meteorology in India and elsewhere give credence to these principles (Guttikunda and Gurjar, 2012; Larissi et al., 2010; Arceo et al., 2016).

[18] An accessible overview of atmospheric particulate transport, including the "Puff" model, in Jacob (1999) Chapter 3. In the related "Box-model" of pollution dispersion, winds are inversely proportional to pollution concentration. Jacob (1999), Chapter 4 describes the impact of wind and the vertical temperature gradient on air quality.

Figure 5 shows that the frequency of high aerosol concentration observations is lower in the half of the sample with high wind speeds. The figures display histograms of annual mean AOD for district-years with below the median of annual mean wind velocity and above the median respectively. Moving from below to above the 50th percentile of annual mean wind velocity results in a 0.91 standard deviation decrease on average in annual AOD.

For the main analysis, I use a semi-parametric first stage because scientific evidence establishes the relationship between air quality and wind velocity is not linear. I estimate the first stage with a step function of monthly district mean wind velocity.[19] I fit the following equation for each firm f in industry i, district d, and year t:

$$a_{dt} = \sum_j \theta_j V_{dtj} + \delta X_{dt} + \tau_t + f_{fid} + r_{fidt}. \tag{6}$$

a_{dt} is the AOD in district d year t. The variables V_{dtj} are the number of months in district d during year t for which the monthly mean wind velocity was in the jth interval of the wind velocity domain. The intervals of monthly district mean wind velocity are depicted in Figure 3. I include additional controls, X_{dt}, for the seasonal means, polynomials, and interactions of weather variables as well as fixed effects for the firm, year, and state by year trends. Firm-year AOD shocks are r_{fidt}.[20]

Figure 6 confirms that the relationship between air quality and wind velocity is both highly significant and non-linear. It plots the coefficients θ_j of the step function. Each coefficient represents the effect of an additional month with mean wind velocity in the corresponding interval on annual mean AOD relative to an additional month with mean wind velocity less than 0.6 meters per second (m/s). A month with mean wind velocity from 1.5 to 1.8 m/s lowers the annual mean AOD 0.0039 units (roughly 0.4 μgm^{-3}) relative to a month with mean wind velocity less than 0.6 m/s. Consistent with a nonlinear relationship, a month with mean wind velocity from 2.7 to 3.0 m/s lowers the annual mean AOD 0.0076 units (0.8 μgm^{-3}) relative to a month with mean wind velocity less than 0.6 m/s. I reject the null hypothesis that the θ_j

[19]Equation 6 follows Deschênes and Greenstone (2011) to permit for a flexible relationship between annual AOD and wind velocity. It classifies the underlying district-month wind velocity data so that high-wind months may impact the annual mean AOD differently than low-wind months. I selected this specification over specifications with polynomials of the annual mean wind velocity because it minimized the Bayesian information criterion. Permitting the non-linear first stage yielded qualitative differences relative to a linear specification in subsequent results. I provide comparisons with linear instrumental variables estimates for the main results in robustness exercises.

[20]The first stage is performed at the firm-year level with dependent variable at the district-year level to maintain consistent weighting of firms throughout. The first stage remains highly significant when estimated at the district-year level.

are jointly equal to zero ($p < 0.001$).[21] I also reject the null hypothesis that the θ_j are equal (p <0.001).

Exclusion Restriction

The assumption underlying the instrumental variables approach is that the district-year distribution of wind velocity is not correlated with manufacturing productivity through channels other than air pollution conditional on the controls. In terms of the model, Equation 3, and first stage, Equation 6, this assumption implies $E(\tilde{\omega}_{fidt}\boldsymbol{V}_{dt}|\boldsymbol{X}_{fidt}) = 0$. The production function estimation imposes additional restrictions on the instrument: variation in the distribution of wind velocity needs to be consistent with the presence of an unanticipated shock to productivity. As a condition for estimating the capital share, I assumed firms do not have prior knowledge of some component productivity, ξ_{fidt}. To remain consistent with this assumption, firms must also not have full anticipation of how winds affect pollution since pollution is a component of productivity. In particular, assuming i) productivity shocks are unknown to firms when they determine capital investment and ii) firms do not fully anticipate the future impact of wind on pollution implies that the contribution of winds to air pollution must be independent of past capital investment decisions.

While it is not possible to formally test the relationship between winds and unobservable components of productivity, the assumption is justified for several reasons. Firms, politicians, and people cannot manipulate wind velocity and changes in the distribution of wind velocity are difficult to accurately predict. Even if firms avoid pollution by locating upwind from a source, they cannot avoid changes in pollution that arise from variable wind speeds since they can neither control nor anticipate those changes. Figure 7 demonstrates this characteristic of the distribution of wind velocity. It plots the coefficients θ_j of the first stage regression (Equation 6) with the future change in AOD as the dependent variable. While the F-statistic is modestly significant, the trend shows that an additional month with any particular wind velocity does not change the trend in AOD next year relative to a month with near zero wind velocity. This evidence indicates firms cannot foresee how the trend in AOD will change in the next year knowing winds in the current year.

Table 3 further demonstrates that variation in AOD predicted from distribution of wind velocity is consistent with the validity criteria. The regressions mirror the second stage: each

[21] As an additional check, I repeat this test clustering the standard errors at the state level. Again, I reject the null: $p = 0.0056$.

dependent variable is regressed on the predicted AOD from Equation 6 with controls X_{dt} and fixed effects τ_t and f_{fid}. Each column reports the predicted AOD coefficient. Columns 1 and 2 report that predicted AOD in t has no effect on log capital and log investment in $t-1$. Consistent with assumption (A3), this indicates that knowledge of the wind distribution did not lead firms to anticipate future AOD when they made production and investment decisions. A further possible concern is that the instrument is correlated with unobserved features of the economy that the make production, and potentially productivity, more or less appealing for firms. To examine this, column 3 shows that predicted AOD is not correlated with the number of firms in a district-year.

The relationship between wind velocity and other meteorological and economic factors might also factor in the instrument's validity. One plausible channel is that wind is correlated with temperature and rainfall, as all are components of the monsoon, and these variables could influence productivity independently of air quality.[22] To account for these potential effects, I include controls for flexible functions and interactions of seasonal weather in the analysis. Another plausible channel is that winds might influence agricultural production and the agricultural sector may have some economic spillovers to the manufacturing sector. Empirical evidence establishing this concern is limited.[23] Further, Table 3 column 4 shows that predicted AOD fails to explain log wheat production. Nevertheless, I include additional robustness exercises separating rural and urban firms and controlling for wheat yields to examine this implications of this possibility on the results.

5 Impact of Air Pollution on Productivity

I examine the impact of air pollution on productivity varying the assumptions of how the effect may differ across industries in Equation 1. I start with the assumption that $\lambda_{it} = \lambda$ so impact of air pollution on productivity is constant and homogeneous. I subsequently assume that $\lambda_{it} = \lambda_i$ so the impact of air pollution on productivity is heterogeneous across industries and constant within industries.

[22] I provide more background on the sources of wind variation in the Appendix A2.2.

[23] Foster and Rosenzweig (2004) find that improvements in agricultural yields do not lead to growth in rural industry. Santangelo (2016) finds spillovers from agriculture to manufacturing only for manufacturing firms producing local goods. Neither study looked specifically at TFP spillovers.

5.1 Homogeneous Pollution Sensitivity

Reduced Form Evidence

Figure 8 shows the effect of the distribution of wind velocity on log TFPR, ω_{fidt}. Like the first stage, the plot depicts the coefficients θ_j from fitting Equation 6 with ω_{fidt} as the dependent variable. Each coefficient represents the effect of an additional month with mean wind velocity in the corresponding interval on ω_{fidt} relative to an additional month with mean wind velocity less than 0.6 m/s. The coefficients are multiplied by 100. While I reject the null hypothesis that the coefficients are jointly equal to zero ($p < 0.01$), the reduced form estimates show that additional months of comparatively high wind velocity do not raise productivity even as they consistently reduced annual mean AOD. For example, an additional month with mean winds between 1.8 and 2.1 m/s raised productivity 0.09 percent relative to a month with mean winds less than 0.6 m/s. An additional month with mean winds over 3 m/s resulted in an even greater reduction in annual mean AOD but still had no significant improvement in productivity. The negative point estimate even indicates a decrease in productivity. The lack of consistent increases in productivity from additional months with very high winds indicates that winds do not effect productivity even if they have a strong effect on AOD.

Instrumental Variables Estimates

I fit the following second stage equation to estimate the effect of pollution on productivity under the assumption of homogeneous effects:

$$\omega_{fidt} = \lambda \hat{a}_{fidt} + \alpha X_{dt} + f_{fid} + \tau_t + \epsilon_{fidt} \tag{7}$$

with log TFPR ω_{fidt}, predicted AOD $\hat{a}_{fidt}$ from Equation 6, firm fixed effects f_{fid}, year fixed effects τ_t, and additional controls X_{dt}.[24]

Several features of this specification ensure consistent estimation. First, the inclusion of predicted AOD from the first stage in lieu of observed AOD removes the components of AOD endogenous to productivity provided the exclusion restriction is satisfied. Specifically, given $E(\tilde{\omega}_{fidt}\boldsymbol{V}_{dt}|\boldsymbol{X}_{fidt}) = 0$, then $E(\hat{a}_{fidt}\epsilon_{fidt}|\boldsymbol{X}_{fidt}) = 0$. Second, firm fixed effects control for time invariant features of each firm that affect productivity and might be correlated with air pollution, such as a firm's location, industry, and average characteristics. Given the fixed effects,

[24] While AOD varies at the district-year level, a_{dt}, the first stage is fit at the firm-year level to remain consistent with the second stage. Accordingly, the predicted AOD varies at the firm-year level, $\hat{a}_{fidt}$.

the estimates reflect the average impact of annual changes in air pollution on productivity within each firm. I also include the control variables X_{dt} for seasonal weather and state-time trends.

Consistent with the reduced form, Table 4 column 1 shows that AOD did not have a significant average effect on manufacturing productivity. The estimated λ implies a 0.01 unit increase in AOD resulted in an 0.19 percent increase in TFPR. The effect is not statistically distinguishable from zero. In units of fine particulate matter, the estimate indicates that a one μgm^3 increase in PM2.5 resulted in a roughly 0.18 percent decrease in productivity. Adjusting for the mean AOD the estimate implies an elasticity of -0.077 percent change in productivity per percent rise in aerosols. The lower bound of the 95 percent confidence interval implies a one μgm^3 increase in PM2.5 resulted a 0.67 percent decrease in productivity on average at most.[25]

To further inspect the result of Table 4 column 1, I repeat the estimation under several alternative assumptions. I provide more details of the checks in section A2.3 and report the results in Table A2. In all scenarios, I fail to detect a significant deviation in the effect of pollution on manufacturing productivity. To summarize, I check that the preparation of the data and estimation of the production function parameters did not influence the findings. I also consider the details of the instrumental variables approach. I show the results assuming the first stage is linear. To ensure that selection is not driving the results, I use a control function approach to instrumental variables with controls for polynomials of the first stage residuals and interactions of the residuals with AOD. I also repeat the results splitting the sample by rural and urban firms to examine how proximity to agriculture drives the results. Finally, I find that adjusting the standard errors for spatial dependence at the state-level does not substantially reduce the precision.[26]

Three distinct characteristics of the setting may explain why the data indicate a negligible effect of air pollution on productivity even when prior research has documented a robust negative relationship. First, the estimate represents the impact of annual variation in air quality whereas prior studies measured the impact of daily variation in air quality. For example, Chang et al. (2016) consider the effect of PM2.5 on productivity at the level of the worker-day for a pear

[25] The sample is large enough to distinguish small estimates from zero. As a benchmark, under a mean log productivity of 2.55 and standard deviation of 1.28, the minimum detectable coefficient with 95 percent power and district clustering is 0.05, roughly one quarter of the estimate. So even with adequate power to detect a small effect and attention to eliminating the main sources of bias, the data did not bear evidence that air pollution lowers TFPR.

[26] An additional concern is that Equation 7 obscures a nonlinear relationship between AOD and productivity. Since the reduced form Figure 8 allows for nonlinearity, yet does not detect a substantial effect of wind, and hence AOD, fitting a nonlinear second stage presents the risk of detecting a spurious relationship between AOD and productivity that reflects the functional assumptions rather than the patterns in the data. Thus, I do report additional variations of Equation 7 with nonlinear AOD in the robustness exercises.

packing plant in California. At 20 μgm^{-3} their estimates imply that an additional one μgm^{-3} in PM2.5 lowers productivity 1.3 percent.[27] By contrast, the lower bound of Table 4 column 1 implies a one μgm^3 increase in PM2.5 resulted a 0.67 percent decrease in productivity, roughly half the benchmark. Over the longer time periods, workers and firms have the opportunity to adjust or simply habituate to the presence of air pollution.[28] Given some adaptation, the impact of pollution from one year to the next would be smaller than the impact from one day to the next.

Second, the outcome of interest, total factor productivity, has not been studied separately from labor productivity in prior work. While this distinction is not appropriate for comparing Table 4 column 1 to studies of short run effects of air pollution such as Chang et al. (2016), it is a reasonable concern for comparisons to settings where firms had time to adjust input intensities.[29] For example, Fu et al. (2017) estimate that a one μgm^{-3} increase in annual mean PM2.5 lead to a 0.85 percent decrease in value added per worker in Chinese industries. For comparison, Table 4 column 2 repeats column 1 with log value added per worker (ln LP), a common measure of labor productivity, as the dependent variable.[30] The estimate signifies that a 0.01 unit increase in AOD resulted in a statistically significant decline in labor productivity of 1.3 percent. In units of PM2.5, this effect translates to a 1.2 percent decline for a one μgm^3 increase in PM2.5.[31] Similarly, column 3 repeats column 1 with log value of output (ln Y) as the dependent variable. The estimate signifies that a 0.01 unit increase in AOD resulted in a statistically significant decline in revenues of 1.4 percent (or 1.3 percent for one μgm^3 PM2.5).[32] While the statistically weak reduced forms and modestly overlapping confidence intervals imply that differences between the impact of pollution on TFP (column 1) and the impact of pollution

[27]See Chang et al. (2016) Table 3 column 3. On average, they estimate that a one μgm^3 lead to 0.6 percent decrease in productivity. In the California sample, the mean PM2.5 is 10 μgm^{-3}; however, the PM2.5 levels in the India sample were almost never below 15 μgm^{-3} so the average estimate from Chang et al. (2016) is not a suitable comparison. Going from a day with PM2.5 between 15-20 μgm^{-3} to a day with PM2.5 between 20-25 μgm^{-3} is a 5 μgm^{-3} average rise in PM2.5 that yields an additional 47 cent (=$-0.53 - -1.00$) reduction in earnings. This translates to 9 cents (=47/5) per μgm^{-3}, or 1.3 percent (=0.09/6.9 * 100) of the mean.

[28]Adhvaryu et al. (2014) document that firms in India adapt to changes in air quality even over short time periods.

[29]As discussed with Equation 5, when firms do not have time to adjust inputs the impact of pollution on labor productivity and total factor productivity are equivalent.

[30]Value added is the deflated value of output minus the deflated value of materials. Value added per unit worker is value added divided by the number of man-days. Fu et al. (2017) employ this metric.

[31]The reduced form effect of the wind distribution on labor productivity is statistically significant, F-test p =0.062, and reported in Figure 9a.

[32]The reduced form effect of the wind distribution on log Y is statistically insignificant, F-test p =0.27, and reported in Figure 9b.

on labor productivity (column 2) should be interpreted with caution, the stark qualitative distinctions in the estimates nevertheless demonstrate the importance of considering a metric of pollution sensitivity unaffected by input adjustments in this setting.

Finally, the estimates of Table 4 consider the impact of air pollution in a diverse sample of firms representative of a range of industries while prior studies have largely focused on individual firms.[33] Under heterogeneous impacts of air pollution on productivity, a plausible scenario is that previous estimates documenting a negative impact of air pollution were internally valid, yet not representative of the whole sector or economy. In the next section, I estimate industry-specific effects of air pollution on productivity to further examine this scenario.

5.2 Heterogeneous Pollution Sensitivity

Instrumental Variables Estimates

I now assume that $\lambda_{it} = \lambda_i$ so pollution has industry-specific impacts on productivity. I estimate the industry-sensitivities, λ_i, with three steps. First, I fit the first stage, Equation 6, separately for firms in each industry to obtain the predicted aerosols $\hat{a}_{fidt}$. Second, I repeat the second stage, Equation 7, separately for firms in each industry using the predicted aerosols from the industry's first stage.[34] Separating the industries allows variables like the time period and the weather to influence the outcomes, AOD and log TFPR, differently for each industry. For each industry, I obtain the $\hat{\lambda}_i$ estimate from the predicted aerosols coefficient. Last, I employ the empirical Bayes (EB) shrinkage method of (Morris, 1983) that is common in the value-added literature to reduce noise in the $\hat{\lambda}_i$ estimates.[35] This step is important since the precision of the mean λ_i and the variance across λ_i are of interest and noise in the $\hat{\lambda}_i$ estimates would lead to imprecise measurement of the mean and overestimates of the extent of heterogeneity. Some small industries did not have enough unique firms or firm-years for the estimation. As a result, I obtain N = 132 coefficients $\hat{\lambda}_i$. The 132 included industries account for 99.5 percent of the output value observed in the full sample of 150 industries.

Figure 10 reports a histogram of the EB-adjusted estimated λ_i weighting each industry by output. Although the histogram does not provide information on the precision of the industry specific-estimates, it shows that air pollution adversely affects a substantial portion of industries

[33] See Chang et al. (2016), Chang et al. (2016), Graff Zivin and Neidell (2012), Adhvaryu et al. (2014).

[34] Repeating the estimation separately by industry is akin to having industry-specific coefficients for all controls in Equations 6 and 7.

[35] For examples, see Kane and Staiger (2002); Jacob and Lefgren (2007); Chandra et al. (2016).

on average. Eighty six of the industry-specific estimates, accounting for 71 percent of output value, had estimates that imply pollution reduced productivity on average. The mean of the output-weighted estimates was -0.21 with 90 percent confidence interval (-0.43, 0.03). According to the industry-specific estimates, two of the most adversely affected industries are mica and jute and mesta pressing and baling.

Table 5 presents the estimated parameters of the underlying distribution of the impact of pollution on productivity.[36] The parameters show that the industry-specific estimates of the impact of pollution on productivity were generated from a prior distribution with mean -0.11 (-0.35, 0.13) and standard deviation 0.67 (0.14 , 1.44).[37] The estimated parameters of the distribution imply that 57 percent of industries are sensitive to air pollution (ie $\lambda_i < 0$). They also reflect variation in the impact of pollution on productivity. At the 25th percentile, a 0.01 unit increase in AOD results in a 0.56 percent reduction in productivity. At the 75th percentile, a 0.01 unit increase in AOD results in a 0.34 percent rise in productivity, an increase of 0.9 percentage points.

Reduced Form Evidence

The industry-level estimates indicate there is meaningful heterogeneity across industries in the impact of air pollution on productivity. In particular, the estimates imply that pollution has a significant negative effect on productivity for some industries with $\lambda_i < 0$ even though there is no average effect of air pollution on productivity. A potential concern is that differences in the industry-level estimates represent an artifact of the estimation procedure rather than underlying differences in the pollution and productivity trends.

To confirm that the distribution of industry-specific pollution sensitivities reflects intrinsic differences across industries, Figures 11a and 11b repeat the reduced form estimation of the effect of wind on productivity separately for industries in the highest quartile (most negative) λ_i and industries in the bottom quartile (least negative) λ_i. The plots show that wind has meaningfully different effects on productivity in each group. Figure 11a shows there is a statistically significant increase in productivity from additional months with high winds among industries with the most negative λ_i (p-value=0.02). By contrast, Figure 11b shows no positive effect on

[36] I assume that industry-specific estimates were drawn with equal probability from a normal prior distribution. I also assume the mean of the prior distribution was equal for all industries, "grand mean" rather than "regression surface" in (Morris, 1983), ie $\lambda_i \sim \mathcal{N}(\lambda, \sigma^2)$.

[37] 90 percent confidence intervals obtained with industry bootstrapping. The parameters do not weight industries by output.

productivity from additional months with high winds among industries with the least negative λ_i (p-value=0.09).[38]

The trends in Figures 11a and 11b further corroborate the results of the estimation procedure. The comparatively large effects for additional high wind months in both reduced forms mirror the first stage relationship between wind and pollution. For example, among industries with the most negative λ_i, an additional month with average wind over 3 m/s resulted in both a larger decline in AOD (0.009 units) and a larger increase in productivity (1.15 percent) over the baseline month (average wind below 0.6 m/s) than an additional month with lower average wind.

6 Determinants of Pollution Sensitivity

To distinguish what makes some industries more sensitive to air pollution than others, I turn to establishing a foundation for heterogeneity in sensitivity to air pollution across industries. In an extension of the model, I allow pollution to affect production by distorting the returns to hired inputs as well as total factor productivity. I show that even if the underlying impact of pollution on inputs and productivity was the same for all firms, there would still be heterogeneity in the effect of pollution across industries resulting from variation in technology. I establish this pattern in the data. I find that labor-intensive industries are most sensitive to air pollution on average.

6.1 Model of Heterogeneous Pollution Sensitivity

To begin, I elaborate on the potential avenues by which pollution may affect productivity and production in Equation 1. I assume pollution may cause inputs to be less effective. Specifically, I let:

$$Y_{fidt} = \left(A^{\gamma_0}\tilde{\Omega}_{fidt}\right)\left(A_{dt}^{\gamma_L}L_{fidt}\right)^{\beta_{Lit}}\left(A_{dt}^{\gamma_K}K_{fidt}\right)^{\beta_{Kit}}\left(A_{dt}^{\gamma_M}M_{fidt}\right)^{\beta_{Mit}} \tag{8}$$

[38]The somewhat negative trend in Figure 11b signals that wind (air pollution) may lower (raise) productivity among industries in this group. One possibility is that firm adaptations lead to a positive impact of air pollution on productivity. For example, a firm with capital or labor stocks of heterogeneous quality facing a pollution shock may keep the most healthy and unimpeded workers and retire its least efficient capital. While this interpretation deviates from the conceptual framework in the model, the data do not indicate that productivity improvements explain the average effect as well as imprecision around zero. The pattern in Figure 11b is not significant at high confidence levels (p-value=0.09) and no EB-adjusted λ_i was significantly greater than zero.

where all the variables and notation remain as in Equation 1 and the distinguishing feature is the additional parameters $\{\gamma_0, \gamma_L, \gamma_K, \gamma_M\}$.

The key alterations from the standard model in Equation 8 are that i) some fraction (or multiple) of each hired input contributes to output and ii) pollution determines how much each hired input contributes to output. For example, the contribution of labor to output, $A_{dt}^{\gamma_L} L_{fidt}$, differs from hired labor L_{fidt} in that it allows distortions in the returns to labor. Distortion in the returns to labor occurs when some of the hired labor does not contribute to production (Greenstone et al., 2012). For example, if a salaried worker suffers from asthma on the job and needs additional breaks, their contributing, or effective, labor is a portion $A_{dt}^{\gamma_L}$ of their hired labor. Pollution and the underlying effect of pollution on factors of production determine portion of hired inputs that contribute to output. In the example, as pollution increases, $A_{dt}^{\gamma_L}$ changes at rate γ_L, so a one percent increase in pollution yields a γ_L percent change in the portion of hired labor that contributes to output. The parameter γ_L is akin to an elasticity of effective labor with respect to pollution.

Equation 8 allows for ample generality in how pollution affects production. Intuition indicates that labor is the most vulnerable to pollution because of the substantial human health impacts of exposure to particulate matter. Nevertheless, Equation 8 allows for the possibility that air pollution depletes the effectiveness of capital and materials.[39] Relatedly, pollution may affect non-input factors of production, productivity, via γ_0. Further, I do not impose an assumption that $\gamma < 0$.

Collecting pollution terms in Equation 8 yields Equation 1 with the addition that sensitivity λ_{it} now reflects the various potential distortions from air pollution. I define:

$$\lambda_{it} = \gamma_0 + \gamma_L \beta_{Lit} + \gamma_K \beta_{Kit} + \gamma_M \beta_{Mit}. \tag{9}$$

As before, the observed TFPR is defined in levels:

$$\Omega_{fidt} = \frac{Y_{fidt}}{L_{fidt}^{\beta_{Lit}} K_{fidt}^{\beta_{Kit}} M_{fidt}^{\beta_{Mit}}} = A_{dt}^{\lambda_{it}} \tilde{\Omega}_{fidt} \tag{10}$$

Thus, the log TFPR is equivalent to Equation 3 and the impact of pollution on log TFPR is equivalent to Equation 4.

Equation 9 provides a foundation for sensitivity to air pollution. It implies that both the impact of pollution on inputs and the technology determine the overall effect of pollution, λ_{it}.

[39] Rao et al. (2014) show that air pollution contributes to costly corrosion of infrastructure and industrial machinery in India. Additional studies are reviewed in Brimblecombe (2015).

Air quality must negatively affect at least one input to observe sensitivity to air pollution. To illustrate, if air pollution is a detriment to workers' productivity and has no other effect on production, then $\gamma_L < 0$ and sensitivity $\lambda_{it} = \gamma_L \beta_{Lit}$, the impact on each unit of labor transformed into units of output.[40] If in addition pollution corrodes materials, $\gamma_M < 0$, sensitivity would lower further.

Moreover, Equation 9 demonstrates that industries can vary in their sensitivity to air pollution by virtue of technology differences alone. Two firms that hire identical workers, materials, and capital in identical quantities may exhibit different sensitivity to air pollution λ_{it} if they use different technology, $\{\beta_{Lit}, \beta_{Kit}, \beta_{Mit}\}$. More broadly, the finding that air pollution has little effect on TFPR would be compatible with findings that pollution greatly harms workers in a world where the detriments to labor are outweighed by intensive use of capital and materials.

6.2 Estimation of Determinants of Pollution Sensitivity

I assemble empirical evidence to corroborate the avenues by which pollution may affect productivity in the model of heterogeneous pollution sensitivity. The substantial human health impacts of exposure to particulate matter imply that air pollution has negative effects on manufacturing workers. If worker health impacts drive sensitivity to air pollution, the model predicts that air pollution will have the greatest negative impact on industries with labor-intensive production technology. I demonstrate that heterogeneity in the impact of pollution reflects differences in the labor-intensity of production technology with reduced form evidence. I estimate the pollution distortion to each input to production. Consistent with the health-channel, I find that air pollution negatively affects labor inputs.

Reduced Form Evidence

Given that pollution distorts labor inputs, $\gamma_L < 0$, the model and parameters predict a larger effect of air pollution on productivity in industries with greater labor factor shares. In Figure 12a, I plot the reduced form estimates of the impact wind on log TFPR from Equation 7 for firms in the highest quartile of the labor factor share β_{Lit}. The plot shows that additional months with high average wind speeds have a significant positive effect on productivity (p-value =

[40] This framework subsumes a simple one-factor scenario where pollution abates the output per unit labor as in Fu et al. (2017). Specifically, let labor be the only input and let $\beta_{Lit} = 1$, then the derivative of log output per unit labor with respect to log pollution is $\lambda_{it} = \gamma_L$.

0.04). Further, the reduced form trend mirrors the first-stage: the greatest improvements in productivity are measured from additional months with the greatest declines in air pollution.

For comparison, in Figure 12b, I plot the analogous reduced form estimates of the impact wind on log TFPR for firms in the lowest quartile of the labor factor share β_{Lit}. The plot shows that in this sample additional months with high average wind speeds do not have a significant effect on productivity (p-value = 0.19). These reduced form plots are consistent with the hypothesis that health effects of pollution combined with labor-intensive production technology lead to a negative effect of air pollution on productivity.

Table 6 reports the estimated impact of AOD on log TFPR from Equation 7 for firms in each quartile of the labor factor share β_{Lit}. Column 1 shows that pollution negatively affects productivity for firms with labor factor share in the highest quartile. The estimate indicates that in this sample, a 0.01 unit increase in AOD (one μgm^3) causes a 1.7 (1.6) percent decline in productivity. Columns 2-4 show that air pollution does not have a significant effect on productivity for firms with low labor factor shares.

Whereas previous work has relied on biological explanations of variation in pollution sensitivity, such as higher average worker respiratory rates indicating occupations where pollution has worse effects (Chang et al., 2016), these findings demonstrate that labor-intensive technology plays a critical role in impact of air pollution on firms. Agricultural sectors (Graff Zivin and Neidell, 2012) and garment making (Adhvaryu et al., 2014) will be more sensitive to air pollution than the average manufacturing firm because they are labor intensive relative to the average.

Declining wages may be an additional signal that pollution takes a toll on labor inputs. Given the assumptions that firms know pollution and can adjust inputs in response to pollution, pollution may cause wages to fall to reflect the decline in marginal product, all else equal. Consistent with this hypothesis, Figure 13 demonstrates that additional months with high average wind speeds result in a significant rise in wages. Analogously, Table 7 shows that a 0.01 unit increase in AOD (one μgm^3) causes a 1.2 (1.1) percent decline in wages. While this evidence is consistent with the finding that pollution affects worker health, other plausible scenarios suggest the pollution-wage relationship would be weaker than observed. For example, wages will not reflect changes in the marginal product of labor if sensitive plants are wage takers. Another possibility is that wages will not fully reflect the effect on labor when labor is mobile because worker movement may equalize wages across locations and firms in polluted locations may offer compensation that counteracts the productivity shock on wages.

Structural Estimates

To measure the effect of air pollution on the inputs to production, I estimate the following regression based on Equation 9:

$$\lambda_i = (\gamma_0 - \gamma_M) + (\gamma_L - \gamma_M)\beta_{Li} + (\gamma_K - \gamma_M)\beta_{Ki}. \tag{11}$$

In this regression, β_{Li} is the average labor factor share for each industry. I note that the data exhibit constant returns to scale (Table 2) so the explanatory variables are nearly collinear. Thus, thus I identify $\gamma_0 - \gamma_M$, $\gamma_L - \gamma_M$, $\gamma_K - \gamma_M$ respectively. I continue to use the sample of N = 132 industry sensitivity estimates; however, I remove outlying estimates as a robustness exercise. I weight the industries by their total output value so that the estimates are representative of the manufacturing sector.

Table 8 reports the results of fitting Equation 11. The data indicate that air pollution considerably reduces the contribution of labor inputs to production. The estimate implies that a 0.01 unit increase in AOD (one μgm^{-3} in PM2.5) reduces the portion of labor inputs that contribute to output by 0.10 percent (0.09 percent) relative to materials, the omitted factor. The estimate is statistically significant (p-value = 0.006). Air pollution does not have a statistically significant effect on capital returns relative to materials.

The magnitude of the estimated input sensitivities and factor shares are consistent with the estimated average impact of pollution on productivity. They imply that going from an industry with technology in 5th percentile of labor intensity to an industry in the 95th percentile would increase the sensitivity to air pollution (lower λ_i) 1.6 percentage points. This is estimate is in the range of the average impact of pollution among industries with high labor factor shares (Table 6). Averaging industries in Equation 9 suggests the mean $\lambda = \gamma_0 + \gamma_L\beta_L + \gamma_K\beta_K + \gamma_M\beta_M$. Supposing that materials are insensitive to pollution, $\gamma_M = 0$, and substituting in the values of the factor shares from Table 2, the model and parameters imply that at the median industry $\lambda_i = -0.21 - 10 * 0.065 + 2.5 * 0.18 = -0.41$. This is within the confidence interval of Table 4 column 1 and Figure 10.

The negative relationship between the labor factor share and pollution sensitivity remains significant under several alternative assumptions. Table A3 presents the results of repeating the estimation of Equation 11 in several robustness exercises. It shows that the estimated γ_L remains negative when I employ λ_i^{EB} as the outcome in lieu of λ_i, use alternative preparations of the data, use alternative approaches to estimating the production function, and vary the functional forms of the first stage and control functions.

7 Evaluating the Costs of Air Pollution

I estimate how the profits would change in a world without excess air pollution to benchmark the overall cost of air pollution in the Indian manufacturing sector .

7.1 Estimation

The welfare-measure of interest is how air pollution changes firms' profits. Returning to the model of profit maximization with pollution (Equation 2), the impact of pollution on profits depends on the change output value net the change in input costs. In turn, these objects depend on the how pollution changes firms inputs and input prices.[41]

To make the computations, I maintain the assumptions from the estimation of the production function that factor markets for labor and materials are perfectly competitive and firms can adjust labor and materials inputs without constraint.[42] I also make the assumption that there is no capital adjustment and no change in capital prices as a result of pollution. This is consistent with assuming prohibitive adjustment costs to capital inputs and taking average variable profits as the measure of producer surplus.

Under these assumptions, I derive the impact of pollution on average variable profits as a function of the change in input prices. I obtain the impact of pollution on input demand from the first order conditions. The effect of an increase in pollution on the log input demand for $j \in \{\ell, m\}$ is:

$$\frac{dj_{fidt}}{da_{dt}} = \beta_{Jit}\lambda_i - \frac{dp^J}{da_{dt}} \tag{12}$$

A productivity shock from pollution causes demand for each input to adjust according to the industry sensitivity and the factor share. If input prices decline to offset the negative productivity shock of air pollution, the impact of pollution on producer surplus will be less severe than if prices do not change.[43] I consider two scenarios. First, I assume input prices do not change. Second, I allow input prices to decline. In lieu of assuming that input prices adjust in each industry to perfectly offset that industry's specific sensitivity to air pollution, I assume all input prices adjust as a function of the average effect of pollution on productivity. Given this imperfect

[41] I continue to assume constant output prices.

[42] Perfectly competitive factor markets further imply that producer surplus, profits, are sufficient to measure welfare.

[43] By contrast, with enough labor mobility, compensating differentials suggest pollution would cause wages to rise. Although I do not consider this scenario, higher input prices would make the impact of pollution on producer surplus even be more severe than if prices did not change.

price adjustment, the effects under price changes are not strictly lower than under no price changes.

I simulate the effect of removing pollution in excess of the global standard on average variable profits. To achieve the standard, India must reduce annual mean PM2.5 to 10 μgm^{-3} in every district and year.[44] I perform the estimation at the firm-year level. I assign to each firm-year observation the change in air quality needed for its district to meet the WHO standard in the year based on the observed air quality in each district-year.

7.2 Results

Table 9 reports the effect on profits of improving air quality to the World Health Organization standard. Assume prices do not change, I estimate that bringing air quality to the standard would result in a 0.36 percent rise in variable profits overall (132 industries) and a 1.18 percent rise among the sensitive industries (86 industries). Allowing for some price adjustment, I find that manufacturing profits would rise 0.26 percent for all industries and 1.07 percent for sensitive industries. As expected, price adjustments attenuate the overall effect of pollution on profits. These losses are small in comparison to other sources of productivity loss in India. Allcott et al. (2016) estimate that electricity shortages cause a 5.6 percent reduction in variable profits in roughly the same sample, implying the an overall cost of electricity shortages exceeds that of air pollution by more than an order of magnitude.

The estimates further underscore the diverse effects of air pollution on industry. In both scenarios, I find stark differences in the impact for sensitive industries in comparison to the full sector. The sensitive industries overstate the overall effect by a factor of 3 to 4. As an additional comparison, the losses are also small in comparison to prior estimates of the impact on PM2.5 on the economy; yet, these differences are more modest when only considering sensitive industries. Extrapolating from one plant, Chang et al. (2016) estimate that the improvement in US PM2.5 concentrations from 1999 to 2008, a fall of 2.79 μgm^{-3} on average, raised manufacturing revenue 2.67 percent. While this amount is many times the estimate for all manufacturing industries in India, it is only slightly more than twice the estimate for sensitive industries. The differences underscore the external validity challenge for studies with data from a single firm as estimates of a single industry are not representative of the overall cost of air pollution.

[44]The World Health Organization guideline for annual mean PM2.5 is 10 μgm^{-3}. So if a district's annual mean PM2.5 is 41 μgm^{-3}, the counterfactual is a decline of 31 μgm^{-3}. No observations in the data met the standard so all counterfactual calculations involve a pollution decline.

8 Conclusion

This study examines the costs of pollution for the manufacturing sector in India. I collate comprehensive geo-spatial data on weather and air quality, an improvement over prior data for the setting, along with an administrative panel of firms. I use a model of production with air pollution to illustrate the effect of air pollution on productivity and production and to establish an analytical foundation for heterogeneity in the influence of air pollution on economic outcomes. To address endogeneity in the pollution-productivity relationship, I use a new instrument, the distribution of wind velocity, for as-if random assignment of pollution when estimating the model of pollution and production.

I find the average effect of air pollution on productivity is small in comparison to previous estimates. Guided by the model, I argue this finding reflects two features of the setting: adaptations that attenuate the impact of air pollution over time and heterogeneity in the damages of air pollution. I estimate industry-specific effects of pollution on productivity and find meaningful differences across industries in the effect of pollution. I use the predictions of the model to explain the heterogeneity: I show that labor-intensive industries are substantially more adversely affected than industries that rely less on labor inputs. To benchmark the welfare implications, I simulate the effect of reducing air pollution to the level of international guidelines. I find that the costs of air pollution are substantial for some sensitive industries, yet the effects for the sensitive industries are not representative of the overall manufacturing sector.

The findings underscore two prominent themes in understanding the role of environmental influences on human capital and economic activity. First, the effect of long-run changes in environmental influences may be substantially weaker than effect of short-run changes in environmental influences. Further research in this vein includes Barreca et al. (2016), Graff Zivin et al. (2018), and Deschênes and Greenstone (2011); a review is in Dell et al. (2014). A important implication of this distinction is that the bulk of economic costs may arise from variation in environmental influences and adaption during transitions rather than changes in the mean level of environmental influences. Second, the effect of environmental influences on human capital and economy-wide output may be highly heterogeneous. Burgess et al. (2017) underscore these distinctions for rural and urban areas of India. Dell et al. (2012), Jones and Olken (2010), and Hsiang (2010) find heterogeneity in the impact of climate variables by income. Heterogeneous damages have several important implications for environmental policy and research. They indicate that policy calculations that ignore heterogeneity risk vastly misrepresenting the scale of damages. Moreover, if unchecked, they point to the possibility of economic distortions arising over time from unequal incidence of environmental damages.

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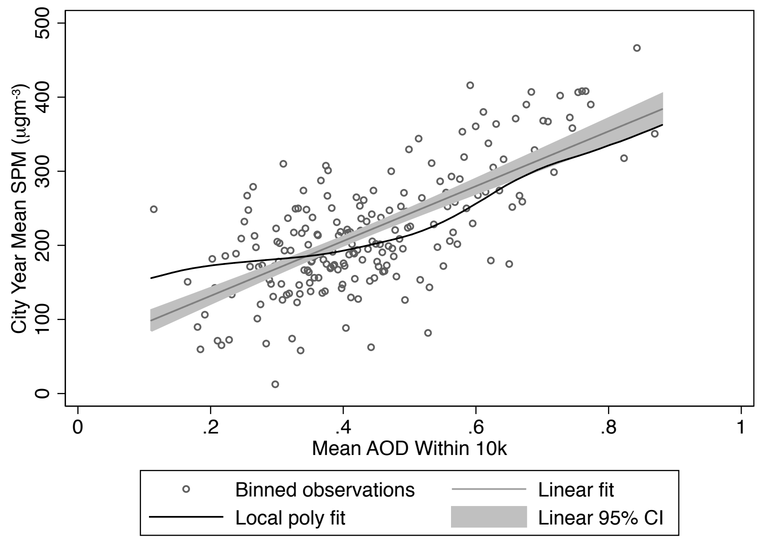
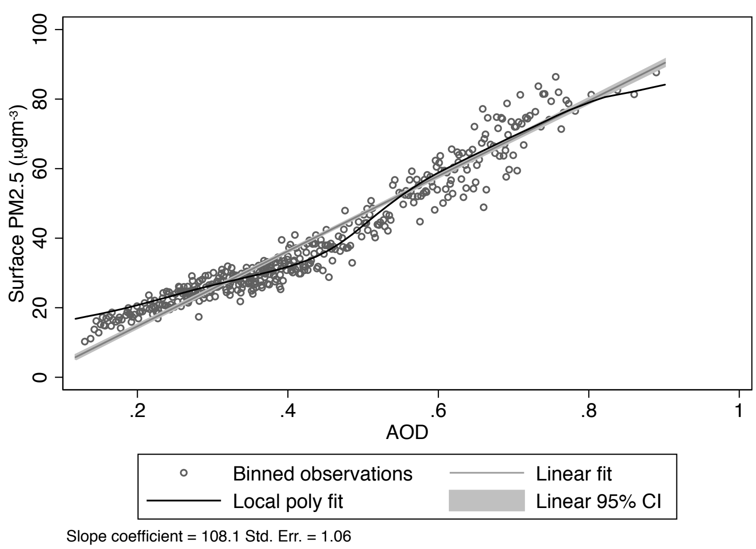
Figure 1: **Validation of AOD**

(a) *Suspended Particulate Matter (SMP)*

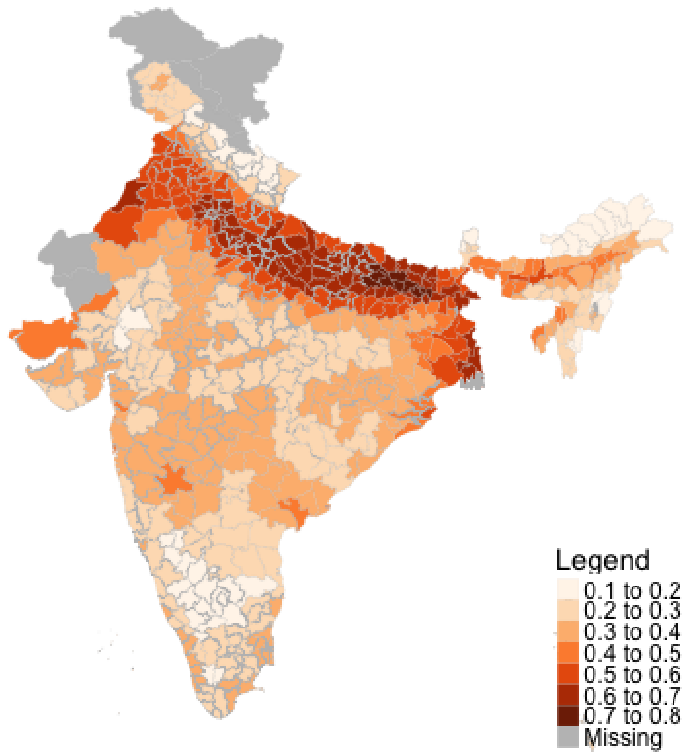


(b) *Ground-level Fine Particulate Matter (PM2.5)*



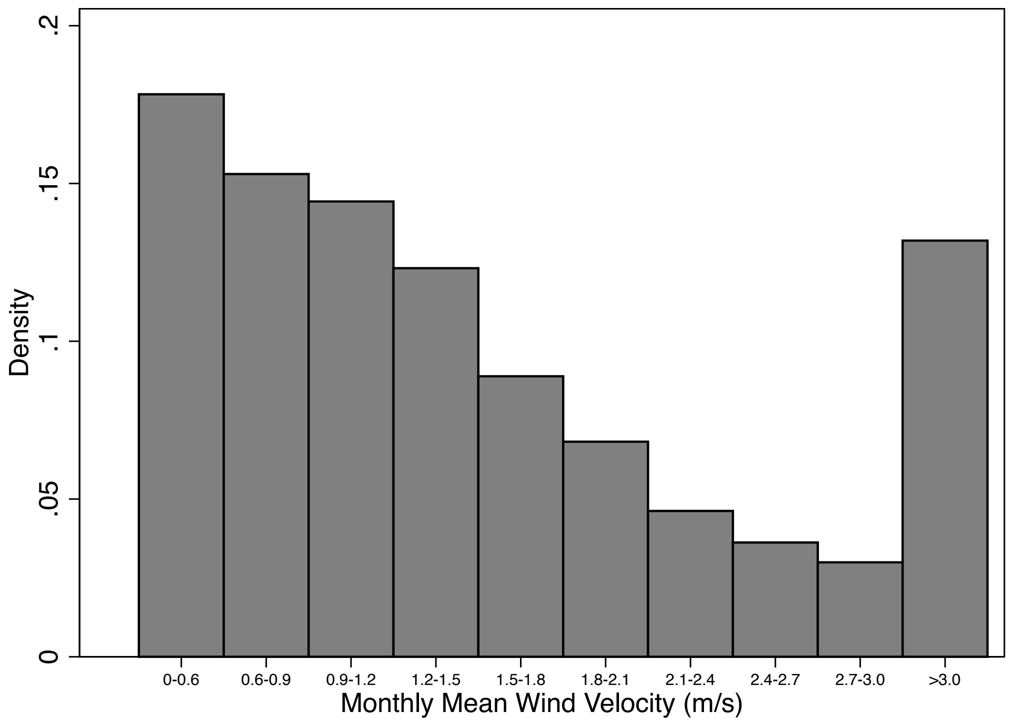
Note: In Panel A, the unit of observation is the city-calendar year. The sample includes all city-years with SPM observed from ground monitors. In Panel B, the unit of observation is the district-calendar year. The sample includes all districts with AOD observed in every month for 2001-2009 inclusive. The diagram depicts i) scatter plot of mean AOD and SPM (Panel A) or PM2.5 (Panel B) for bins of 10 observations, ii) linear fit and 95 percent confidence interval, and iii) local polynomial fit. SPM from Greenstone and Hanna (2014), PM2.5 from Van Donkelaar et al. (2016), and AOD from MODIS.

Figure 2: **District Mean AOD 2000/01 - 2009/10**



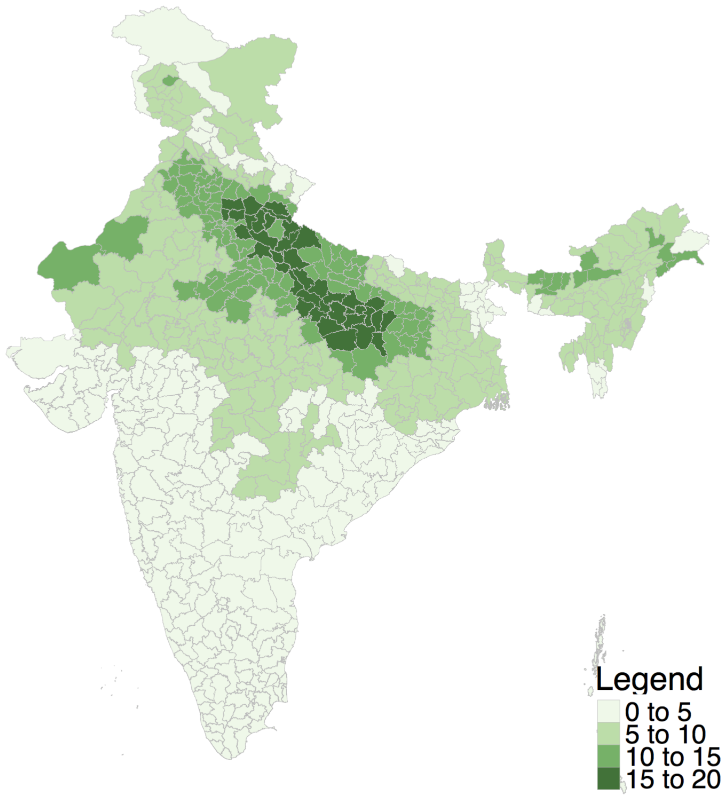
Note: Boundaries depict the 2001 districts of India. Shading represents the mean of annual average AOD for ASI years 2000/01 to 2009/10. Annual averages exclude July and August. AOD data from MODIS.

Figure 3: **Distribution of Monthly Mean Wind Velocity**



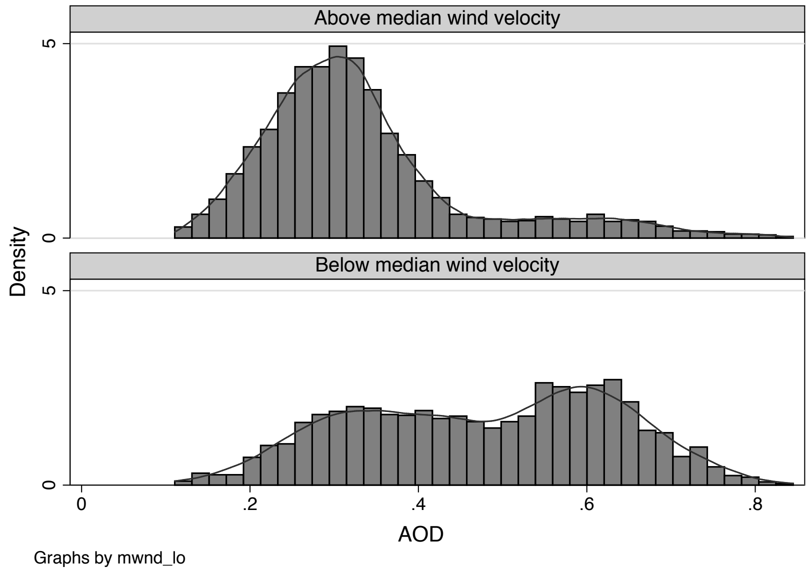
Note: The unit of observation is the district-month. The sample includes all district-months for ASI years 2000/01-2009/10. The histogram bars depict the fraction of district-months with AOD in each interval.

Figure 4: **District Average Absolute Percent Deviation From Mean Wind Velocity 2000/01-2009/10**



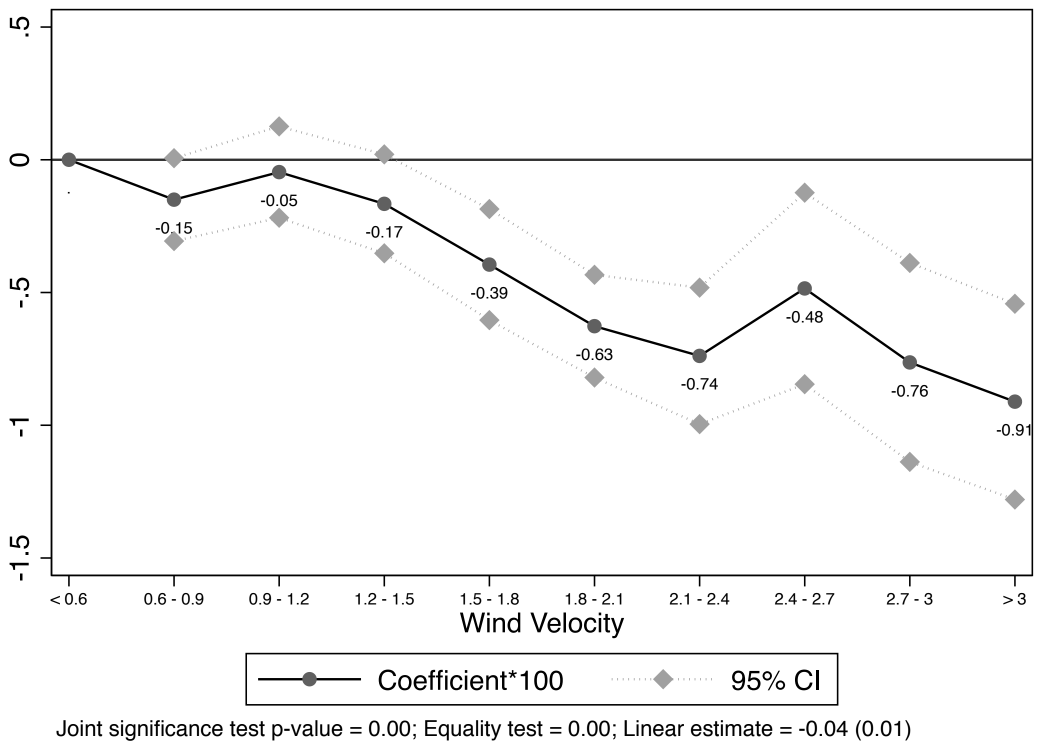
Note: Boundaries depict the 2001 districts of India. Shading represents the average percent of absolute deviation from the district mean wind velocity from ASI year 2000/01 to 2009/10. Wind velocity data are from Wentz and J. Scott (2015).

Figure 5: **Distribution of AOD by Low and High Wind Districts**



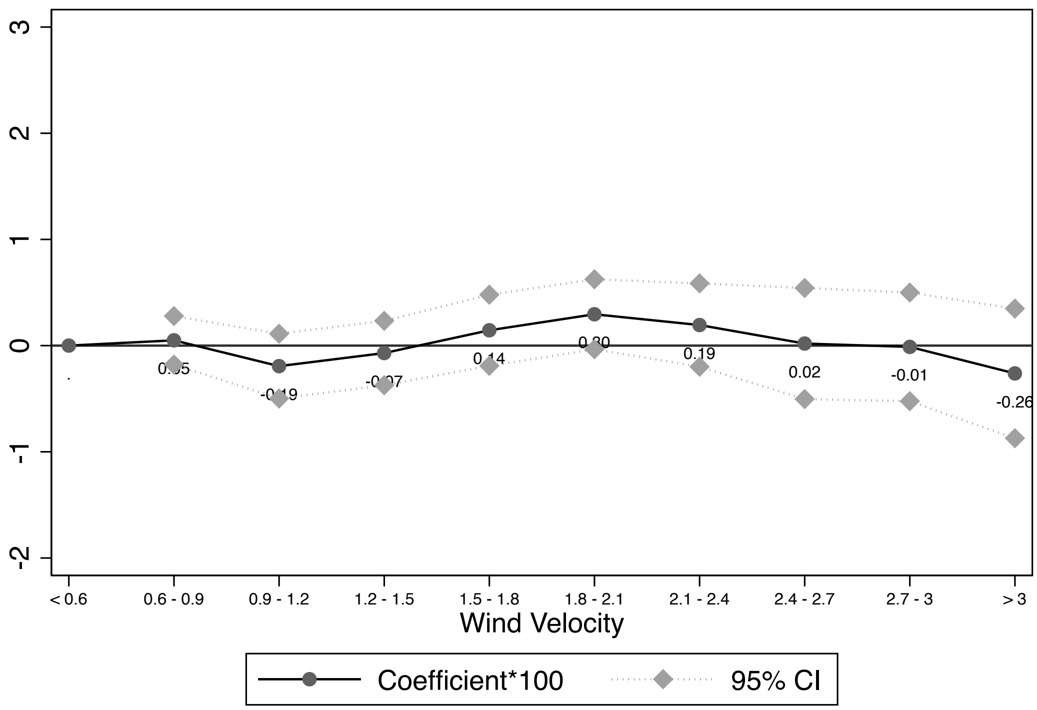
Note: The unit of observation is a district-year. The sample includes all districts with a firm in the ASI panel years 2000/01-2009/10. AOD data are from MODIS. Wind velocity data are from Dee et al. (2011). The plot shows a histogram of the district annual mean AOD for i) district-years above the median wind velocity and ii) district-years below the median wind velocity.

Figure 6: **Semi-Parametric Relationship Between AOD and Wind Velocity**



Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. The figure plots the $\hat{\theta}_j$ obtained from estimating Equation 6. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on the annual mean AOD. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. The regression uses survey weights. See text for details.

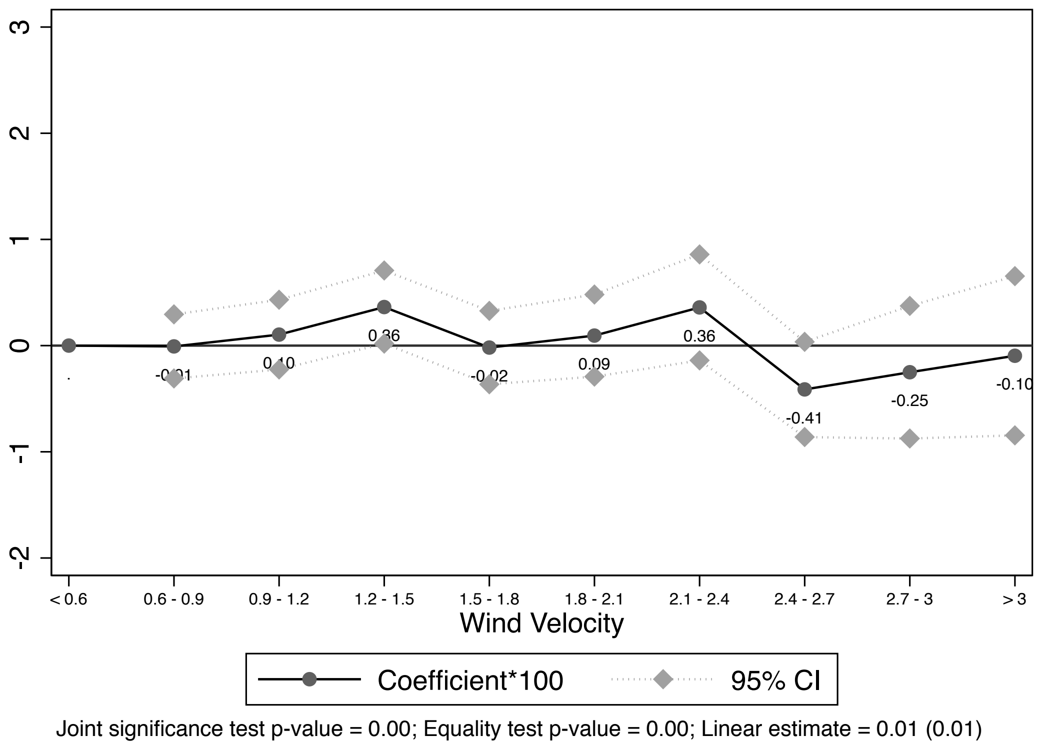
Figure 7: **The Effect of Wind Velocity on Future Change in AOD**



Joint significance test p-value = 0.04; Equality test p-value = 0.03; Linear estimate = 0.02 (0.01)

Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. The figure plots the $\hat{\theta}_j$ obtained from estimating Equation 6 with Δa_{dt+1} as the dependent variable. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on the annual mean Δa_{dt+1}. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. The regression uses survey weights. See text for details.

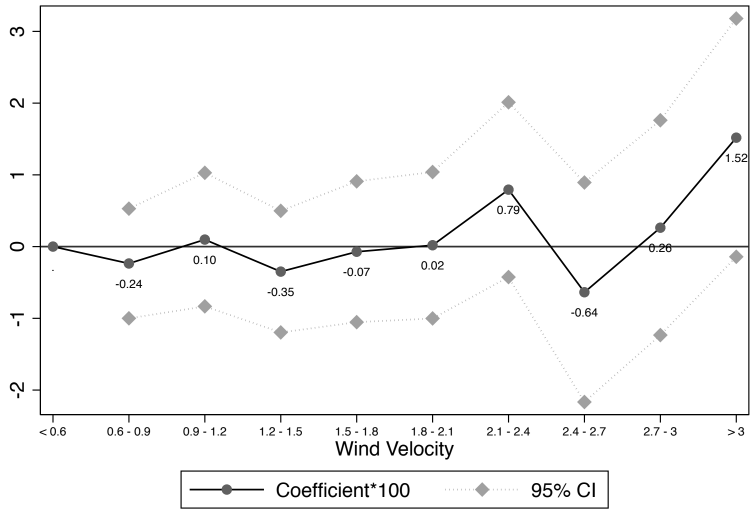
Figure 8: **The Effect of Wind Velocity on Productivity**



Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. The figure plots the $\hat{\theta}_j$ obtained from estimating Equation 6 with log total factor productivity ω_{fidt} as the dependent variable. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on ω_{fidt}. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. The regression uses survey weights. See text for details.

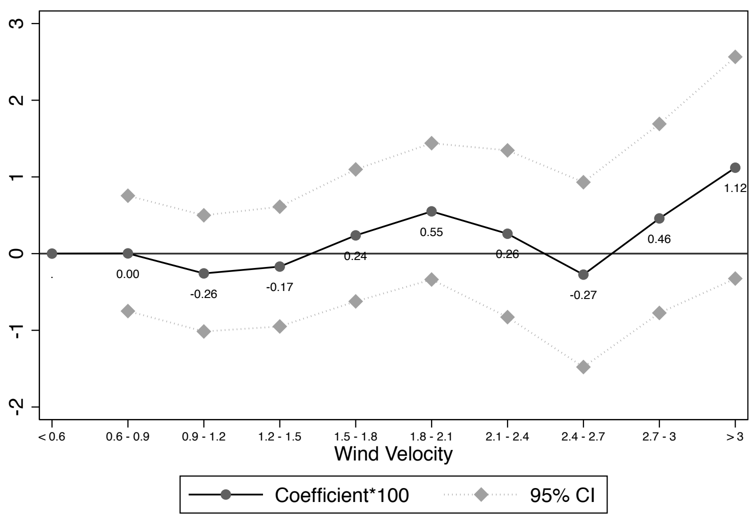
Figure 9: **The Effect of Wind Velocity on Output Measures**

(a) *ln(Value-Added Per Unit Labor)*



Joint significance test p-value = 0.06; Equality test p-value = 0.04; Linear estimate = 0.05 (0.03)

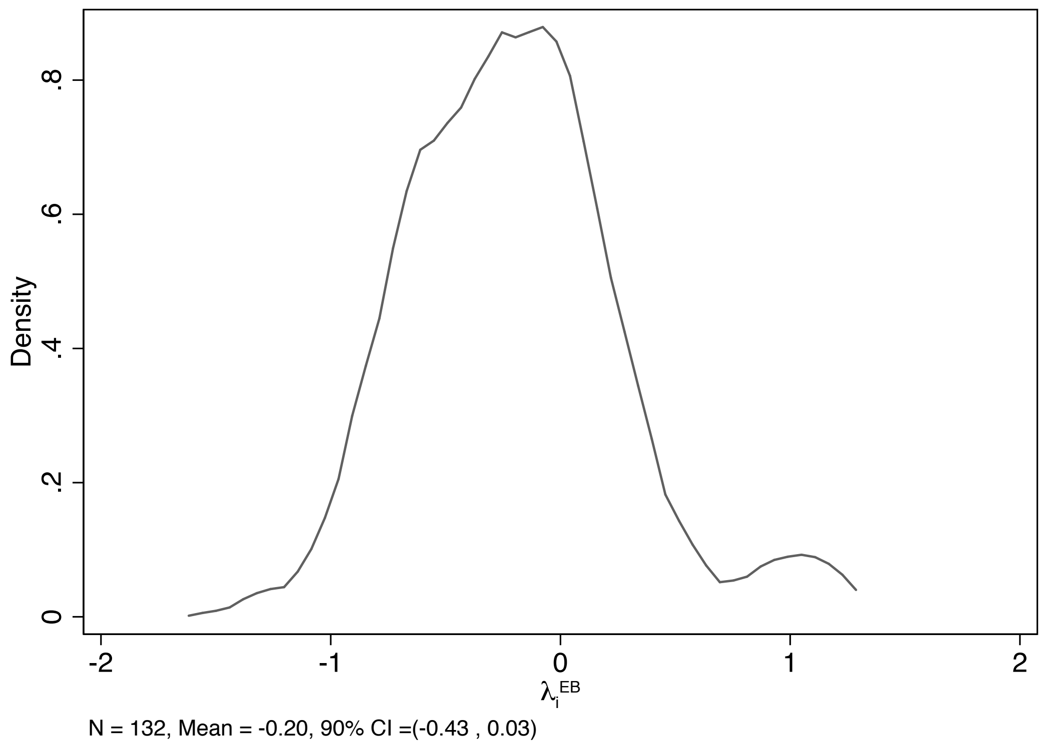
(b) *ln(Output Value)*



Joint significance test p-value = 0.27; Equality test p-value = 0.20; Linear estimate = 0.04 (0.02)

Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. The figures plot the $\hat{\theta}_j$ obtained from estimating Equation 6 with log value added per unit labor as the dependent variable in Panel A and log output value as the dependent variable in Panel B. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on the outcomes. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. The regression uses survey weights. See text for details.

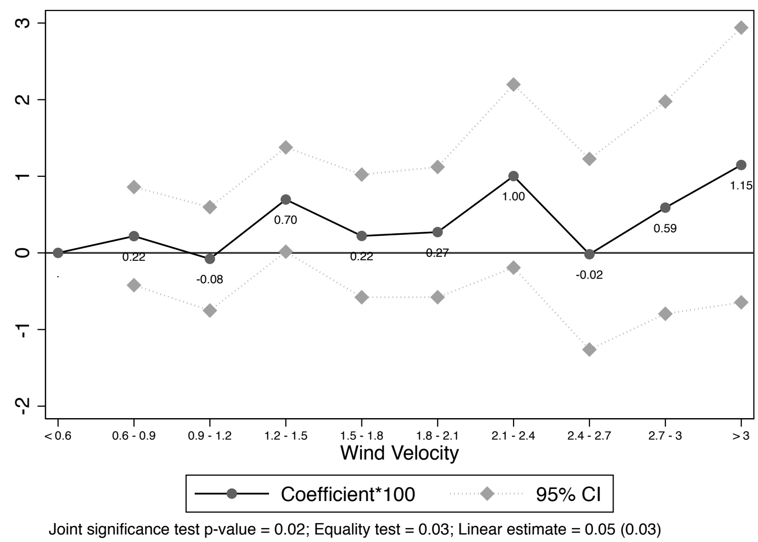
Figure 10: **Distribution of the Effects of Air Pollution on Productivity**



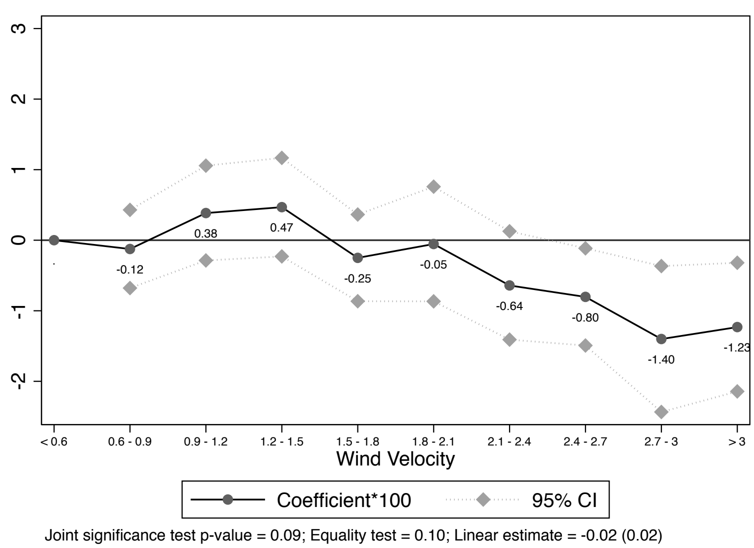
Note: The unit of observation is the three-digit industry. The sample includes manufacturing industries in the ASI panel years 2000/01-2009/10. The plot shows a histogram of estimated industry-specific effects of air pollution on productivity, λ_i, with industries weighted by their total output. See Section 6 for details on the variable construction.

Figure 11: **The Effect of Wind Velocity on Productivity by Sensitivity**

(a) *Lowest Quartile* λ_i



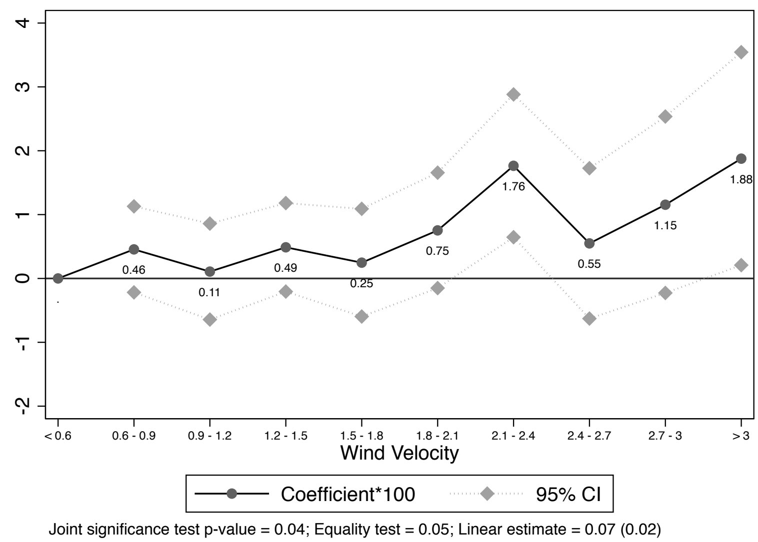
(b) *Highest Quartile* λ_i



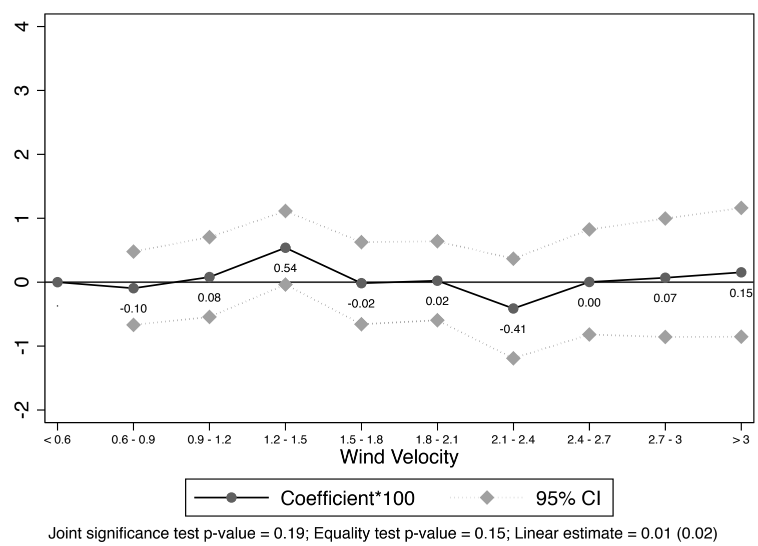
Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Panel A restricts the sample to firms in industries with λ_i in the lowest quartile. Panel B restricts the sample to firms in industries with λ_i in the highest quartile. The figures plot the $\hat{\theta}_j$ obtained from estimating Equation 6 with log total factor productivity ω_{fidt} as the dependent variable. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on ω_{fidt}. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. Regressions use survey weights. See text for details.

Figure 12: **The Effect of Wind Velocity on Productivity by Labor Share**

(a) *Highest Quartile* β_{Lit}

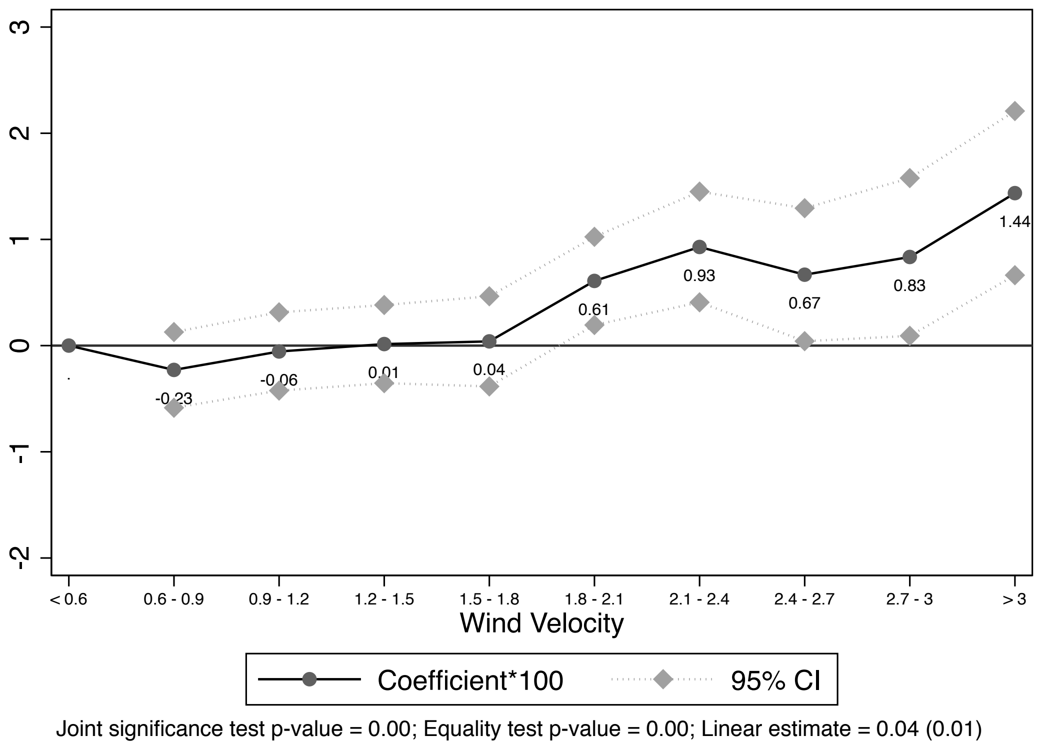


(b) *Lowest Quartile* β_{Lit}



Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Panel A restricts the sample to firms in industries with β_{Lit} in the highest quartile. Panel B restricts the sample to firms in industries with β_{Lit} in the lowest quartile. The figures plot the $\hat{\theta}_j$ obtained from estimating Equation 6 with log total factor productivity ω_{fidt} as the dependent variable. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on ω_{fidt}. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. Regressions use survey weights. See text for details.

Figure 13: **The Effect of Wind Velocity on Wages**



Note: The unit of observation is a firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. The figure plots the $\hat{\theta}_j$ obtained from estimating Equation 6 with log wage as the dependent variable. The depicted coefficients are 100 times the estimated effect of an additional month with mean wind velocity in the corresponding interval relative to a month with mean wind velocity less than 0.6 m/s on log wage. Robust standard errors were clustered at the district level. The confidence intervals are $\pm$ 1.96 standard errors. A solid line at zero shows estimates that are significant at the 95 percent level. The regression uses survey weights. See text for details.

Table 1: **Summary of AOD and Weather**

	mean	sd	p10	p50	p90	count
AOD	0.41	0.16	0.22	0.36	0.64	4809
Wind Velocity (m/s)	1.68	0.82	0.78	1.42	2.82	4809
Precipitation (cm/month)						
January- March	1.85	2.43	0.07	0.99	4.56	4803
April-June	9.84	11.47	1.81	6.39	22.48	4803
July-September	24.18	15.94	8.40	21.77	40.28	4803
October-December	4.18	5.84	0.14	2.03	11.77	4803
Temperature (deg C)						
January- March	21.49	4.18	17.39	21.47	26.33	4803
April-June	30.02	3.29	26.05	30.83	32.95	4803
July-September	27.79	2.62	24.77	28.32	30.20	4803
October-December	22.41	3.10	19.98	22.47	25.70	4803
Vapor Pressure (hPa)						
January- March	14.52	4.91	9.50	13.47	22.06	4809
April-June	21.95	5.61	15.53	21.70	29.65	4809
July-September	29.58	3.47	25.22	29.98	33.48	4809
October-December	17.73	4.91	12.19	17.97	23.98	4809

Note: The unit of observation is the district-year. The sample includes all districts with a firm in the ASI panel years 2000/01-2009/10. AOD data are from MODIS AOD. Wind velocity data are from Wentz and J. Scott (2015). Precipitation and temperature data are from Willmott and Matsuura (2015). Vapor pressure data are from Harris et al. (2014).

Table 2: **Estimation of Production Function Parameters**

	mean	sd	p5	p50	p95	count
ω_{fidt}	2.55	1.28	0.70	2.39	4.97	207316
β_{Lit}	0.08	0.06	0.02	0.07	0.18	207316
β_{Mit}	0.68	0.15	0.42	0.68	0.91	207316
β_{Ki}	0.18	0.09	0.06	0.18	0.35	207316
CRS coefficient	0.95	0.06	0.83	0.96	1.01	207316

Note: The unit of observation is a firm-year. Data from Annual Survey of Industries 2000/01-2009/10. All statistics use survey weights. CRS coefficient is the sum of β_{Lit}, β_{Mit}, and β_{Ki}.

Table 3: **Statistical Properties of Wind Instrumental Variable**

	(1) $\ln(K_{fidt-1})$	(2) $\ln(I_{fidt-1})$	(3) $\ln(N_d)$	(4) ln(wheat)
$\hat{a}_{dt}$	0.0997	0.167	586.3	-3.024
	(0.486)	(1.783)	(922.5)	(3.536)
Observations	107,149	92,938	204,275	138,411
R-squared	0.022	0.015	0.364	0.326
Number of permid	36,144	31,511	55,790	39,046
Weather controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State * year trends	Yes	Yes	Yes	Yes

Note: The unit of observation is the firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Estimates are obtained from Equation 7 with dependent variables lagged log capital (column 1), lagged log investment (column 2), district log number of firms (column 3), and district log wheat production. The coefficient standard error is reported in parenthesis beneath. Robust standard errors were clustered at the district level. Regressions use survey weights. See text for details.

Table 4: **Impact of AOD on Productivity and Production**

	(1) ln(TFPR)	(2) ln(LP)	(3) ln(Y)
$\hat{a}_{dt}$	-0.189	-1.310**	-1.403**
	(0.276)	(0.587)	(0.543)
Observations	204,275	193,444	204,275
R-squared	0.194	0.023	0.056
Number of permid	55,790	54,850	55,790
Weather controls	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
State * year trends	Yes	Yes	Yes

Note: The unit of observation is the firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Estimates are obtained from Equation 7 with dependent variables log total factor productivity (column 1), log value added per unit labor (column 2), and log value output (column 3). The sample in column 2 differs from column 1 because log value added is undefined for all firm-years with higher value materials input than value of output. The coefficient standard error is reported in parenthesis beneath. Robust standard errors were clustered at the district level. Regressions use survey weights. See text for details.

Table 5: **Estimated Parameters of Pollution Sensitivity Distribution**

	(1) Mean	(2) p5	(3) p95
λ	-0.11	-0.35	0.14
σ	0.67	0.14	1.44

Note: Each parameter is a scalar. Estimates are calculated assuming a normal prior distribution of industry-specific effects of air pollution on productivity, $\lambda_i \sim \mathcal{N}(\lambda,\, \sigma^2)$. λ is the mean of the distribution of industry-specific effects and σ is the standard deviation. The estimates are not representative of the manufacturing sector as they do not weight industries by output. Confidence intervals obtained with industry-level bootstrapping.

Table 6: **Impact of AOD on Productivity by Labor Share**

	(1) Highest Quartile	(2) 3rd Quartile	(3) 2nd Quartile	(4) Lowest Quartile
$\hat{a}_{dt}$	-1.720***	0.186	0.571	0.345
	(0.582)	(0.457)	(0.429)	(0.364)
Observations	51,045	54,024	52,733	46,473
R-squared	0.102	0.181	0.161	0.248
Number of permid	17,502	19,933	20,453	15,774
Weather controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State * year trends	Yes	Yes	Yes	Yes

Note: The unit of observation is the firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Column 1 restricts the sample to firms in industries with β_{Lit} in the highest quartile. Columns 2, 3, and 4 restrict the sample to firms in industries with β_{Lit} in the second, third, and fourth quartiles respectively. Estimates are obtained from Equation 7 with dependent variables log total factor productivity. The coefficient standard error is reported in parenthesis beneath. Robust standard errors were clustered at the district level. Regressions use survey weights. See text for details.

Table 7: **Impact of AOD on Wages**

	(1) ln(wage)
$\hat{a}_{dt}$	-1.219***
	(0.268)
Observations	204,275
Number of permid	55,790
R-squared	0.032
Weather controls	Yes
Firm fixed effects	Yes
Year fixed effects	Yes
State * year trends	Yes

Note: The unit of observation is the firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Estimates are obtained from Equation 7 with dependent variable log wage. The coefficient standard error is reported in parenthesis beneath. Robust standard errors were clustered at the district level. Regressions use survey weights. See text for details.

Table 8: **Input Contributions to λ_i**

	(1)
	λ_i
β_{Li}	-9.982**
	(4.786)
β_{Ki}	2.493
	(3.307)
Constant	-0.210
	(0.478)
Observations	132
R-squared	0.048

Note: The unit of observation is the three-digit industry. The sample includes manufacturing industries in the ASI panel years 2001-2010. Column 1 reports the coefficients of estimating Equation 11. Industries are weighted by their total output. Robust standard errors reported in parenthesis.

Table 9: **Percent Change in Output of Reducing PM2.5 to WHO Standard**

	(1) No price adjustment	(2) Price adjustment
(1) All industries	0.36	0.26
	(0.11,0.58)	(0.07,0.44)
(2) Sensitive industries	1.18	1.07
	(0.90,1.45)	(0.84,1.34)

Note: The unit of observation is the firm-year. The sample includes firms from the ASI panel years 2000/01-2009/10 and in 132 industries represented in Figure 10. The cell in row 1 column 1 reports the mean percent improvement in average variable profits from reducing air pollution in every district and year to the WHO standard, 10 μgm^{-}3 assuming no changes occur in input prices. The cell in row 2 column 1 reports repeats the estimate in row 1 column 1 and reports the mean among firms in the subset of industries with $\lambda_i^{EB} < 0$. The cell in row 1 column 2 repeats row 1 column 1 assuming labor and materials prices adjust to perfectly reflect the output weighted mean productivity effect (ie substituting the mean on the industry-specific effects times the factor share for the price change in Equation 12 so the input changes are nearly zero). The cell in row 2 column 2 repeats the estimate in row 1 column 2 and reports the mean among firms in the subset of industries with $\lambda_i^{EB} < 0$. All estimates use survey weights. 95 percent confidence intervals reported in parenthesis. Standard errors obtained from 1000 bootstrap samples at the industry level.

Appendices

A1 Datasets

A1.1 Annual Survey of Industries

Table A1 presents descriptive statistics of the firms in the sample. In total, there are 207,176 observations of 57,724 unique firms. The median firm earns 18 million rupees in a year and employs 26 people. The distributions of number of workers, value of output, output per worker, and labor cost in the sample closely match previous research with the dataset (Allcott et al., 2016).

A1.2 MODIS Aerosol Optical Depth

MODIS Aerosol optical depth (AOD) is developed with advanced versions of basic physical principals of remote sensing I describe here. As electromagnetic radiation travels through the atmosphere, it can be deflected off atmospheric particles, called scattering, or it can be transformed into kinetic energy, called absorption. AOD is defined as the extent to which aerosols attenuate the transmission of light by absorption or scattering. The degree of attenuation depends on the size and composition of particles in the atmosphere, the wavelength of light, and the distance through the atmosphere that the light passed, which in turn depends on the angles of the sun and the sensor.

Thus, the model of potential paths of light from the sun to the sensor allows for absorption and scattering to abate the radiance measured at the sensor from the target pixel and for atmospheric upwelling to increase radiance at the sensor. MODIS AOD products are derived from an algorithm that builds on this model of light-atmosphere interaction, but also accounts for how aerosol particle size and total amount, or load, affect the amount of light transmitted (see Remer et al. (2006) page 26 for the equation). The algorithm relies on a large database where the radiance at the sensor is calculated for many combinations of potential aerosols, angles of sun and sensor, elevation, etc over which the algorithm “inverts” the data. The process is described in detail in Remer et al. (2006). The following is a very simplified version:

1. Discard pixels identified as water, clouds, snow, extremely dark, or extremely light.

2. Calculate path radiance from remaining dark pixels and calculate surface reflectance.

3. Match observed path radiance to most likely aerosol combination.

A2 Estimation Details and Robustness Checks

A2.1 First Stage Robustness

Atmospheric models predict an instantaneous relationship between meteorological conditions and air quality; however, an instantaneous relationship does not imply annual averages reflect the same relationship. One concern is that the instantaneous relationship between air quality and wind velocity does not scale into annual averages and the observed pattern is instead reflects anomalies in data availability, such as seasonal missing AOD data. Since firm outcomes are measured annually, I cannot relate pollution to productivity more frequently than annually. Instead, to ensure that the annual pattern is consistent across the year and across locations, I repeated the first stage with monthly data. Figure A1 shows that monthly mean wind velocity is significantly correlated with monthly mean AOD conditional on controls for weather in all months except the rainy season, August, September, and October. This pattern is consistent with expectations: since rain deposits aerosols, wind has little effect aerosol concentration conditional on rain when rain is very high.

A2.2 Exclusion Restriction

Atmospheric pressure gradients determine wind velocity. In India, the primary source of annual variation in wind velocity is the intensity and geographic distribution of the seasonal monsoon. Districts that are closest to where pressure gradient driving the monsoon is most steep have the greatest variation in winds. Figure 4 illustrates this pattern. The districts with the greatest variation in wind are located at latitudes where the inter-tropical convergence zone shifts during the monsoon, called the monsoon trough.

Many factors contribute to the pressure gradient driving the monsoon so the monsoon trough and timing are unpredictable each year. Besides conventional anomalies, ocean-atmosphere interactions contribute to year-to-year variation in the spatial distribution of atmospheric pressure. For example, the El Nino Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) are two patterns of sea-surface temperature changes that affect the weather in India via teleconnections.

A concern is that if patterns such as ENSO and PDO lead to changes in other meteorological characteristics besides wind, then it is possible that the instrument, wind, is correlated with other channels that also influence productivity, such as temperature and precipitation. In addition to precipitation from the monsoon, temperature is a concern for inference as it is known to have an effect on productivity (Sudarshan et al., 2015). For these reason, I allow for precipitation, temperature, and vapor pressure to affect productivity by including their means, second degree polynomials, and interactions by season as exogenous variables in the first stage and IV.

A2.3 Impact of Air Pollution on Productivity Robustness

Table A2 reports the results of robustness exercises examining the impact of pollution on productivity. Row 1 reports the predicted AOD coefficient (column 1), p-value (column 2), and sample size (column 3) from a regression of log TFPR (Equation 7) as in Table 4. The coefficient standard error is reported in parenthesis beneath. Robust standard errors were clustered at the district level.

Rows 2-4 and 10-11 examine the instrumental variables research design. Row 2 repeats row 1 with a linear first stage using the annual mean wind velocity as the excluded instrument. Row 3 repeats row 1 using AOD a_{dt} and a control function in lieu of fitted values, $\hat{a}_{fidt}$. The control function includes the first stage residuals, $\hat{r}_{fidt}$ from Equation 6, squared residuals $\hat{r}^2_{fidt}$, and interactions $a_{dt} * \hat{r}_{fidt}$. This approach is less restrictive than 2SLS and allows for identification of the average effect when the most sensitive firms avoid exposure to pollution ($E(\lambda_i a_{dt}) \neq 0$) provided the relationship is linear ($E(\lambda_i | a_{dt} V_{dt}) = \psi_1 a_{dt} + \psi_2 V_{dt}$) (Garen, 1984; Chay and Greenstone, 2005). Row 4 repeats row 1 with the addition of wheat yields in X_{idt}. Although yields are not a prefect measure of the impact of wind on agricultural markets, this specification measures the estimate controlling for some of the relationship between wind and agriculture, which may have spillovers to manufacturing productivity. Relatedly, rows 10 and 11 separate the sample by rural and urban firms. If a concern is that either i) wind attenuates productivity through agricultural yields or ii) urban areas experience substantially higher levels of local pollution, this separation shows that even among urban firms where i) is unlikely and ii) is likely there was still no significant effect of pollution on productivity.

To ensure the preparation of the ASI data does not influence the results, Row 5 repeats row 1 with the firm survey weights from ASI 2000-2001. Row 6 repeats specification 1 with the firm survey weights from ASI 2009-2010.

Rows 7-9 examine the assumptions of the production function estimation. Row 7 replicates row 1 under the assumption of constant returns to scale, $\beta_{Ki} = 1 - \beta_{Li} - \beta_{Mi}$, with β_{Li} and β_{Mi} the means of β_{Lit} and β_{Mit}. Row 8 repeats row 1 with the computation of capital factor share using lagged investment in lieu of lagged capital in Equation in (A3). This variation allows for measurement error in capital inputs Collard-Wexler and De Loecker (2016). Row 9 repeats specification 1 allowing for adjustment costs in labor inputs in the computation of the labor factor share.

Rows 12-13 examine how seasonality affects the results. Row 10 repeats row 1 with the subsample of firms in the lowest 25 percent of days open and row 11 does so with the subsample of firms in the highest 75 percent of days open. This separation shows that seasonal firms appear substantially more sensitive to air pollution. This evidence suggests heterogeneity in an important feature in the setting. Heterogeneity is explored further in the industry-specific estimates.

Last, row 14 repeats row 1 with standard errors clustered at the state level. A concern is that district level standard errors overstate the precision when the grid cells of spatial data are large relative to the districts. This is the case in a small portion of the sample with urban districts.

Moreover, the higher geographic level of clustering allows for additional spatial dependence in the controls. Even with state-level clustering (31 clusters), the standard error of the estimate increases little.

A2.4 Structural Estimates of Input Contributions

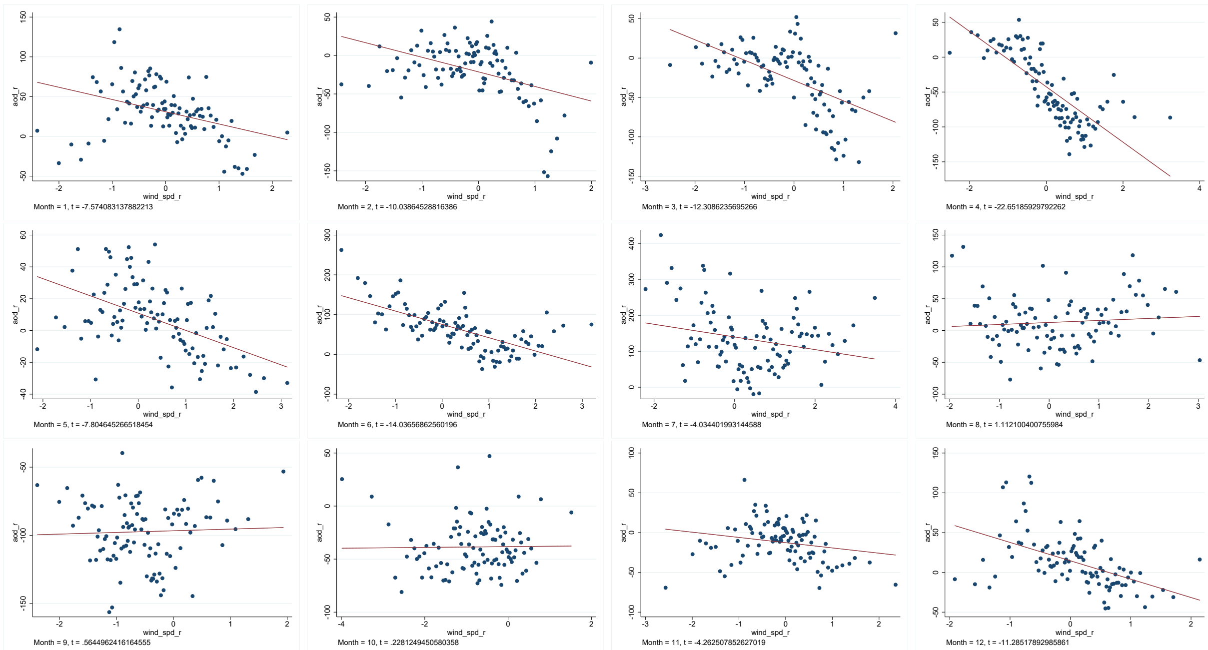
Table A3 reports the results of robustness exercises examining the impact of labor intensive technology on the industry-specific effect of pollution on productivity. The cells of row 1 report the coefficients of estimating Equation 11. The outcome variable is industry sensitivity to air pollution and the explanatory variables are the factor shares. The unit of observation is the three-digit industry. The robust standard errors are reported in parenthesis beneath. All regressions weight industries by their total output.

Rows 2 and 3 examine the influence of noise. Row 2 repeats row 1 with EB-adjusted industry-specific effects, λ_i^{EB}, as the outcome in lieu of λ_i. Row 3 repeats row 1 excluding λ_i more than 3.5 standard deviations from the output weighted mean. In both cases the impact remains statistically significant.

Row 4 repeats the specification of 1 with the capital factor share omitted in lieu of the materials factor share. This estimate shows that the labor factor share predicts a lower (more negative) industry-specific effect of air pollution on productivity regardless of the omitted factor.

The remaining rows replicate the robustness exercises of Table A2. Rows 5-7 and 13-14 examine the instrumental variables research design. They are analogous to rows 2-4 and 10-11. Rows 8-9 ensure the preparation of the ASI data does not influence the results. They are analogous to rows 5-6. Rows 10-12 examine the assumptions of the production function estimation. They are analogous to rows 5-7.

Figure A1: **Conditional Wind and AOD for Each Month**



Note: Each point represents binned of averages of district-month mean wind velocity and mean AOD. Line depicts a linear regression of AOD on log wind velocity conditional on rain, temperature, district and year fixed effects.

Table A1: **Summary of ASI Firm Characteristics**

	mean	sd	p5	p50	p95	count
Revenues (million Rupees)	163.66	660.78	0.98	18.60	664.49	220200
Number of Employees	96.02	278.72	6.00	26.00	392.00	220200
Capital Stock (million Rupees)	51.00	379.41	0.11	2.75	165.89	220200
Materials Cost (million Rupees)	103.34	408.12	0.39	12.82	426.65	220200

Note: Data from Annual Survey of Industries 2001-2010. The unit of observation is the firm-year. All statistics use survey weights.

Table A2: **Impact of AOD on Productivity Robustness Checks**

	(1) λ	(2) p-value	(3) N
(1) Baseline	-0.19 (0.28)	0.50	204,275
(2) Linear first stage	-0.23 (0.30)	0.44	204,275
(3) Alternative control function	-0.20 (0.28)	0.47	204,275
(4) Yield included	-0.08 (0.26)	0.75	140,625
(5) 2001 survey weights	-0.07 (0.28)	0.80	204,275
(6) 2010 survey weights	-0.23 (0.28)	0.40	204,275
(7) Constant returns to scale	-0.51 (0.22)	0.02	204,275
(8) Exogenous investment	-0.19 (0.28)	0.51	204,275
(9) Labor adjustment cost	-0.07 (0.27)	0.81	203,990
(10) Rural	-0.09 (0.43)	0.84	88,035
(11) Urban	-0.30 (0.32)	0.35	116,232
(12) Low working days	-0.68 (0.75)	0.36	51,329
(13) High working days	-0.08 (0.28)	0.78	152,946
(14) State-level clustering	-0.19 (0.32)	0.56	204,275

Note: The unit of observation is the firm-year. The sample includes firms in the ASI panel years 2000/01-2009/10. Estimates are obtained from Equation 7 with dependent variable log total factor productivity. The predicted AOD coefficient is reported in column 1 with standard error in parenthesis beneath. Column 2 reports the p-value of the coefficient significance test and column 3 reports the sample size. Robust standard errors were clustered at the district level unless otherwise noted. Regressions use survey weights. See text for details.

Table A3: **Input Contributions to λ_i Robustness Checks**

	(1) γ_L	(2) γ_K	(3) γ_0	(4) γ_M	(5) N
(1) Baseline	-9.98	2.49	-0.21		132
	(4.79)	(3.31)	(0.48)		
(2) EB adjusted	-3.83	0.79	-0.11		132
	(1.28)	(0.78)	(0.14)		
(3) Outliers excluded	-10.42	3.07	-0.28		129
	(4.75)	(3.44)	(0.48)		
(4) Capital omitted	-13.00		2.36	-2.80	132
	(7.33)		(2.59)	(3.10)	
(5) Linear first stage	-41.48	4.03	3.48		132
	(34.27)	(9.26)	(3.85)		
(6) Alternative control function	-9.96	2.18	-0.17		132
	(5.03)	(3.55)	(0.50)		
(7) Yield included	-6.15	7.32	-1.30		130
	(5.57)	(2.33)	(0.54)		
(8) 2001 survey weights	-8.69	2.68	-0.15		132
	(5.02)	(3.52)	(0.50)		
(9) 2010 survey weights	-13.40	4.26	-0.28		132
	(4.44)	(2.44)	(0.45)		
(10) Constant returns to scale	-9.74	2.75	-0.56		131
	(5.12)	(3.22)	(0.63)		
(11) Exogenous investment	-8.69	1.10	-0.08		131
	(4.53)	(3.37)	(0.58)		
(12) Labor adjustment cost	3.11	-1.46	-0.86		131
	(2.02)	(2.25)	(0.71)		
(13) Rural	1.64	1.88	-1.05		117
	(3.47)	(4.55)	(0.87)		
(14) Urban	-0.27	1.58	-0.59		130
	(2.77)	(2.50)	(0.86)		

Note: The unit of observation is the three-digit industry. The sample includes manufacturing industries in the ASI panel years 2000/01-2009/10. Estimates are obtained from fitting Equation 11. Column 1 reports the β_{Li} coefficient with robust standard errors in parenthesis beneath. The β_{Ki}, constant, and β_{Mi} estimates are reported analogously in columns 2, 3, and 4 respectively if applicable. Column 4 reports the sample size. All regressions weight industries by their total output. See text for details.