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Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China

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Abstract

An emerging literature estimates air pollution's effects on productivity but only for small groups of workers of particular occupations or firms. To provide more comprehensive estimates necessary for nationwide policy analysis, we estimate effects for a nationally representative sample of all of China's manufacturing firms from 1998 to 2007 and capture all channels by which pollution influences productivity.

We use thermal inversions as an instrument to estimate the causal effect of pollution on productivity. A one $\mu g/m^3$ decrease in $PM_{2.5}$ increases productivity by 0.82% with an elasticity of -0.44. Firms respond by hiring more workers attenuating the elasticity of output with respect to pollution to -0.17. Using the differential effect of China's accession into the WTO on coastal versus inner regions, we estimate the causal effect of output on pollution (elasticity of 1.43) to simulate the dynamic, general-equilibrium effects of $PM_{2.5}$ yielding an elasticity of -0.31. Lowering $PM_{2.5}$ by 1% nationwide through methods other than reducing manufacturing output would generate annual productivity increases of CNY 39.7 thousand for the average firm and CNY 6.3 billion or 0.043% of GDP across all firms.

JEL Codes: Q51; Q53; D62; R11
Keywords: air pollution; productivity; environmental costs and benefits; firm competitiveness

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1 Introduction

An emerging literature documents the effect of air pollution on short-run productivity, an important driver of economic growth. These papers significantly advance our understanding of how pollution affects productivity and convincingly demonstrate that air pollution can decrease productivity. However, because these studies utilize detailed measures of hourly or daily output per worker, they focus on narrow groups of workers in particular occupations such as fruit picking (Graff Zivin and Neidell, 2012), garment assembly (Adhvaryu *et al.*, 2014), pear packing (Chang *et al.*, 2016), call center services (Chang *et al.*, 2019) or textile assembly (He *et al.*, 2019). While these estimates are useful for evaluating narrowly-targeted environmental policies or evaluating the costs and benefits for certain groups, their external validity is of concern in evaluating broad-based pollution reduction policies.

We provide comprehensive, nationwide causal estimates of air pollution's effect on short-run productivity for manufacturing firms in China encompassing all channels of effects. Using satellite data to measure pollution we are able to consider all firms in China's manufacturing survey in our estimates. The survey includes all state-owned enterprises (SOEs) and all non-SOEs with more than CNY 5 million in annual sales rendering evaluations of nationwide environmental policies feasible. Having moved to nationwide estimates, it is necessary but challenging to quantify the general-equilibrium effects taking account of output's effect on pollution. To do so, we supplement the partial-equilibrium estimate with an estimate of the causal effect of output on pollution using an instrumental variable approach and then simulate the general-equilibrium effects.

For our partial-equilibrium estimates, we find an elasticity of productivity with respect to pollution of -0.44 for particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$). Holding inputs constant, an increase in $PM_{2.5}$ by 1% nationwide from sources other than manufacturing would decrease the average firm's output by USD 7.4 (CNY 56.3)[1] thousand and decrease output across all firms by USD 1.2 billion annually (0.060% of China's average gross domestic product (GDP) over the sample period). Firms compensate for this productivity loss by hiring more workers which partially offsets it. The combined effect of the productivity loss and additional hiring is an elasticity of -0.17 for output with respect to pollution. We do not find significant differences in these effects between China's major manufacturing centers and elsewhere.

We combine this partial-equilibrium estimate with a causal estimate of output's effect on pollution and embed them in an intertemporal general-equilibrium model of China's economy (àla Nordhaus, 1992) to simulate the general equilibrium effects. Calibrating

[1] Throughout the paper we measure output by value added and use these terms interchangeably since we abstract away from intermediate inputs. A 2007 exchange rate of 7.6 is used throughout the paper.

the model to observed values, we find that the effects are amplified when taking account of how output effects pollution. A 1% increase in $PM_{2.5}$ over the sample period decreases total output by 0.31% on average over the sample period. Dynamically, the effect is greater than the partial-equilibrium effects in the first period of the sample and increases over time as capital is accumulated. These are significant effects and can be used in cost-benefit analyses of nationwide environmental policies.

The primary obstacles in estimating pollution's effect on output are simultaneity and omitted-variable biases. Simultaneity bias in ordinary least squares (OLS) estimates could result from the production process itself in the absence of any effect of pollution on productivity or from compensating actions taken by firms in the presence of such effects. In the absence of any effects the more output a region's firms produce the worse its pollution, biasing OLS estimates upward towards or above zero. If pollution lowers productivity, this will lower output and pollution biasing OLS estimates downward. Bias may also result if firms compensate by substituting to other inputs: upward if these other inputs are low-polluting or downward if high-polluting. Omitted variable bias could result from region-specific, time-varying correlations between pollution and output induced by production decisions, industrial policies, or regulations.[2] These could bias OLS estimates upward or downward depending on whether low-productivity regions adopt cleaner or dirtier technologies over time in response to these actions.

Previous papers in this literature maintain exogeneity by using a short time period and focusing on one or a few firms which do not materially impact overall pollution levels. Estimating with a national sample over a longer period no longer affords this condition. To overcome the simultaneity and omitted variables biases while achieving comprehensive estimates we employ the number of days with thermal inversions in geographic areas corresponding to counties to instrument for pollution. Thermal inversions form due to exogenous meteorological factors yet trap pollutants such as $PM_{2.5}$ near the ground degrading air quality. Previous papers using thermal inversions as an instrument include Arceo *et al.* (2016); Hicks *et al.* (2016); Jans *et al.* (2018); Sager (2019); Chen *et al.* (2017); Dechezleprêtre *et al.* (2018). The instrument is highly predictive and, when applied, reveals more negative productivity effects than OLS estimates.

A second estimation obstacle is potential spatial sorting across regions of low- versus high-skilled workers or low- versus high-polluting firms in response to pollution. Using OECD (2011)'s criteria, we classify firms by technology intensiveness and find that pollution is not predictive of the year-by-year fraction of employment in low- versus high-technology firms across locations suggesting that the migration of workers is

[2] Our specification includes firm fixed effects ruling out time-invariant sources of bias.

limited in the short run. Few firms move during the sample period consistent with no significant sorting by extant firms. Excluding firms that relocate results in greater effects on productivity indicating that pollution's effect may be even greater if these are representative of the full sample. Pollution is not predictive of firm entry or exit consistent with endogenous choice of entry and exit and survival bias having limited effect on our estimates.

Since previous papers focus on small sets of firms or workers, general-equilibrium effects could be ignored. For proper policy analysis, nationwide estimates must incorporate the feedback effect of output on pollution. Estimating output's effect on $PM_{2.5}$ also raises endogeneity issues. Most directly, pollution deters production which will bias OLS estimates. Estimates are also affected by all the same simultaneity and omitted-variable biases as the estimates for productivity. To address this, we use China joining the World Trade Organization (WTO) in 2001 as an exogenous shock to output in China's more-developed coastal regions vis-à-vis its less-developed inner regions. This approach is widely used in the trade literature (Goldberg and Pavcnik, 2005; Verhoogen, 2008; Topalova, 2010). We find an elasticity of $PM_{2.5}$ with respect to output of 1.43. This estimate is useful in and of itself as there are few causal estimates of output's effect on pollution. Combining this with our partial-equilibrium estimate of pollution's effect on output, we simulate the general-equilibrium effect of pollution using a slightly modified version of the Dynamic-Integrated-Climate-Economy (DICE) model of Nordhaus (1992). Using economy-wide data for our sample period and parameterizing the production and utility functions with realistic parameters we closely match actual output and pollution. From this we simulate counterfactuals quantifying pollution's effect on output incorporating effects on both productivity and labor supply.

This paper makes three primary contributions. First, we provide nearly exhaustive measures for the causal effect of pollution on the short-run productivity of a country's manufacturing sector. Previous studies examine only small sets of workers in particular occupations or a small set of firms. An exception is a subsequent paper by Dechezleprêtre *et al.* (2018) that examines effects of $PM_{2.5}$ on GDP and population across European regions (roughly counties) using aggregated data. Cost-benefit analyses of national environmental policies require comprehensive estimates since effects on particular occupations, firms, or industries may be idiosyncratic. We provide such a nationwide estimate for China and find larger estimates than previous, more focused studies. A possible reason is that we estimate annual cumulative effects rather than those of shorter duration; however, this may also relate to the scope of our estimates. They reflect all manufacturing industries, firms and occupations rather than specific settings and they capture all channels by which productivity is affected including per-hour productivity and working hours. Our methodology is general and could be applied to any country experiencing sufficient variation in thermal inversions.

Second, we provide general-equilibrium estimates of pollution's effect on output including effects on both productivity and labor supply. Previous papers avoided this complication because they considered only small sets of workers or firms so that it was unnecessary to consider the feedback effect of output on pollution. This also distinguishes our work from Dechezleprêtre *et al.* (2018) which examines only partial-equilibrium effects. We do so by simulating these effects in a dynamic-general equilibrium model of China's economy. Calibrating the model to observed economic values incorporating the causal effect of output on pollution, we find that pollution's general-equilibrium effects are greater than its partial-equilibrium effects. These estimates can be used to evaluate environmental policies that reduce manufacturing output or reduce pollution through improved abatement technologies. We believe ours is the first paper to provide general-equilibrium estimates relating productivity and air pollution. The simulation approach is general and can be applied in any setting in which partial-equilibrium estimates of pollution's effect on output and output's effect on pollution are available.

Third, there is relatively little evidence concerning pollution's effect on high-skilled workers (exceptions are Archsmith *et al*. (2018) on umpires, Heyes *et al*. (2016a) on investors, Heyes *et al.* (2016b) on politicians, and Kahn and Li (2019) on judges). We estimate the effects of $PM_{2.5}$ on productivity separately for firms in high- and low-technology industries based on the OECD (2011) classification and find significant effects for both. This suggests that the results apply not just to older, traditional manufacturing firms but also to those employing newer, more advanced technologies.

Estimates for China are important in and of themselves. China is the world's most populous country and a large source of manufacturing and the resultant pollution. China represented 22% of the world's manufacturing output in 2012.[3] The findings also have implications for the global economy as China incurs a disproportionate fraction of the world's pollution because of its substantial exports. Depending on the type of pollutant, 17 to 36% of China's air pollution is attributable to exports (Lin *et al.*, 2014). Our estimates imply that policies that reduce China's air pollution can generate substantial increases in productivity in addition to health benefits and, given China's extensive exports, benefit other countries via trade. Our estimates complement the literature that estimates the social costs of reduced health due to China's air pollution (Matus *et al.*, 2012; Chen *et al.*, 2013; Ebenstein *et al.*, 2015; Bombardini and Li, 2016; Ebenstein *et al*., 2016; He *et al.*, 2016; Ito and Zhang, 2016).

Many developing countries are hesitant to implement measures to reduce air pollution for fear of hindering growth (Hanna and Oliva, 2015). Figure 1 illustrates the

[3] "China has a Dominant Share of World Manufacturing," United Nations and MAPI, January 6, 2014 (https://www.mapi.net/blog/2014/01/china-has-dominant-share-world-manufacturing).

environmental pollution resulting from China's development. It plots the average concentration of $PM_{2.5}$ across all regions of China over the sample period against annual value added for all firms in our sample. The rapid increase in output has resulted in accompanying rapid increases in air pollution, especially after China joins the WTO in 2001. Our finding of significant productivity gains from reducing pollution provides additional impetus to implement pollution control measures. Because of China's severe pollution, the central government has designed many policies to reduce air pollution but these have often gone unenforced or under-enforced because local governments lack incentives to do so or their incentives emphasize alternative goals such as economic growth (Li and Zhou, 2005; Chen *et al.*, 2016; Jia, 2017). Our findings suggest local governments may underestimate the benefits to local economic growth of reducing air pollution.

[Insert Figure 1 here.]

The rest of the paper is organized as follows. The next section discusses related literature. Section 3 describes the data; Section 4 specifies the econometric models and discusses identification issues and strategies. Section 5 presents our partial-equilibrium results and Section 6 the general-equilibrium analysis. Section 7 concludes.

2. Pollution and productivity

How does air pollution affect short-run productivity? An extensive literature documents the negative effects that a high concentration of air pollution can have on human health. According to the Environmental Protection Agency (EPA), short-run exposure can lead to decreased lung function, irregular heartbeat, increased respiratory problems, nonfatal heart attacks, and angina.[4] These short-run effects can result in decreased physical stamina at work and missed work days. Long-run exposure may lead to cardiopulmonary diseases, respiratory infections, lung cancer (EPA, 2004), and asthma (Neidell, 2004). These long-run health problems can manifest themselves in the short run if high levels of pollution trigger conditions resulting from previously accumulated exposure. Infant and elderly morbidity resulting from air pollution (Chay and Greenstone, 2003; Deryugina *et al.*, 2016) can require working adults to miss work to care for them (Hanna and Oliva, 2015; Aragón *et al.*, 2017). Long-term exposure can also reduce life expectancy (Chen *et al.*, 2013; Ebenstein *et al.*, 2017) which can result in experienced workers being replaced by new, inexperienced ones.

Air pollution can also lower cognitive ability, alter emotions, increase anxiety, and have other negative psychological effects (Levinson, 2012; Lavy *et al.*, 2014; Pun *et al.*, 2017;

[4] See the EPA websites: https://www.epa.gov/pm-pollution; https://www.epa.gov/so2-pollution; and https://www.epa.gov/co-pollution.

Chen *et al.*, 2018) which would affect the performance of both physical and knowledge workers. All of these effects can be compounded by spillovers to other workers (Arnott *et al.*, 2005, Chapter 4). Moreover, $PM_{2.5}$ can seep into buildings (Thatcher and Layton, 1995; Vette *et al.*, 2001), making avoidance behavior costly or impossible for workers unless their employer provides proper filtration equipment. While our estimates are unable to distinguish between these various channels they capture all of them.

Pollution can affect output through productivity, the intensive margin, and labor supply, the extensive margin (pollution can also affect capital supply but we ignore this here since we do not find significant effects in our estimates). The intensive and extensive margins depend on the context and the time unit measured. In our context, time is measured in worker-years. Therefore, our productivity estimates capture all possible channels that affect per-hour productivity (intensive margin) and hours worked (one type of extensive margin) although we cannot distinguish them. We separately estimate the labor supply effects on number of worker-years (another type of extensive margin). Pollution could also affect capital productivity through firms investing in pollution-reduction measures, either in response to regulation or to offset decreases in productivity that arise from pollution. For example, abatement equipment that consumes some output.

To illustrate this, consider a constant-returns-to-scale, Cobb-Douglas production function in capital (K) and labor (L):

$$Q = (A_K K)^{\gamma}(A_L L)^{1-\gamma}, \text{(1)}$$

where A_K is capital productivity and A_L is labor productivity. Logging both sides:

$$ln(Q) = [\gamma ln(A_K) + (1-\gamma)ln(A_L)] + \gamma ln(K) + (1-\gamma)ln(L). \text{(2)}$$

The first term in brackets on the right-hand side is also total factor productivity: $TFP = [\gamma ln(A_K) + (1-\gamma)ln(A_L)]$. The effects of pollution (Ω) are given by (ignoring effects on capital supply as noted above):

$$\frac{dln(Q)}{dln(\Omega)} = \left[\gamma \frac{dln(A_K)}{\mathrm{dln}(\Omega)} + (1-\gamma)\frac{dln(A_L)}{\mathrm{dln}(\Omega)}\right] + (1-\gamma)\frac{dln(L)}{\mathrm{dln}(\Omega)}. \text{(3)}$$

There are two potential effects: the effect on productivity (the first term in brackets on the right-hand side) and the effect on labor supply. We estimate these two separately. For productivity, we use two different approaches following Syverson (2011): the effect on output per worker and the effect on TFP.

We can use this setup to relate our results to the previous literature. In our setting L is measured in worker-years and Q annually. Suppose per-hour labor productivity is a and each worker's annual hours is H then $A_L = a * H$. In the data we observe L but not a

or H. Our productivity estimates (both TFP and output per worker) hold the number of worker-years constant so that:

$$\frac{d(TFP)}{dln(\Omega)} = \frac{dln(Q/L)}{dln(\Omega)}\bigg|_L = \gamma \frac{dln(A_K)}{\mathrm{dln}(\Omega)} + (1-\gamma)\left[\frac{dln(a)}{\mathrm{dln}(\Omega)} * H + a * \frac{dln(H)}{\mathrm{dln}(\Omega)}\right]. \quad (4)$$

Our estimates therefore capture both the intensive (per-hour productivity) and one type of extensive margin (hours worked) effects on productivity. We also separately estimate the effect on labor supply (L) (another extensive margin) to determine the effects on total output given by Equation (3).

Extant studies of pollution and productivity observe worker hours (H) and therefore measure effects on per-hour productivity $(dln(a)/\mathrm{dln}(\Omega))$; many also separately estimate effects on hours worked $(dln(H)/\mathrm{dln}(\Omega))$ but find little effect. $PM_{2.5}$ reduces per-hour productivity of pear-packing workers in California but has little effect on labor supply as measured by hours worked or absenteeism (Chang *et al.*, 2016). $PM_{2.5}$ also reduces per-hour productivity of garment factory workers in India with no effect on absences (Adhvaryu *et al.*, 2014). $PM_{2.5}$ and SO_2 reduce per-hour output of textile workers at two sites in China but has little effect on hours worked (He *et al.*, 2019). Ozone reduces per-hour productivity of outdoor fruit pickers in California but not hours worked or absenteeism (Graff Zivin and Neidell, 2012) and pollution measured by the air pollution index (API) affects call center workers (Chang *et al.*, 2019) with no effect on hours worked.

To provide precise measures of daily output, all of these previous studies focus on a small group of firms or a particular type of worker. Although this helps establish a causal link because pollution is exogenous to the activities of a small number of firms, the results may not generalize. A few other papers examine pollution's effect on performance in other environments. Air pollution increases students' absences (Currie *et al.*, 2009) and their cognitive performances and test scores (Ebenstein *et al.*, 2016). It also has negative effects on short-run performance of outdoor athletic participants including soccer players (Lichter *et al.*, 2017) and marathon runners (Guo and Fu, 2019).

3. Primary data

We estimate firm-level productivity combining comprehensive data on firm characteristics with air pollution data for highly-specific geographic areas across all of China from 1998 to 2007. While several different pollutants' effects on productivity have been studied we focus on $PM_{2.5}$ because of its severe effects. Due to its small size it can enter the lungs and bloodstream causing severe health problems and reduced stamina. Our pollution measure is monthly concentration of $PM_{2.5}$ derived from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by the National

Aeronautics and Space Administration (NASA).[5] We use the AOD data because it provides the most comprehensive measure of air pollution across China's geography and over time. AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution even in areas lacking ground-based monitoring stations (Gupta *et al.*, 2006; van Donkelaar *et al.*, 2010; Kumar *et al.*, 2011). Chen *et al.* (2017) validate the AOD data using ground-based, station data in China, and find that the difference between them is statistically insignificant conditional on geographic and year fixed effects. The $PM_{2.5}$ concentrations are calculated following Buchard *et al.* (2016).

The AOD data have several advantages compared to ground-based pollution data. First, it predates the beginning of our firm sample in 1998 while ground-based pollution data are available beginning only in 2000 giving us two more years of data. Second, it covers the whole country while ground-based pollution data cover only 42 cities in 2000 increasing to 113 in 2010. Third, ground-based pollution data are potentially subject to human manipulation (Andrews, 2008; Ghanem and Zhang, 2014) while the satellite data are not. The AOD pollution data are reported in grids of 50 by 60 kilometers which we aggregate to the county level – the smallest administrative unit in China to which we can match firm locations.[6] We then average by year to obtain annual mean concentrations of $PM_{2.5}$ in each county-year.

Although the AOD data is remarkably accurate in measuring ground-level $PM_{2.5}$ our paper faces a problem present in much of the literature: different pollutants are highly correlated which may prevent us from isolating a single pollutant's effects. We are potentially aided by the fact that we instrument using thermal inversions and not all pollutants are affected by them. Nonetheless, thermal inversions do affect other pollutants (*e.g.*, carbon monoxide as described by Arceo *et al.* (2016)) and inversions may therefore not be specifically correlated with $PM_{2.5}$ vis-à-vis other pollutants. Therefore, our estimates can be interpreted as air pollution impacts more broadly not necessarily specifically from $PM_{2.5}$.

[5] The AOD data are obtained from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) and are available at https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_V5.12.4/summary?keywords=Aerosols#. We utilize M2TMNXAER version 5.12.4 which reports monthly AOD data within each 0.5 degrees latitude by 0.625 degrees longitude (corresponding to 50 by 60 kilometers) grid.

[6] The six-digit administrative code is published by the NBS' Administrative Division: http://www.stats.gov.cn/tjsj/tjbz/xzqhdm/201401/t20140116_501070.html (in Chinese). In constructing the pollution and thermal inversion measures based on the satellite data, we take spatially-weighted averages across a county of all pixels based on the proportion of the county that each pixel represents. Specifically, we interpolate within the original 50 by 60 kilometer grids using the bilinear method (Hijmans *et al.*, 2015) to obtain 10 by 12 kilometer grids to better accommodate counties that are smaller than 50 by 60 kilometers. For counties that span more than one 10 by 12 kilometer grid we use a weighted-average (by area) across all grids that it spans.

Since the satellite pollution measure covers the entire country we can include all manufacturing firms for which we have data. Our firm-level output and characteristics data is from annual surveys of manufacturing firms conducted by China's National Bureau of Statistics (NBS). The survey includes all state-owned enterprises (SOEs) regardless of size and all non-SOEs whose annual sales exceed CNY 5 million (USD 0.8 million) and contains detailed information on firm location,[7] accounting measures, and firm characteristics. This captures 90.7% of China's total manufacturing output in the later years (Brandt *et al.*, 2012). During our sample period this includes 2,082,823 firm-year observations and 544,308 unique firms across all years.

Following the matching algorithm described in Brandt *et al.* (2012) we match firms over time to form an unbalanced panel.[8] This matching process is careful and avoids interpreting name changes as different firms (Brand *et al.* (2012), Section A.2 of their online appendix). The panel is very unbalanced due to China's rapid growth during this period which leads to a large number of new firms surpassing the CNY 5 million revenue threshold year-by-year.[9] We also follow Brandt *et al.* (2012) in converting nominal into real values using industry-level price indices. We drop observations with missing or unreliable data following the previous literature (Cai and Liu, 2009; Brandt *et al.*, 2012; Yu, 2014).[10] These represent 10.3% of observations and 7.9% of total manufacturing output. The biggest loss of data in estimation is due to firms appearing in only one year and dropped with the inclusion of firm fixed effects. These represent 16.1% of observations and 30.5% of total manufacturing output.[11]

Finally, we winsorize the top and bottom 0.5% of data based on each of the values of output, value added, employment, and capital to be consistent with the previous literature (Cai and Liu, 2009) and because of the risk that these involve data entry or reporting errors. However, we show that the results are similar using the non-

[7] Firm location is known at least up to the six-digit administrative code level used to match to the pollution data. Specific addresses are known only for a small share of firms and thus using these to match would make our data far less comprehensive.

[8] Their Stata programs are posted at: http://feb.kuleuven.be/public/N07057/CHINA/appendix.

[9] Brandt *et al.* (2012) confirm that these appearances are *de novo* and not due to firm restructuring. The annual rate of exit is less than 14% (Section A.2 of their online appendix).

[10] We drop observations with missing or negative values for output, value added, employment, or capital; firms with fewer than eight employees since they may not have reliable accounting systems; and firms violating accounting identities such as the components of net assets exceeding total assets or current depreciation exceeding cumulative depreciation.

[11] Because of China's rapid growth during this time, 43% of these single-year firms occur in the last year of the sample. For the remaining 57% that occur in earlier years, 8% are SOEs and therefore must be due to actual entry and exit. The remaining 92% are non-SOEs so we do not know whether they appear in only a single year because they enter and then exit or they move above and then below the CNY 5 million threshold to appear in the sample. However, as Online Appendix 1 shows, the characteristics of these firms are similar to the full sample except that they are smaller. Given the large number of single-year firms, we comment more below on the potential effects of censoring due to the CNY 5 million threshold.

winsorized data. We also show that the results are robust to excluding the few multi-plant firms in the data which cannot be uniquely matched to a single location. The final data include 1,593,247 firm-year observations for 356,179 unique firms. Geographically, the sample includes 2,755 counties with an average of 58 firms per county-year.

One issue with obtaining broad-based measures of productivity is how to measure it. Previous papers in the literature focused on one or a small set of firms producing a single well-defined product where output quantity is directly measurable. Pooling all manufacturing firms, as we do, requires an alternative measure. Since we abstract from intermediate inputs we use value added as the measure of output. Value added is reported directly in the data and equals total production (including both sales and inventory) of all goods produced in the year valued at their market prices less the cost of all intermediate inputs employed in producing them. Value added per worker is commonly used as a measure of productivity in the general-productivity literature (Syverson, 2011; Brandt *et al.*, 2012) and in the temperature-productivity literature (Hsiang, 2010; Dell *et al.*, 2012). However, it raises two issues.

First, using value added requires that prices do not reflect market power in either the primary or downstream input markets. If they do not, monetary-based measures are preferred over quantity-based measures as they reflect quality differences (Syverson, 2011). As with other studies that use data sets with many firms, we cannot guarantee that prices are independent of market power; however, thermal inversions are independent of firm-level market power allowing us to consistently estimate pollution's effect on productivity via instrumented pollution. The second issue concerns multi-product firms. Their mix of products is not discernible from the firm's value added and may be correlated with pollution levels. However, our instrumenting strategy addresses this issue: thermal inversions are uncorrelated with a firm's decision of product mix thereby removing any bias in the instrumented results.

We obtain daily, station-level weather variables that could affect both air pollution and productivity including temperature, precipitation, relative humidity, wind speed, sunshine duration, and barometric pressure from the National Meteorological Information Center of China. We convert the daily station data to daily-county level using the inverse-distance weighting method (Deschênes and Greenstone, 2011) to give less weight to stations more distant from the geographic centroid. To allow for extreme weather events to have differential effects from more normal ones, we follow Deschênes *et al.* (2017) and calculate twenty quantiles for each weather variable based on the daily distribution and include the annual number of days within each quantile. The weather measures are then matched to the firm data by county-year.

For our instrument, we obtain thermal inversion data from NASA.[12] The data report air temperatures every six hours at 42 vertical layers from 110 meters to 36 thousand meters within 50- by 60-kilometer grids. We aggregate from the grid to the county level within each six-hour period and for each layer. Following Arceo *et al.* (2016), we define a thermal inversion as the temperature of the second layer (320 meters) being higher than that of the first layer (110 meters). We determine this within each six-hour period of each day for each county. Since thermal inversions are short-lived (on the order of a few weeks) relative to the annual output measure, we use a cumulate annual measure of inversions to make them temporally consistent. For our instrument, we calculate for each county the annual number of days that have at least one inversion.

Table 1 presents summary statistics of the key variables. The firm characteristics are at the firm-year level and reflect a high degree of variation in productivity. The pollution and thermal inversion data are at the county-year level. The pollution levels are such that they are likely to have an effect on mental and physical health and therefore productivity. The World Health Organization (WHO) recommends a maximum annual mean of ten $\mu g/m^3$ for $PM_{2.5}$ and a maximum mean of twenty $\mu g/m^3$ within a 24-hour period (WHO, 2006). In the sample, the mean annual $PM_{2.5}$ level is 53.5 with a high of 134.8. The annual number of days with thermal inversions displays significant variation ranging from zero to 333 days per year with a mean equal to a little under one-half year.

[Insert Table 1 here.]

4. Model specification and identification

Our primary econometric model is:

$$Productivity_{it} = \beta_0 + \beta_1 \Omega_{it} + \beta_2 W_{it} + \alpha_i + \rho_t + \varepsilon_{it}, \quad (5)$$

where i indicates firm and t year. Ω measures pollution and W contains the vector of weather variables faced by firm i in year t. We aggregate the annual pollution and weather measures to the county level because the location of most firms is known only at the county level and not finer. Because of this, we also check the robustness to clustering the standard errors at the county-year level. The coefficient β_1 captures the effect of pollution on productivity.

Firm fixed effects (α_i) capture time-persistent firm attributes that affect productivity. Since very few firms switch counties (7%) over the time period of our sample, these also absorb most county-specific time-invariant factors that affect productivity. Similarly, no

[12] Specifically, we use product M2I6NPANA version 5.12.4 from MERRA-2 available at https://disc.sci.gsfc.nasa.gov/datasets/M2I6NPANA_V5.12.4/summary?keywords=%22MERRA-2%22%20M2I6NPANA&start=1920-01-01&end=2017-01-16.

firms switch industries so that all time-invariant, industry-specific unobservables affecting productivity are absorbed by the firm fixed effects. Year fixed effects (ρ_t) capture annual national shocks to firm output such as business cycle or macroeconomic effects. The error term (ε_{it}) captures time-varying, firm-specific unobservables that affect productivity. In our baseline estimation we cluster standard errors by firm to allow for serial correlation in productivity within firm over time but we show robustness to various other clustering patterns.

We use two different measures for productivity: output per worker $ln(Y_{it}/L_{it})$ where Y is value added and L is number of workers and total factor productivity TFP_{it} for firm i in year t.[13] In estimating TFP, we instrument for firms' endogenous choices of inputs using two different approaches: investment as an instrument (Olley and Pakes, 1996) and intermediate inputs as an instrument (Levinsohn and Petrin, 2003). Table 1 provides the summary statistics for TFP estimated under both approaches. The correlation between TFP (using the OP method) and output per worker is 0.71 significant at better than the 0.01% level. We use output per worker for our primary results to be consistent with the environmental economics literature but the results are robust, although with somewhat smaller effects, using TFP. For TFP, we use a two-step approach as in Wang and Wang (2015), Yu (2015), and Brandt *et al.* (2017). In the first step we estimate TFP and in the second step relate TFP to pollution including controls.

Identification requires that, conditional on the control variables, pollution is independent of the error in Equation (5). The causal identification issues that are specific to our context include simultaneity bias, omitted variable bias, and spatial sorting.

4.1 Causal identification issue – simultaneity and omitted variable biases

Simultaneity bias can lead OLS estimates of pollution's effect on productivity to be biased either upward or downward. Absent any effect of pollution on productivity, higher productivity in a county leads to both more output and more pollution, biasing OLS estimates upward toward or above zero. On the other hand, if pollution decreases productivity this will lower output and therefore pollution biasing OLS estimates downward away from zero. If pollution lowers productivity, firms may also compensate by using more of alternative inputs. If these inputs are high-polluting (for example dirty energy) this would bias OLS estimates downward while compensation to clean inputs would bias them upward.

[13] Estimating output per worker has been criticized because it depends on the level of capital employed (Syverson, 2011). This is not a problem in our setting because our instrumented pollution measure is orthogonal to inputs.

Omitted-variable bias due to local, time-varying conditions could also lead to either an over- or under-statement of pollution's effect on productivity in OLS estimates (since we include firm fixed effects time-invariant conditions will not create bias). For example, counties with more productive firms may implement more advanced, lower-polluting technology over time leading to an upward bias. Alternatively, firms that have older, higher-polluting technology may have low productivity and insufficient funds to upgrade their production technology over time leading to a downward bias as technology degrades. Local trends in regulatory conditions may also bias OLS estimates. For example, counties with high-productivity workers may press for implementation of more stringent environmental regulations over time leading to a downward bias. On the other hand, an upward bias could result if counties with older, less productive and higher polluting technology face environmental "crises" and initiate more stringent regulations. Similarly, industrial policies might be used to stimulate production in less-polluted counties over time introducing upward bias. We address these identification issues using instrumental variables.

A valid instrument is correlated with a county's air pollution but uncorrelated with its resident firms' productivity except via pollution. Our instrument is the annual number of days with at least one thermal inversion for each county. Normally, air temperature decreases with altitude above the Earth's surface. A thermal (or temperature) inversion is a deviation from this. It occurs when a mass of warmer, less dense air moves above a cooler, denser air mass trapping dust and pollutants near the ground and increasing air pollution. Since thermal inversions are a meteorological phenomenon and, after conditioning on weather variables, are unrelated with production except via pollution, it is a valid instrument. A few studies have applied this identification strategy to estimate the effects of air pollution on various outcomes (Arceo *et al.*, 2016; Hicks *et al.*, 2016; Jans *et al.*, 2018; Sager, 2019; Chen *et al.*, 2017; Dechezleprêtre *et al.*, 2018). A caveat to this approach is that inversions can affect the efficacy of pesticides and fertilizer in agriculture. Although our firm data does not include agriculture there could be knock-on effects upstream or downstream in manufacturing that could affect the instrument's exogeneity.

With this as our instrument we employ two-stage least squares (2SLS) with the first-stage equation:

$$\Omega_{it} = \gamma_0 + \gamma_1 I_{it} + \gamma_2 W_{it} + \alpha_i + \rho_t + \eta_{it}, \quad (6)$$

where I_{it} is the number of thermal inversion days in firm i's county in year t. The weather controls from the second stage are included because these same variables affect the formation of inversions (Arceo *et al.*, 2016) and are also needed to ensure the exclusion restriction is met in the second stage.

4.2 Causal identification issue – spatial sorting

Spatial sorting results from either firms or workers self-selecting into particular counties based on their pollution levels. Firms may choose to locate in counties with less severe pollution because it leads to higher productivity which would bias estimates of pollution's effect on productivity upward toward or above zero. Alternatively, firms may choose to locate in counties with more severe pollution because it reflects less stringent underlying local environmental regulations and therefore lower costs – the "pollution haven" effect (Becker and Henderson, 2000; Greenstone, 2002; Brunnermeier and Levinson, 2004). In this case, the direction of the bias induced depends on whether firms with higher pollution output are more or less productive. If they are more productive, estimates will be biased upward toward or above zero and if less productive downward away from zero.

The firm fixed effects included in estimation absorb any initial endogenous sorting of firms across counties so that only sorting that occurs during the sample period will introduce bias.[14] Only 7% of firms relocate counties during the sample period. Excluding these from estimation suggests some sorting effects and larger productivity effects absent sorting. Firm entry and exit during the sample period could introduce bias through endogenous selection. To check for this possibility we estimate the effect of pollution on the fraction of firms exiting and entering each county in each year (controlling for endogeneity) and find no significant effect for either.

A second possible type of spatial sorting is workers choosing their location based on their willingness to pay for air quality. High-skilled workers generally have a higher willingness-to-pay for better air quality and are more productive than low-skilled workers. This would result in dirty cities having a high proportion of low-skilled workers and low firm productivity and clean cities having a high proportion of high-skilled workers and high firm productivity (Lin, 2017) exacerbating pollution's negative effect on firm productivity.

Inclusion of firm fixed effects means that any initial endogenous sorting of workers will be absorbed in them and only movement of workers during the sample period will create bias. This effect is not likely large since we estimate annual effects and such migration would likely occur over longer periods,[15] but we check for evidence of this occurring. Based on OECD (2011) we categorize each firm as high, medium-high, medium-low, and low technology and, based on their employment, compute the fraction of workers in each of the four categories in each county-year. Changes in

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[14] Sorting could also occur by industry but since no firms switch industries this is absorbed by the firm fixed effects.

[15] For example, Chen *et al.* (2017) find that people migrate in response to air pollution over a five-year period.

pollution (controlling for endogeneity) is not predictive of changes in these fractions over time except for a small, positive effect on the low-technology fraction.

5. Results

5.1 Baseline results

We first present estimates not accounting for any endogeneity bias between productivity and pollution. Table 2 presents OLS estimates of Equation (5) using output per worker. Without weather controls (Column (1)), $PM_{2.5}$ pollution has no effect on productivity. Including weather controls (Column (2)), reveals a positive effect of pollution on productivity.

[Insert Table 2 here.]

Because of the simultaneity and omitted-variable biases, OLS produces inconsistent estimates. We use the annual number of days with a thermal inversion as an instrument for pollution concentration. We first check whether thermal inversions are predictive of productivity in a reduced-form estimate. Columns (3) and (4) of Table 2 show the results without and with weather controls. Both specifications yield statistically significant results and the coefficient with weather controls implies that one additional day with an inversion annually decreases productivity by 0.03%.

Columns (5) and (6) in the top panel of Table 2 show that the instrument is a powerful predictor of $PM_{2.5}$ concentrations. The coefficient on annual days with thermal inversions is positive and highly significant both with and without weather controls and the Kleibergen-Paap Wald rk *F*-statistic (KP) (Kleibergen and Paap, 2006) for weak identification is much larger than the Stock-Yogo critical value of 16.38.[16] One additional day with an inversion increases $PM_{2.5}$ by 0.036 $\mu g/m^3$ controlling for weather. These are big effects. Using the results with weather controls, a one standard deviation increase in the annual number of days with inversions increases $PM_{2.5}$ by 2.8 $\mu g/m^3$ (5.3%).

The lower panel of Columns (5) and (6) show the second-stage results. Consistent with the instrument correcting for endogeneity, the coefficient moves to being significantly negative. Without weather controls, instrumented $PM_{2.5}$ has a negative and very significant effect on output per worker. A one $\mu g/m^3$ increase in $PM_{2.5}$ decreases productivity by 0.80%. Evaluating this at the mean $PM_{2.5}$ in the sample (53.5) yields an elasticity of -0.43. Controlling for weather changes increases the estimate slightly and

[16] Stock and Yogo (2005) critical values apply when model errors are independent and identically distributed. No critical values are available for the case when the model allows for standard errors that are robust to heteroskedasticity and clustering.

makes it even more significant. A one $\mu g/m^3$ increase in $PM_{2.5}$ decreases productivity by 0.82% implying an elasticity of -0.44. Dechezleprêtre *et al.* (2018) find a lower elasticity (-0.11) for European regions which could be due either to lower levels of pollution in Europe or due to their data including both manufacturing and services. Using TFP as our productivity measure yields slightly lower estimates: an elasticity of -0.26 using the OP estimator and -0.19 using the LP estimator (Columns (7) and (8)). Throughout the rest of the paper we focus on results using output per worker since previous papers estimating pollution's effect have used this measure. However, the results are robust to, but somewhat lower, using TFP. Also, since controlling for weather is preferred we do so throughout the remainder of the paper.

How large are these effects? Consider lowering $PM_{2.5}$ by one percent nationwide through means other than lowering manufacturing output. This could include reducing other pollution sources like road dust, automobile exhaust, and power generation or by decreasing pollution per unit of manufacturing output via pollution abatement equipment that does not reduce output. The resulting productivity improvement would increase the average firm's value added by CNY 56.3 (USD 7.4) thousand annually and increase total value added across all firms by CNY 9.0 (USD 1.2) billion annually.[17] This represents 0.060% of China's GDP.[18]

Online Appendix 2 compares estimates for counties in China's three major economic centers (Jing-Jin-Ji, Yangtze River Delta, and Pearl River Delta)[19] to the rest of the country. The estimates for the two are fairly close to each other and significant implying that air pollution has an effect on productivity even outside the major manufacturing centers.

Since our estimates capture pollution's effect on both per-hour productivity and working hours, it is useful to disentangle the two for comparisons to previous estimates of per-hour productivity effects.[20] We borrow estimates from Aragón *et al*. (2017) which finds an elasticity of working hours with respect to $PM_{2.5}$ of -0.21 in Lima, Peru. Assuming $PM_{2.5}$'s effect on working hours is the same in China, our estimated elasticity of per-hour productivity with respect to pollution is -0.23. It is also similar to the upper end of estimates by He *et al.* (2019) for textile workers in two firms in two Chinese

[17] A 1% decrease in $PM_{2.5}$ increases annual output by 0.44%. The mean annual output per firm in the sample is CNY 12.82 million implying an annual increase of CNY 56.3 thousand. There is an average of 159,325 firms present in each year of the sample implying an annual increase in output across all firms of CNY 9.0 billion annually.

[18] China's average annual real GDP over the ten-year sample period is CNY 14.85 trillion.

[19] The Jing-Jin-Ji region includes Beijing, Tianjin, and Hebei; the Yangtze River Delta region includes Shanghai, Jiangsu, Zhejiang, and Anhui; and the Pearl River Delta region includes Guangdong.

[20] This makes use of the fact that the elasticity of productivity equals the elasticity of productivity per hour plus the elasticity of hours worked as shown in Equation (3).

provinces. They find elasticities ranging from -0.035 to -0.30 from $PM_{2.5}$ exposure if effects are accumulated over 25 to 30 days.

Our estimate exceeds that in Adhvaryu *et al.* (2014), which finds an elasticity of -0.052 for per-hour productivity with respect to $PM_{2.5}$ for garment factory workers in India. It is also larger than the elasticity of -0.062 for $PM_{2.5}$ found in Chang *et al.* (2016) for indoor pear packers in California and the estimate in Chang *et al.* (2019) which finds an elasticity of per-hour labor productivity with respect to the API of -0.023 although the latter is for services workers. The fact that we estimate elasticities that are at least as great as or greater than previous papers could be due to two factors. First, previous estimates apply only to particular worker types or small sets of firms. Second, previous studies measure daily or monthly effects while we capture annual cumulative effects.

We can also compare our estimates to studies that estimate the effect of $PM_{2.5}$ on economic outcomes other than productivity. To do so, we normalize results to the monetary impact of a one-percent decrease in $PM_{2.5}$, which in our case increases productivity by USD 1.2 billion annually. Deryugina *et al*. (2016) estimate the short-run effect of $PM_{2.5}$ on mortality in the U.S. They find that a one-percent decrease in $PM_{2.5}$ concentration (0.11 μg/m^3) leads to a gain of USD 0.45 billion annually in avoided mortality – about one-third of our estimate. Bishop *et al*. (2017) estimate the long-run effect of $PM_{2.5}$ on dementia in the U.S. They find that a one-percent decrease in $PM_{2.5}$ concentration (0.09 μg/m^3) reduces medical expenditure on dementia by USD 0.11 billion annually which is about one-tenth of our estimate for productivity. Chen *et al*. (2018) estimate the short-run effect of $PM_{2.5}$ on mental illness in China. They find that a one-percent decrease in $PM_{2.5}$ concentration (0.48 μg/m^3) reduces expenditure on mental illness treatment by USD 0.60 billion annually – about one-half of our estimate for productivity.

5.2 Robustness checks

Online Appendix 3 shows robustness to different assumptions about the model compared to the baseline results replicated in Column (1). Since some of our explanatory variables are grouped at the county-year level and there may be time-invariant unobserved factors affecting productivity at the county level, the standard errors may be biased downward (Kloek, 1981; Moulton, 1986). We check this in several different ways. Column (2) allows for two-way clustering of errors by firm and county-by-year (Cameron *et al*., 2011). This allows for serial correlation in productivity within firms as well as spatial correlation within each county-year. Although some significance is lost, the results remain significant. Since there is no standard way to cluster with multi-way clustering (Cameron and Miller, 2015) we try two other methods. Column (3) clusters the standard errors by county-year, which allows unobservables to be spatially correlated within each county-year. The standard errors are similar to those under two-way clustering. Clustering at the county level, which allows for spatial and serial correlation within county, in Column (4), increases standard errors only slightly and the results remain significant at better than the 5% level.

Our baseline results use year fixed effects to control for time trends. We test for robustness to regional trends in four different ways: year-by-region fixed effects[21] in Column (5); year-by-province fixed effects in Column (6); province-specific quadratic time trends in Column (7); and year fixed effects along with province-specific quadratic time trends in Column (8). All four yield very significant results and all yield point estimates that are larger than our baseline estimates except for province-specific quadratic time trends. We continue to use year fixed effects as the baseline model because the province-specific time trends impose a specific functional form. The year-by-province fixed effects allow more flexibility but we prefer the more conservative estimates using year fixed effects.

Our baseline estimates weight all observations equally. Column (2) of Online Appendix 4 re-estimates weighting observations by value added per firm. The coefficient yields a slightly higher elasticity (-0.47) than the baseline estimates shown in Column (1). Column (3) shows that not winsorizing the data leads to very similar results as the baseline estimates (an elasticity of -0.47 evaluated at the mean $PM_{2.5}$ of 53.3). Column (4) uses the raw data (before eliminating the unreliable observations as described in footnote 10 and without winsorizing) which yields a somewhat greater elasticity (-0.58) using mean $PM_{2.5}$ of 53.3. The survey is at the firm level and therefore it is possible that a firm has multiple plants in different locations leading to an incorrect match with the pollution data. However, more than 95% of the firms in the survey are single-plant (Brandt *et al.*, 2012). Column (5) eliminates the few multi-plant firms from the sample. The estimated elasticity if very similar to the baseline (-0.47) based on mean $PM_{2.5}$ of 53.9. Finally, Column (6) uses log rather than linear pollution. The elasticity (-0.52) is very close to that estimated using a linear function.

As a test of whether it is inversions that are causing the shifts in pollution and therefore productivity we run a placebo test in which we randomly reassign the pollution to the inversion and weather data across years. We repeat this one hundred times and re-estimate the model. Online Appendix 5 shows the estimates along with 95% confidence intervals compared to the baseline estimate. Only four of the one hundred estimates are significantly different than zero and all four barely so.

5.3 Tests for firm sorting

Firms may relocate to places with better air quality to improve productivity or to places with lax environmental regulation to lower costs. Table 3 shows tests for this potential

[21] We divide China into eight regions following Zhang *et al.* (2018).

spatial sorting. Column (2) estimates excluding firms that relocated across counties (about 7% of firms) during the sample period. The estimated elasticity (-0.67) based on a mean $PM_{2.5}$ of 53.7 is larger than that of the baseline estimate (-0.44) using all firms (replicated in Column (1)) consistent with either firms avoiding pollution to increase their productivity or a "pollution haven" effect and high-polluting firms being more productive. This also means that our baseline estimates may understate pollution's effect on productivity to the extent that the non-relocating firms are representative of the full sample.

[Insert Table 3 here.]

Although the inclusion of firm fixed effects in our main results controls for any initial sorting of firms based on pollution levels, new firms that enter during the sample period may choose locations endogenously based on pollution. To see if this might affect the results, Column (3) of Table 3 tests whether a county's instrumented pollution significantly affects the fraction of new firms entering the county in the following year. We aggregate to the county-level for this analysis because we do not observe firms prior to entry and therefore cannot create an entry variable at the firm level. In addition to the weather controls we include county and year fixed effects so that identification derives from within-county variation over time. We cluster standard errors at the county level to allow spatial correlation in unobserved factors within counties and intertemporal variation across years within counties. Year 1998 data is dropped because it is the first year of our sample period and thus we cannot determine the level of entry. The estimated effect of entry is close to zero and insignificant consistent with pollution not affecting firm location choice on entry.

If pollution's effect on productivity is strong enough firms may exit the market. Estimates using the full sample are conditional on survival, potentially understating the productivity effect. To see if this might be a major factor, Column (4) of Table 3 tests whether a county's instrumented pollution significantly affects the fraction of firms exiting the county in the following year. This county-level regression is analogous to the entry regression and includes the same control variables and uses the same clustering of standard errors. Year 2007 data is dropped in this estimation since we cannot observe whether firms present in 2007 exit in 2008. The estimate is close to zero and insignificant suggesting that exit bias is not a major concern.[22] This also suggests that any actions taken by the government induced by thermal inversions to shut down firms in high-polluting areas are minimal.

[22] Estimates using a balanced panel could address this issue as well as any selection effects by entering firms. However, only 7% of firms are present in all years due to China's rapid growth as discussed in Section 3. For this small sample, the estimates are very significant and the estimated elasticities are much greater presumably due to pollution exposure levels that differ from those in the full sample.

We also repeated the entry and exit analyses to see whether there was significant spatial sorting in response to the most important environmental policy that occurred during our sample period. This policy, known as the Air Pollution Prevention and Control Law 2000 Revision, was officially issued on April 29, 2000. It identified 47 key cities and imposed stringent environmental regulations in these cities. We divided the sample into these cities versus all others. The results are shown in Online Appendix 6 and do not reflect any significant effect of pollution on firm entry or exit in the affected or non-affected cities.

Since the sample censors non-SOE firms with less than CNY 5 million in annual revenues ("below-scale" firms), this may confound entry measures. To see if this is so, we simulate the magnitude of censoring required to substantially change the results. Using cross-sectional data available on the full sample of all firms in 2004 when a manufacturing census rather than a survey was conducted, we calculate each county's "below-scale" and total firms as a fraction of the total number nationwide. We then adjust that county's observed entry rate in each year by assuming that *r*% of firms that entered nationwide actually became "below-scale." For each county we weight *r* by the ratio of the county's fraction of "below-scale" firms relative to fraction of total firms in 2004. This allows the county-level adjustments to be made based on whether they have a disproportionately small or large number of "below-scale" firms relative to other counties in 2004.

For example, suppose that 9% of firms nationwide appeared for the first time in a given year. Consider a county that had 0.04% of the nation's below-scale firms in 2004, 0.05% of the nation's total firms in 2004, and that 8% of its firms appeared for the first time in that year. For *r* equal to 10% (fraction of firms that appeared nationwide that we assume moved from "below-" to "above-scale" rather than entering), we would adjust this county's entry rate to be 8% - 9%*0.1*(0.0004/0.0005) = .0728. Having adjusted these rates for all years and counties, we re-run the entry regression varying *r* from 0 to 1 but bounding the entry rate to be non-negative. Online Appendix 7 describes the procedure in more detail and Online Appendix 8 shows the results for increments of 0.1 for *r*. Instrumented pollution has no significant effect on entry over the entire range of *r* providing suggestive evidence that censoring does not affect the results.

We modify the exit rate in an analogous manner to test the sensitivity of our exit regression to the censoring of "below-scale" firms. That is, we adjust each county's exit rate in a given year by assuming that *r*% of firms that exited nationwide actually became "below-scale" rather than exiting. For each county we again weight *r* by the ratio of the county's fraction of "below-scale" firms relative to fraction of total firms in 2004 bounding the exit rate to be non-negative. The results are shown in Online

Appendix 9. The results are again insensitive to the value of *r* over the entire range – instrumented pollution has no significant effect on exit.

5.4 Tests for worker sorting

It is also possible that workers endogenously select their location based on local air quality. High-skilled workers are more productive and generally have a higher willingness to pay for better air quality. If this leads to significant sorting of worker skill levels across counties, then pollution's effect on productivity should be attenuated for firms with high-skilled workers. To test whether workers sort based on pollution levels, we test whether a county's instrumented pollution in a year affects the fraction of workers employed by high- versus low technology firms in that county in that year. We classify firms' technological intensity based on their industry following OECD (2011), which classifies industries as high, medium-high, medium-low, and low technology. Based on each firm's employment, we then compute the fraction of workers employed in each of these categories in each county-year. Since these classifications are at the industry level we must aggregate to the county-year level for this analysis. In addition to weather controls, we include county and year fixed effects so that the effects are identified by variation within county over time. We cluster standard errors by county to allow for spatial and inter-temporal correlation of unobservables within each county.

Columns (1) through (4) of Table 4 show the results of estimating how instrumented pollution affects the fraction of employment in each of these four categories. The effects are all insignificant except for the fraction in low-technology industries, which is increased by air pollution. This is consistent with low-productivity workers sorting to more polluted areas although the effects are small. A one $\mu g/m^3$ increase in $PM_{2.5}$ increases the fraction of employment in low-skilled industries by 0.0033 which is only 0.86% of the average fraction of low-technology employment across counties. To test for the robustness of the technology classifications and make sure that a small number of firms within each category are not an issue, Columns (5) and (6) repeat the estimation combining the two high-technology categories into one category and similarly for the two low-technology categories. Instrumented pollution has no significant effect on the fraction of employment in either category.

[Insert Table 4 here.]

5.5 Effect by worker skill level

We are aware of only four papers that consider the effect of pollution on productivity of high-skilled workers and these focus on specific worker categories: Archsmith *et al*. (2018) on umpires, Heyes *et al*. (2016a) on investors, Heyes *et al.* (2016b) on politicians, and Kahn and Li (2019) on judges. Air pollution is commonly thought to primarily affect outdoor workers because of their unfiltered exposure and their holding occupations which are more physically demanding than high-skilled indoor workers. However, $PM_{2.5}$ can permeate indoors making it possible for it to affect indoor workers. Our data allow us to offer some evidence by skill level for manufacturing firms in China. We categorize firms' technological intensity based on the four industry categories in OECD (2011) and estimate the effect of pollution on productivity separately for the sub-sample in each category.

The results are shown in Columns (2) through (5) of Table 5 alongside estimates for the full sample in Column (1). The effects are above those of the full sample for the high-technology firms (elasticity of -0.73) and below for the low-technology firms (elasticity of -0.33). This is consistent with higher-skilled workers employed by more technologically-intensive firms having a higher marginal effect on productivity than lower-skilled workers so that an equivalent level of pollution diminishes absolute productivity more for high-technology firms. These results also suggest that the previous evidence for specific high-skilled workers extends to manufacturing firms and is consistent with evidence that air pollution affects cognitive not just physical effort. This suggests that air pollution's effects extend to a larger portion of economic output that includes knowledge workers and services industries. Columns (6) and (7) show that this result continues to hold if only two categories of worker skill levels are used.

[Insert Table 5 here.]

5.6 Effect on number of workers, capital, and output

Our estimates capture the effect on productivity conditional on the number of workers. Pollution may also affect the number of workers employed. To assess this, we estimate Equation (5) with log number of workers in each firm as the dependent variable using annual number of days with a thermal inversion as the instrument. The survey data capture both permanent and contract employment thereby making it likely we can capture annual adjustments in response to pollution. The survey measures end-of-year employment so that employment changes due to pollution over the course of a year would be captured.

The results are shown in Column (2) of Table 6. A one $\mu g/m^3$ increase in $PM_{2.5}$ increases employment by 0.51% implying an elasticity of 0.27. Although firms increase employment to compensate for some of the productivity loss, it is not enough to offset the negative effect on productivity. Moreover, employing additional workers imposes costs on firms. We can use the average wage in the sample to produce a ballpark estimate of these costs. A one percent increase in $PM_{2.5}$ increases employment by 0.27%, or 0.56 additional workers per firm. The average annual wage per worker in the sample is CNY 12,650 (USD 1,664) implying an additional cost per firm of CNY 7,147 (USD 940).

Aggregated across all firms this equals CNY 1.14 billion (USD 0.15 billion) annually or 12.7% of the productivity loss from the 1% increase in $PM_{2.5}$.

[Insert Table 6 here.]

In Column (3) of Table 6, we show the results of estimating Equation (5) with log capital as the dependent variable.[23] There is no significant effect. Column (4) estimates the effect of pollution on log value added. The effect is significant and the elasticity of value added with respect to pollution is -0.17. This equals the summed effect of pollution's effect on productivity (-0.44) and its effect on labor supply (0.27) and will also be used below in our general-equilibrium simulation.

5.7 Mitigation of pollution-productivity effect

As shown above, firms compensate for the reduced productivity that pollution causes by hiring more labor. It is useful to know whether high-polluting firms compensate more or less than low-polluting firms since this has ramifications for the resulting level of pollution and output. Columns (2) and (3) of Table 7 compare the effect of pollution on labor supply for "polluting" versus "clean" firms.[24] The effects do not differ significantly between the two types of firms. Columns (5) and (6) provide one possible explanation for this. "Clean" firms experience a larger negative productivity shock than "dirty" firms. While this would imply a greater incentive for "clean" firms to hire more workers than "dirty" firms, "clean" firms may be more likely to utilize high-skilled labor which is also likely to be in less elastic supply than low-skilled labor. This could result in similar effects on hiring for "clean" and "dirty" firms.

[Insert Table 7 here.]

Firms may respond to the lower productivity caused by inversions vis-à-vis pollution by adjusting their production processes. To test for this we run reduced-form estimates relating the number of inversions to productivity distinguishing counties with a large number of inversions (above the median) versus low. The results in Online Appendix 10 show that inversions reduce productivity more in areas with fewer inversions consistent with firms in high-exposure regions adjusting their production in response to the level of inversions. This also means that our estimates are inclusive of the effects of this avoidance behavior.

Environmental regulations could result in differential effects on firms in different industries or locations including due to different strategic responses to these regulations (Zou, 2018). However, we are unable to test for these for two reasons. Differential effects will only be reflected in our results if they are correlated with thermal inversions.

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[23] We calculate capital stock using the perpetual inventory method in Brandt *et al.* (2012).

[24] We define "dirty" and "clean" based on the 3-digit SIC codes in Mani and Wheeler (1997).

Moreover, prior to 2008 environmental regulation in China was minimal and the policies in place were often unenforced or under-enforced. We suspect prior to this, GDP-based promotion criteria for local government officials led them to emphasize GDP growth to the exclusion of environmental quality.

5.8 Explaining productivity dispersion

To place our results in the context of the larger productivity literature we quantify pollution's role in explaining productivity dispersion across firms (Syverson, 2011). We do so using both output per worker and TFP since the latter is commonly used in the general productivity literature. We follow Fox and Smeets (2011) in using R^2, adjusted-R^2, and standard deviation of residuals to quantify the reduction in dispersion. Unfortunately, because we must instrument pollution we cannot quantify these for the structural equation and instead must rely on generalized R^2 and generalized residuals (Pesaran and Smith, 1994). This understates pollution's influence because it only quantifies the effect of the exogenous shocks to pollution (that due to thermal inversions). However, we also show quantifications using non-instrumented pollution. These are only suggestive since non-instrumented pollution is endogenous.

Online Appendix 11 compares the productivity dispersion explained by the weather controls and pollution. We quantify this by regressing output per worker and TFP respectively on weather controls and pollution incrementally. We do not include firm fixed effects in this exercise since our goal is to explain dispersion across firms cross-sectionally and not just over time.[25] The results using the OP and LP approaches for estimating TFP are virtually identical. Weather controls explain 4.7 to 6.1 percentage points of variance and reduce the spread of residuals by 2.4 to 3.1%. Instrumented pollution has only a slight effect on either variance or the residuals. The impact is greatest (0.03 percentage points) when explaining output per worker. Thus, while pollution is important in explaining overall levels of output it is not an important contributor to dispersion in productivity vis-à-vis inversions across firms. Non-instrumented pollution has a much greater effect (1.5 to 2.5 percentage points' reduction in variance and 0.8 to 1.3% reduction in the spread of residuals) but this is only suggestive since it is not exogenous. These effects are smaller than the effects of labor quality (7.4 percentage points reduction in R^2 and a 14.9% reduction in the spread of residuals) found by Fox and Smeets (2011).

[25] Not including firm fixed effects means that even instrumented pollution may be correlated with the error term (*e.g.*, due to firm sorting) so this is an added reason to treat these results as only suggestive.

6. General-equilibrium effects

Thus far we have ignored how output affects pollution over time. To incorporate these effects we utilize the DICE model (Nordhaus, 1992, 1993). The DICE model is an intertemporal general-equilibrium model in which a representative agent chooses period-by-period consumption to maximize utility discounted by the rate of social time preference subject to an economic constraint and an emissions-climate-economy constraint.

We adapt the model in two ways to suit our purposes. First, rather than modeling the global economy we model only China and assume it is a closed economy. While the latter is obviously a simplification given that China is a large exporter during our sample period, we are interested only in production not demand-side effects. Thus, our simplifying assumption is that the consumer is representative of both domestic and export consumers. Second, we replace the climate-change dynamics of the original DICE model with a pollution production function relating contemporaneous pollution to output consistent with our estimating only the contemporaneous effects of $PM_{2.5}$.[26] We assume that $PM_{2.5}$ is created only by the manufacturing sector:[27]

$$\Omega(t) = [\lambda(t)Q(t)]^{\mu(t)}, \quad (7)$$

where $\lambda(t)$ is the fraction of total output produced by the manufacturing sector and $\mu(t)$ is the elasticity of pollution with respect to output in year t.

To estimate $\mu(t)$ we take advantage of China joining the World Trade Organization in late 2001 as an exogenous shock to output for firms in China's coastal regions relative to that in its inner regions. This approach of comparing high-and low-exposure regions before and after trade liberalization shocks has been widely used in the trade literature (*e.g.*, Goldberg and Pavcnik, 2005; Verhoogen, 2008; Topalova, 2010). This provides a differences-in-differences estimator with counties in coastal regions as a treatment group and those in inner regions as a control group:

$$\mathrm{Q}_{ct} = \beta_0 + \beta_1 \mathrm{I}_{t>2001} \mathrm{I}_{c\in Coast} + \alpha_c + \rho_t + \nu_{it}, \quad (8)$$

where c indexes counties, Q_{ct} is output in county c in year t, $\mathrm{I}_{t>2001}$ is an indicator variable set to one in years after 2001 and zero otherwise, $\mathrm{I}_{c\in Coast}$ is an indicator variable set to one if the county is on the coast and zero otherwise, and α_c are county

26 Therefore, the only dynamics in the model are the capital accumulation process. The original DICE model also included the dynamics of the accumulation of greenhouse gas emissions into concentrations consistent with it being a much longer process than $PM_{2.5}$'s dynamics.

27 The services sector produces little $PM_{2.5}$. Our manufacturing data also does not include power plants so we are making an implicit assumption that $PM_{2.5}$ created by power plants scales proportionally with manufacturing output.

fixed effects. Obtaining estimates, we then form the exogenous predicted values $(\widehat{\mathrm{Q}}_{ct})$ and use them in the second-stage to estimate μ:

$$\Omega_{ct} = \delta_0 + \mu\widehat{\mathrm{Q}}_{ct} + \alpha_c + \rho_t + \omega_{it}. \quad (9)$$

The key identifying assumption for Equation (8) is that the pre-treatment trends are parallel for coastal and inner regions prior to China joining the WTO. Online Appendix 12 plots coefficients and 95% confidence intervals from regressing county-level output on year dummies interacted with $\mathrm{I}_{c\in Coast}$ conditioning on county fixed effects and non-interacted $\mathrm{I}_{c\in Coast}$. The interaction terms (normalized to zero in 2001) show no obvious trend prior to 2002 and display an upward trend after 2002.

Online Appendix 13 reports the estimates of Equations (8) and (9) using data for our sample period. The instrument is reasonably powerful and yields an elasticity of 1.43 for $PM_{2.5}$ with respect to output which is statistically very significant. The OLS estimate is about one-third of this consistent with negative feedback from pollution on output. We use this as the value of $\mu(t)$ in 2002. Online Appendix 14 describes how we calibrate the other years and other parameters of the model.

We simulate the model using economy-wide data for China as described in Online Appendix 14. Following Nordhaus (1993) we simulate over a sufficient number of periods that the outcome over our sample period is not significantly affected by endpoint conditions. We found that simulating 100 years is sufficient to stabilize the solution for the sample period. Similar to Nordhaus (1993) our chosen parameters result in simulated levels of output and pollution that are close to the actual during the sample period as discussed in Online Appendix 14.

Having calibrated the model we then run counterfactuals to assess the general-equilibrium effects of pollution. We vary $\mu(t)$ slightly to generate a local derivative of output with respect to pollution. A 1% decrease in $PM_{2.5}$ over the sample period increases manufacturing output by 0.31% on average over the sample period compared to the partial equilibrium increase of 0.17%. The resulting productivity improvement would increase the average firm's value added by CNY 39.7 (USD 5.2) thousand annually and increase total value added across all firms by CNY 6.3 (USD 0.8) billion annually or 0.043% of China's GDP. This is robust to 2002 values of $\mu(t)$ ranging from at least 1.2 to 1.6.[28] Output is more responsive to pollution when general equilibrium effects are considered because of the feedback effects: decreased output results in somewhat less pollution and thus somewhat more output. Consistent with this, the elasticity in the first year (-0.20) is somewhat greater than the partial-equilibrium

[28] The absolute level of pollution is greatly affected even though the elasticity of output with respect to pollution is not. The absolute level of output, on the other hand, is relatively unaffected.

elasticity (-0.17). The elasticity steadily increases to -0.34 by the last year as capital is accumulated courtesy of the greater output.

These results can be used directly to evaluate the general-equilibrium effects of policies. For example, a 1% reduction in $PM_{2.5}$ through other means would increase manufacturing output by 0.31%. Equivalently, improvements in pollution-reduction technologies such as abatement equipment can also be evaluated (a decrease in $\mu(t)$). For example, China's Air Pollution Prevention and Control Action Plan enacted in 2013 stipulated that by 2017 $PM_{2.5}$ concentrations should fall by 25%, 20%, and 15% in Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Pearl River Delta regions respectively[29] which are China's main industrial centers. Using the midpoint of these three goals (20%) and scaling our elasticity estimate linearly, the productivity boost from reaching this target would be 3.4% (0.47% of GDP) assuming that pollution decreases originate from actions other than reducing manufacturing output. This, however, assumes that our estimates extrapolate fairly far outside the sample range.

It is useful to place these benefits in context by quantifying the costs of reducing $PM_{2.5}$. Unfortunately, we are unaware of direct estimates of the costs of reducing $PM_{2.5}$. The best we can do is to rely on indirect measures for other pollutants estimated from policy interventions. The most useful estimate comes from the US. Pollution-intensive industries in counties subject to regulation under the Clean Air Act lost on average USD 7.9 billion of output annually relative to counties that were not (Greenstone, 2002). At the same time, air pollution declined by roughly 12% more in non-attainment relative to attainment counties (Chay and Greenstone, 2005).[30] Combining these two estimates, a back-of-the-envelope calculation indicates that a 1% reduction in pollution costs USD 0.66 billion. This is a lower bound on the costs because the estimate from Greenstone (2002) is a partial equilibrium estimate that does not consider the effect of output on pollution. This is 83% of our estimate of the benefits of reducing $PM_{2.5}$ by one percent (USD 0.8 billion annually) although the pollutants differ.

There are other studies that provide more indirect measures of the costs of reducing pollution. All of the pollution-reduction measures taken during the 2008 Beijing Olympic Games decreased PM_{10} concentrations from 24% to 33% in the city (Chen *et al.*, 2013; He *et al.*, 2016). Restricting 1% of vehicles in Beijing one-day-per week reduces PM_{10} by 1% (Viard and Fu, 2015). Investments in public transit infrastructure can lower air pollution: each one standard deviation in increase in subway density in Beijing reduced particulate matter by 2% (Li *et al.*, 2019) and a subway opening decreases

[29] Issued by the State Council on September 10, 2013 (http://www.gov.cn/zwgk/2013-09/12/content_2486773.htm).
[30] This is for "total suspended particulate," an older measure of particulate pollution but the closest measure available at the time to the pollutant we examine.

particulate concentrations by 4% around a city center (Gendron-Carrier *et al.*, 2017). Derivation of these costs and explanations of the pollutants are contained in Online Appendix 15.

7. Conclusion

Using a large micro dataset on manufacturing firms in China, we estimate the effect of air pollution on productivity. To deal with the reverse causality of output and pollution and other potential endogeneity issues we take an instrumental variable approach. For the effect of pollution on output we use thermal inversions, which are meteorologically determined. The approach attenuates the endogeneity bias and indicates a significant negative effect of air pollution on productivity. For the effect of output on pollution we use the differential effects of China's entry into the WTO on coastal versus inner regions of China. Combining these in a general-equilibrium model we quantify the general-equilibrium effects of pollution on output.

Our study shows a significant economic loss in productivity and therefore output in China due to air pollution. This also suggests a huge social benefit of improving air quality in terms of increasing productivity and total output. Our study contributes to the emerging literature on air pollution's effect on short-run productivity by providing comprehensive, nationwide empirical evidence that captures all channels through which pollution can affect productivity and taking account of the general-equilibrium effects of output on pollution. These estimates can be used directly for short-run effects in cost-benefit analyses of broad-based environmental policies.

Our findings shed new light on the debate about whether environmental regulations positively or negatively affect firm competitiveness (Jaffe *et al.*, 1995). Historically, this debate has focused on the extent to which decreased competitiveness from environmental compliance costs is offset by process innovations that are both cleaner and of lower cost. Our results confirm another channel that influences this debate. Environmental regulations that decrease air pollution will in turn increase productivity and at least partially offset the decreased productivity due to complying.

Since our identification relies on yearly variation we are unable to estimate long-run effects of pollution on productivity. In the long run firms may take steps to respond to pollution such as protecting indoor workers or moving to lower-pollution areas to boost productivity. Workers also may move in the long run to avoid pollution, especially high-skilled workers who have a greater willingness to pay to avoid pollution. We find little evidence of such sorting in our short-run results but this may occur over longer periods and would attenuate the productivity effects. Future work on these long-run effects would be useful.

Although we can capture all channels by which pollution can influence productivity, we are unable to decompose the exact channels by which pollution lowers productivity. Significant effects on productivity per hour would indicate that there are large benefits from protecting workers from air pollution while at work. Effects on hours worked might indicate exposure to pollution by a worker's family members in addition to workplace exposure. These would be useful avenues for future research.

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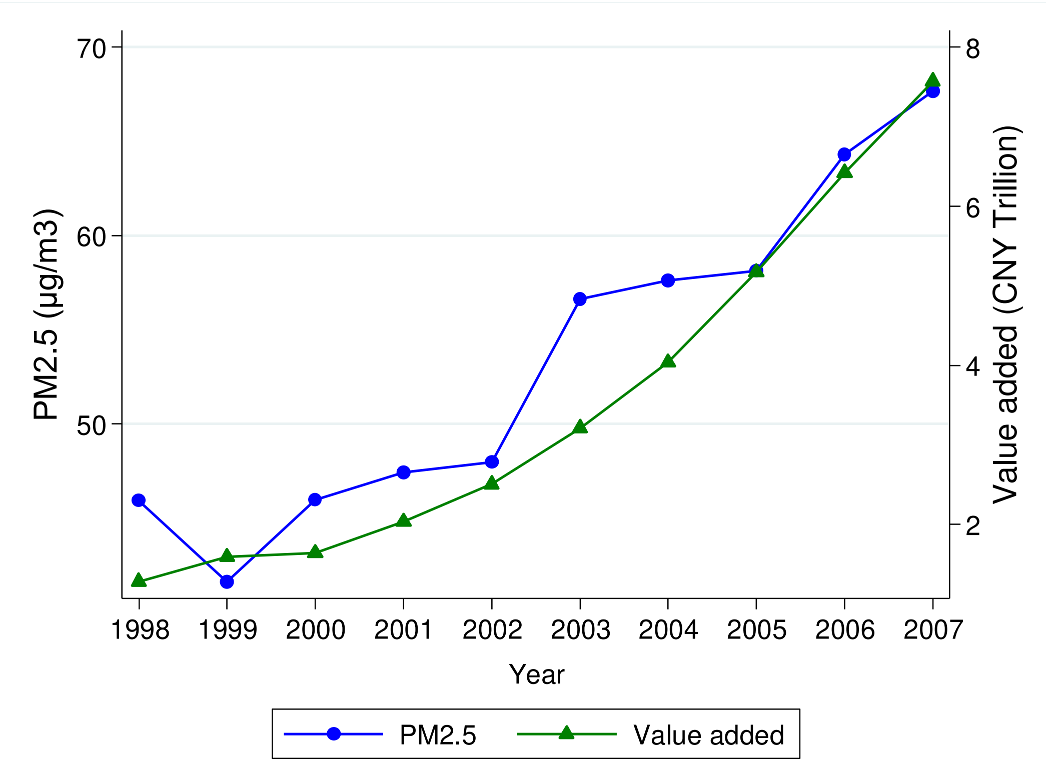
Figure 1: Time trend of air pollution and value added in China (1998 to 2007)



Notes: This graph displays national average of county-level $PM_{2.5}$ and aggregate value added of China's manufacturing sector from 1998 to 2007. Value added includes all state-owned enterprises (SOEs) and all non-SOEs with sales above CNY 5 million.

Table 1: Summary statistics for firm-level productivity and county-level pollution data

Variables	Mean	Standard deviation	Min	Max
Firm-year sample				
Firm				
Value added (1,000 CNY)	12,821	23,540	74	366,426
Employment (person)	207	299	10	3,013
Capital (1,000 CNY)	14,531	30,872	64	350,801
Output per worker (1,000 CNY/worker)	88	160	0.13	16,248
Total factor productivity (OP estimates)	2.91	1.03	-3.23	8.44
Total factor productivity (LP estimates)	5.38	0.97	0.01	10.03
County-year sample				
Air pollution				
Particular matter ($PM_{2.5}$) ($\mu g/m^3$)	53.52	25.46	2.62	134.84
Thermal inversions				
Annual days with thermal inversions	156.95	78.75	0.00	333.00

Notes: Firm-year sample size: 1,593,247 including 356,179 firms. County-year sample size: 25,359 including 2,755 counties. Sample period: 1998-2007. Total factor productivity are estimates based on Olley-Pakes (1996) and Levinsohn-Petrin (2003) instrumenting approaches.

Table 2 OLS and 2SLS estimates (effect of air pollution on productivity) and reduced-form estimates (effect of thermal inversions on productivity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS		**Reduced form**		**2SLS**			
					First stage			
Dependent variable:			**ln(Value added/worker)**		**$PM_{2.5}$**			
Annual days with inversions			-0.0002***	-0.0003***	0.0300***	0.0356***	0.0300***	0.0356***
			(0.0000)	(0.0001)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
KP F-statistic					5,520	8,249	5,520	8,249
					Second stage			
Dependent variable:	**ln(Value added/worker)**				**ln(Value added/worker)**		**TFP (OP)**	**TFP (LP)**
$PM_{2.5}$	0.0003	0.0004**			-0.0080***	-0.0082***	-0.0049***	-0.0036***
	(0.0002)	(0.0002)			(0.0016)	(0.0014)	(0.0014)	(0.0014)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Weather controls	N	Y	N	Y	N	Y	N	Y
# firms	356,179	356,179	356,179	356,179	356,179	356,179	356,179	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247

Notes: All models include firm fixed effects, year fixed effects, and weather controls (in both stages for 2SLS). Sample period: 1998 - 2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 3: 2SLS estimates – tests for firm sorting based on air pollution

	(1)	(2)	(3)	(4)
	Firm-year sample		**County-year sample**	
Dependent variable:	**ln(value added per worker)**		**Fraction of firms entering**	**Fraction of firms exiting**
	Baseline	**Exclude relocating firms**		
$PM_{2.5}$	-0.0082***	-0.0124***	0.0033	0.0016
	(0.0014)	(0.0018)	(0.0027)	(0.0018)
KP *F*-statistic	8,249	12,377	218	322
Firm fixed effects	Y	Y	N	N
County fixed effects	N	N	Y	Y
Year fixed effects	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
Clustering	Firm	Firm	County	County
Sample size	1,593,247	1,432,765	23,091	22,684

Notes: Sample period: 1998 - 2007 in Columns 1 and 2; 1998 - 2006 in Column 3 to measure exit in the following year; 1999 to 2007 in Column 4 to measure entry from the prior year. Columns 1 and 2 are firm-year data; Column 1 includes all firms and Column 2 all firms that did not relocate during the sample period. Columns 3 and 4 are county-year data and aggregate all firms to the county level. All models use annual number of days with thermal inversions as first-stage instruments. All models include year fixed effects and weather controls in both stages. Models in Columns 1 and 2 include firm fixed effects and models in Columns 3 and 4 county fixed effects. Standard errors are clustered at the firm level in Columns 1 and 2 and at the county level in Columns 3 and 4 and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 4: 2SLS estimates – tests for worker sorting based on pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Fraction of employment**					
	Four categories				**Two categories**	
	High technology	**Medium-high technology**	**Medium-low technology**	**Low technology**	**High technology**	**Low technology**
$PM_{2.5}$	-0.0001	-0.0011	-0.0021	0.0033*	-0.0012	0.0012
	(0.0008)	(0.0015)	(0.0019)	(0.0018)	(0.0017)	(0.0017)
KP *F*-statistic	207.9	207.9	207.9	207.9	207.9	207.9
County fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y
Clustering	County	County	County	County	County	County
Sample size	25,357	25,357	25,357	25,357	25,357	25,357

Notes: All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. The technology intensity definition in Columns (2) through (6) is from https://www.oecd.org/sti/ind/48350231.pdf. We group high technology and medium high technology into high technology into Column (5), and group low technology and medium low technology into low technology into Column (6). Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 5: 2SLS estimates – effect of air pollution on productivity by firm technology level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**ln(value added per worker)**						
		Four categories				**Two categories**	
	Full sample	**High technology**	**Medium-high technology**	**Medium-low technology**	**Low technology**	**High technology**	**Low technology**
$PM_{2.5}$	-0.0082***	-0.0119**	-0.0134***	-0.0061**	-0.0060***	-0.0128***	-0.0061***
	(0.0014)	(0.0056)	(0.0028)	(0.0028)	(0.0022)	(0.0025)	(0.0017)
KP *F*-statistic	8249	365.6	1796	2495	3902	2178	6348
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y
# firms	356,179	24,652	102,699	97,918	130,910	127,351	228,828
Sample size	1,593,247	112,792	467,768	435,842	576,845	580,560	1,012,687
Share of sample size (%)	100.0	7.1	29.4	27.4	36.2	36.4	63.6

Notes: All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. The technology intensity definition in Columns (2) through (7) is from https://www.oecd.org/sti/ind/48350231.pdf. We group high technology and medium high technology into high technology into Column (6), and group low technology and medium low technology into low technology into Column (7). Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 6: 2SLS estimates – effects of air pollution on productivity, employment, capital, and value added

Dependent variable:	(1) **ln(value added per worker)**	(2) **ln(number workers)**	(3) **ln(capital)**	(4) **ln(value added)**
$PM_{2.5}$	-0.0082***	0.0051***	-0.0003	-0.0032**
	(0.0014)	(0.0011)	(0.0013)	(0.0015)
KP *F*-statistic	8,249	8,249	8,249	8,249
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
# firms	356,179	356,179	356,179	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247

Notes: All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 7: 2SLS estimates – effects of air pollution on employment and productivity split by “clean” versus “polluting” firms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**ln(number workers)**			**ln(value added per worker)**		
	Full Sample	**"Polluting firms"**	**"Clean firms"**	**Full Sample**	**"Polluting firms"**	**"Clean firms"**
$PM_{2.5}$	0.0051***	0.0056***	0.0047***	-0.0082***	-0.0046*	-0.0104***
	(0.0011)	(0.0019)	(0.0013)	(0.0014)	(0.0025)	(0.0017)
KP *F*-statistic	8,249	2,488	5,804	8,249	2,488	5,804
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y
# firms	356,179	117,312	238,867	356,179	117,312	238,867
Sample size	1,593,247	530,827	1,062,420	1,593,247	530,827	1,062,420

Notes: All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. The pollution intensity definition in Columns (2), (3), (5), and (6) is from http://www.oecd.org/industry/inv/investmentstatisticsandanalysis/2076285.pdf. Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 1: summary statistics for firms with a single year of data versus all firms in the sample

	All firms		Single-year firms		
Variables	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**	**Difference**
Value added (1,000 CNY)	12,407	23,203	6,967	17,316	5,440
Employment (person)	201	295	124	226	77
Capital (1,000 CNY)	14,091	30,574	8,314	25,660	5,777
Labor productivity (1,000 CNY/worker)	3.89	1.02	3.77	1.10	0.12
Particular matter ($PM_{2.5}$) ($\mu g/m^3$)	69.71	22.56	72.11	24.51	-2.40
Number observations	1,714,564		121,317		

Notes: All firms sample includes 477,496 firms and single-year sample includes 121,317 firms. Sample period: 1998-2007.

Appendix 2: 2SLS estimates (effect of pollution on productivity) comparing three major economic centers to rest of country

	(1)	(2)	(3)
Dependent variable:		**ln(value added per worker)**	
	Baseline	**3 economic centers**	**All other**
$PM_{2.5}$	-0.0082***	-0.0061**	-0.0058**
	(0.0014)	(0.0026)	(0.0027)
KP F-statistic	8,249	3,036	2,154
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Weather controls	Y	Y	Y
# firms	356,179	200,933	155,249
Sample size	1,593,247	913,848	679,391

Notes: All models include firm fixed effects, year fixed effects and weather controls in both stages. Column 1 includes all firms; Column 2 includes all firms in Jing-Jin-Ji, Yangtze River Delta, and Pearl River Delta economic centers; Column 3 includes all firms not in these three centers. Sample period: 1998-2007. Number of observations in Columns 2 and 3 do not equal those in Column 1 due to the small number of firms that switch locations during the sample period. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 3 2SLS estimates (effect of air pollution on productivity) – robustness to clustering of standard errors and regional time trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	**ln(value added per worker)**							
	Baseline	**Clustering of standard errors**			**Time fixed effects and trends**			
		By firm and county-year	**By county-year**	**By county**	**Year-by region FE**	**Year-by-province FE**	**Provincial quadratic trends**	**Year FE + provincial quadratic trends**
$PM_{2.5}$	-0.0082***	-0.0082**	-0.0082**	-0.0082**	-0.0119***	-0.0132***	-0.0056***	-0.0085***
	(0.0014)	(0.0038)	(0.0037)	(0.0040)	(0.0037)	(0.0037)	(0.0008)	(0.0015)
KP *F*-statistic	8,249	162	164	129	1,331	1,802	30,374	10,273
Cluster by firm	Y	N	N	N	Y	Y	Y	Y
Cluster by firm and county-year	N	Y	N	N	N	N	N	N
Cluster by county-year	N	N	Y	N	N	N	N	N
Cluster by county	N	N	N	Y	N	N	N	N
# firms	356,179	356,179	356,179	356,179	356,179	356,179	356,179	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247

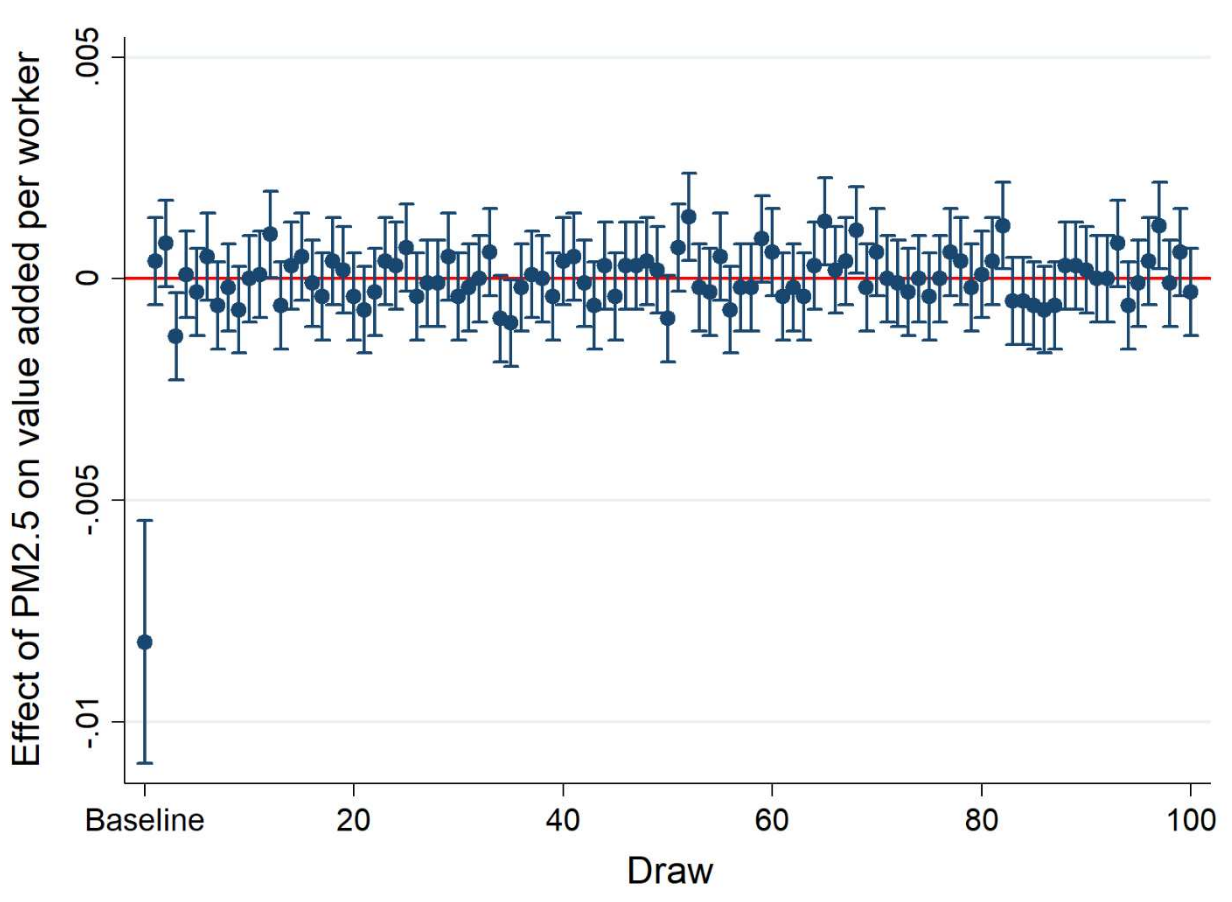
Notes: Sample period: 1998 - 2007. All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects and weather controls in both stages. Columns 1 through 4 also include year fixed effects, Column 5 year-by-region fixed effects, Column 6 year-by-province fixed effects, Column 7 provincial-specific quadratic time trends, and Column 8 year fixed effects along with provincial-specific quadratic time trends. Standard errors are clustered at the firm level in Columns 1 and 5 through 8, at the firm and county-by-year level in Column 2, at the county-by-year level in Column 3, at the county level in Column 4, and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 4 2SLS estimates (effect of air pollution on productivity) – robustness to weighting, sample composition, and functional form

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**ln(value added per worker)**					
	Baseline	Weighted	Non-winsorized	Raw data	Single-plant	Log function
$PM_{2.5}$	-0.0082***	-0.0088***	-0.0088***	-0.0108***	-0.0087***	
	(0.0014)	(0.0023)	(0.0016)	(0.0017)	(0.0015)	
Log $PM_{2.5}$						-0.5225***
						(0.0902)
KP F-statistic	8,249	1,911	8,783	7,878	8,070	7,265
Cluster by firm	Y	Y	Y	Y	Y	Y
Weighting by value added	N	Y	N	N	N	N
Winsorized	Y	Y	N	N	N	Y
# firms	356,179	356,179	379,349	388,277	344,453	356,179
Sample size	1,593,247	1,593,247	1,746,850	1,767,917	1,499,158	1,593,247

Notes: All models use annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. Sample period: 1998-2007. Column 3 uses non-winsorized sample, Column 4 uses all data including the unreliable observations, and Column 5 uses only firms with a single plant location. Standard errors are clustered at the firm level and are reported in parentheses. The regression is weighted by value added in column 2. In Columns 1 through 6, $PM_{2.5}$ is measured in levels and in Column 7 in log form. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 5: coefficients and 95% confidence intervals for 100 placebo tests reassigning pollution data randomly to a different year's productivity and weather data



Notes: Coefficients and 95% confidence intervals from 100 placebo 2SLS estimates (effect of air pollution on productivity) using annual number of days with thermal inversions as an instrument. Placebo tests performed by randomly reassigning one year's productivity data to a different year's pollution and weather data.

Appendix 6: 2SLS estimates – tests for firm sorting based on air pollution (key versus non-key cities under the Key City policy)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Fraction of firms entering**			**Fraction of firms exiting**		
	Full sample	**Key cities**	**Non-key cities**	**Full sample**	**Key cities**	**Non-key cities**
$PM_{2.5}$	0.0033	0.0045	0.0052	0.0016	-0.0008	0.0007
	(0.0027)	(0.0038)	(0.0035)	(0.0018)	(0.0022)	(0.0025)
KP *F*-statistic	218.4	81.5	131.8	322.2	116.1	188.4
County fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y
Clustering	County	County	County	County	County	County
Sample size	23,091	4,582	18,509	22,684	4,495	18,189

Notes: Sample period: 1998 - 2007 in Columns 1 and 4; 1999 to 2007 in Columns 2 and 3 to measure entry from the prior year; 1998 - 2006 in Columns 4 and 5 to measure exit in the following year. All columns are county-year data and aggregate all firms to the county level. All models use annual number of days with thermal inversions as first-stage instruments. All models include year fixed effects, county fixed effects, and weather controls in both stages. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 7: Sensitivity of entry and exit regressions to censoring of “below-scale” firms

This appendix describes how we modify the entry and exit rates to test the sensitivity of the entry and exit regressions to censoring on below-scale firms.

Using the 2004 census data, determine the number of below-scale firms in county i as a fraction of below-scale firms nationwide in 2004:

$$bsfrac_i = \frac{bs_i}{\sum_i bs_i}, \text{ (A1)}$$

where bs_i is the number of below-scale firms in county i in year 2004. The unadjusted entry rate for county i in year t is:

$$entry_{it} = \frac{a_{it}}{f_{it}}, \text{ (A2)}$$

where a_{it} is the number of firms that appeared in the sample in county i in moving from year $t-1$ to year t and f_{it} is the number of firms in county i in year t.

We modify each county’s entry rate to assume that r percent of firms that appeared nationwide ($\sum_i a_{it}$) moved from being “below- scale” to being “above-scale” rather than entering. We apply this adjustment proportionally to each county based on its fraction of “below-scale” firms in 2004 bounding the rate to be non-negative:

$$\widehat{entry}_{it} = max\left[0, entry_{it} - bsfrac_i * \frac{r * \sum_i a_{it}}{\sum_i f_{it}}\right]. \text{ (A3)}$$

We modify the exit rate in an analogous manner to test the sensitivity of the exit regressions to truncation for “above-scale” firms. The unadjusted exit rate for county i in year t is:

$$exit_{it} = \frac{d_{it}}{f_{it}}, \text{ (A4)}$$

where d_{it} is the number of firms that disappeared from the sample in county i in moving from year t to year $t+1$.

We modify each county’s exit rate to assume that r percent of firms that disappeared nationwide ($\sum_i d_{it}$) became “below-scale” firms rather than exiting. As with the modified entry rate, we apply this adjustment proportionally to each county based on its fraction of the nation’s “below-scale” firms in 2004 bounding the rate to be non-negative:

$$\widehat{exit}_{it} = max\left[0, exit_{it} - bsfrac_i * \frac{r * \sum_i d_{it}}{\sum_i f_{it}}\right]. \text{ (A5)}$$

We then re-estimate our exit regressions varying the value of r between 0 and 1.

Appendix 8: sensitivity of entry regression to censoring of “below-scale” firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable:	**Fraction of firms entering (modified)**										
	r=0	**r=0.1**	**r=0.2**	**r=0.3**	**r=0.4**	**r=0.5**	**r=0.6**	**r=0.7**	**r=0.8**	**r=0.9**	**r=1**
$PM_{2.5}$	0.0030	0.0028	0.0027	0.0027	0.0023	0.0019	0.0017	0.0019	0.0022	0.0021	0.0019
	(0.0038)	(0.0036)	(0.0035)	(0.0033)	(0.0032)	(0.0031)	(0.0030)	(0.0028)	(0.0027)	(0.0026)	(0.0025)
KP *F* -statistic	77.84	77.84	77.84	77.84	77.84	77.84	77.84	77.84	77.84	77.84	77.84
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustering	County	County	County	County	County	County	County	County	County	County	County
Sample size	22,895	22,895	22,895	22,895	22,895	22,895	22,895	22,895	22,895	22,895	22,895

Notes: Sample period: 1999 to 2007 to measure entry from the prior year. Dependent variable is county entry rate modified as described in Online Appendix 7 for different values of *r* . County-year data aggregating all firms to the county level. All models use annual number of days with thermal inversions as first-stage instruments. All models include year fixed effects, county fixed effects, and weather controls in both stages. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 9: sensitivity of exit regression to censoring of “below-scale” firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable:	**Fraction of firms exiting (modified)**										
	r=0	**r=0.1**	**r=0.2**	**r=0.3**	**r=0.4**	**r=0.5**	**r=0.6**	**r=0.7**	**r=0.8**	**r=0.9**	**r=1**
$PM_{2.5}$	0.0023	0.0023	0.0022	0.0022	0.0022	0.0020	0.0019	0.0017	0.0014	0.0012	0.0011
	(0.0023)	(0.0022)	(0.0021)	(0.0020)	(0.0020)	(0.0019)	(0.0018)	(0.0018)	(0.0017)	(0.0016)	(0.0016)
KP *F*-statistic	142.6	142.6	142.6	142.6	142.6	142.6	142.6	142.6	142.6	142.6	142.6
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustering	County	County	County	County	County	County	County	County	County	County	County
Sample size	22,493	22,493	22,493	22,493	22,493	22,493	22,493	22,493	22,493	22,493	22,493

Notes: Sample period: 1998 to 2006 to measure exit in the next year. Dependent variable is county exit rate modified as described in Online Appendix 7 for different values of r. County-year data aggregating all firms to the county level. All models use annual number of days with thermal inversions as first-stage instruments. All models include year fixed effects, county fixed effects, and weather controls in both stages. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 10: effect of inversions on productivity (reduced-form estimates distinguishing counties with high and low numbers of inversions)

	(1)	(2)
Dependent variable	**ln(Value added per worker)**	
Inversions	-0.0003***	-0.0004*
	(0.0001)	(0.0002)
Inversions*1(high-inversion region)		0.0002**
		(0.0001)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Weather controls	Yes	Yes
Observations	1,593,247	1,593,247
Number of firms	356,179	356,179

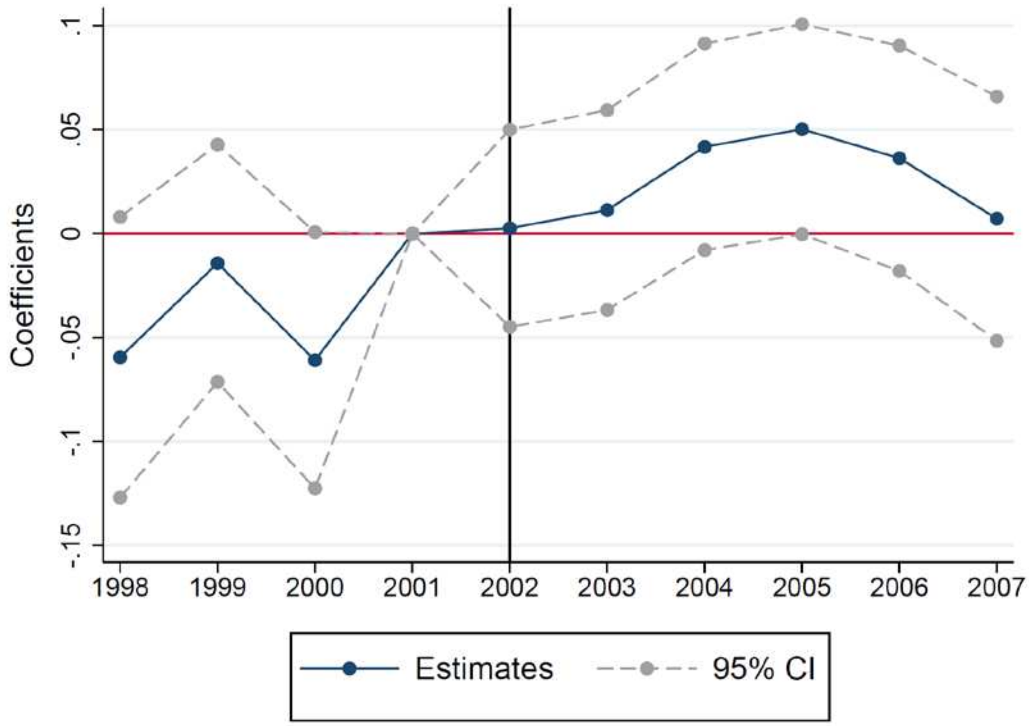
Notes: All models include firm fixed effects, year fixed effects, and weather controls. Sample period: 1998-2007. "High-inversion regions" in Column (2) are defined as counties with annual number of days with an inversion above the median. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 11: dispersion in firm productivity (output per worker and TFP) explained by weather and pollution

	R^2	Increment explained	Adj. R^2	Increment explained	SD	% reduction
Output per worker						
Constant	-		-		1.0100	
Add weather controls	0.0608		0.0607		0.9789	-3.09%
Add instrumented pollution	0.0610	0.0003	0.0610	0.0003	0.9787	-0.01%
Add non-instrumented pollution	0.0856	0.0249	0.0856	0.0249	0.9658	-1.33%
TFP (OP)						
Constant	-		-		1.0322	
Add weather controls	0.0521		0.0520		1.0050	-2.64%
Add instrumented pollution	0.0521	0.0000	0.0521	0.0000	1.0049	0.00%
Add non-instrumented pollution	0.0673	0.0152	0.0672	0.0152	0.9969	-0.80%
TFP (LP)						
Constant	-		-		0.9679	
Add weather controls	0.0470		0.0469		0.9448	-2.38%
Add instrumented pollution	0.0470	0.0000	0.0469	0.0000	0.9448	0.00%
Add non-instrumented pollution	0.0632	0.0163	0.0632	0.0163	0.9367	-0.86%

Notes: R^2, adjusted-R^2, and standard deviation of residuals explained by weather controls and instrumented pollution in regressions of output per worker and TFP (using OP and LP methods to instrument for unobserved productivity). Generalized R^2, generalized adjusted-R^2, and standard deviation of generalized residuals explained by non-instrumented pollution in regressions of output per worker and TFP.

Appendix 12: Test of parallel trends for coastal versus inner regions before China joins the WTO in late 2001



Notes: β_{1t} coefficients and 95% confidence intervals from estimating a regression of county-level output on county fixed effects, year fixed effects, and interactions between year fixed effects and coastal counties: $Q_{ct} = \beta_0 + \sum_t \beta_{1t}\rho_t I_{c\in Coast} + \alpha_c + \rho_t + \nu_{it}$.

Appendix 13: OLS and 2SLS estimates (effect of output on pollution) using effect of China joining WTO on coastal versus inner regions as an instrument

	(1)	(2)
	OLS	**2SLS**
		First stage
Dependent variable:		**ln(Value added)**
Coast*post 2001		0.0574***
		(0.0147)
KP *F*-statistic		15.3
		Second stage
Dependent variable:	**ln($PM_{2.5}$)**	
ln(Value added)	0.0048***	1.4317***
	(0.0012)	(0.3666)
County fixed effects	Y	Y
Year fixed effects	Y	Y
Sample size	25,357	25,357

Notes: Both models include county and year fixed effects (in both stages for 2SLS). Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP F-statistic is the Kleibergen-Paap Wald rk F-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Appendix 14: General-equilibrium model setup, solution, calibration, and data

Model setup

Following Nordhaus (1992) (his Equation (2)), the model maximizes the sum of discounted utility for a representative consumer with a population $P(t)$ using a logarithmic utility function of per-capita consumption $\left(c(t)\right)$:

$$\max_{c(t)} \sum_{t=1}^{T} P(t) ln[c(t)](1+\rho)^{-t}, \text{ (A1)}$$

where ρ is the annual rate of social time preference.

Output is a standard Cobb-Douglas production function in exogenously-given technology $\left(A(t)\right)$, capital $\left(K(t)\right)$, labor, and a pollution damage function $\left(\Omega(t)^{\theta}\right)$. The pollution damage function can capture both effects that we find in our partial-equilibrium analysis: changes in productivity and changes in labor supply (fraction of the population that works). That is, population is exogenous but labor supply is not:[1]

$$Q(t) = \Omega(t)^{\theta} A(t) K(t)^{\gamma} P(t)^{1-\gamma}, \text{ (A2)}$$

where γ is the elasticity of output with respect to capital and θ is the elasticity of output with respect to pollution. This is Nordhaus (1992) Equation (3) with the pollution damage function corresponding to his climate factor function.

We replace Nordhaus (1992) Equations (7) through (13) which model the dynamic relationship between output and temperature with a pollution production function that relates contemporaneous pollution to output:

$$\Omega(t) = [\lambda(t) Q(t)]^{\mu(t)}, \text{ (A3)}$$

where $\mu(t)$ is the elasticity of pollution with respect to manufacturing output. We assume that only the manufacturing sector produces pollution and $\lambda(t)$ is the fraction of total output from manufacturing.

Gross output is divided between investment $I(t)$ and aggregate consumption $C(t)$:

$$Q(t) = C(t) + I(t), \text{ (A4)}$$

and per-capita consumption is:

$$c(t) = C(t)/P(t). \text{ (A5)}$$

The law of motion for capital is:

$$K(t) = (1-\delta)K(t-1) + I(t), \text{ (A6)}$$

where δ is the rate of capital depreciation. Equations (A4), (A5), and (A6) follow Nordhaus (1992) Equations (4), (5), and (6) exactly.

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[1] To see this, suppose that pollution affects both productivity and fraction of population working: $Q(t) = \Omega(t)^{\theta_1} A(t) K(t)^{\gamma} \left[\Omega(t)^{\theta_2} P(t)\right]^{1-\gamma}$. This is Equation (A2) with $\theta = \theta_1 + \theta_2(1-\gamma)$.

Model solution

Substituting Equation (A3) into (A2) we obtain:

$$Q(t) = \left[\tilde{A}(t)K(t)^{\gamma}P(t)^{(1-\gamma)}\right]^{\eta(t)}, \text{(A7)}$$

where $\eta(t) = 1/[1 - \theta\mu(t)]$ and $\tilde{A}(t) = \left[\lambda(t)^{\theta\mu(t)}A(t)\right]$.

Substituting Equation (A7) into (A4) and then solving for $C(t)$:

$$C(t) = \left[\tilde{A}(t)K(t)^{\gamma}P(t)^{(1-\gamma)}\right]^{\eta(t)} - I(t). \text{(A8)}$$

Using Equation (A6) for $K(t)$ and substituting it into (A8):

$$C(t) = \left\{\tilde{A}(t)[(1-\delta)K(t-1) + I(t)]^{\gamma}P(t)^{(1-\gamma)}\right\}^{\eta(t)} - I(t). \text{(A9)}$$

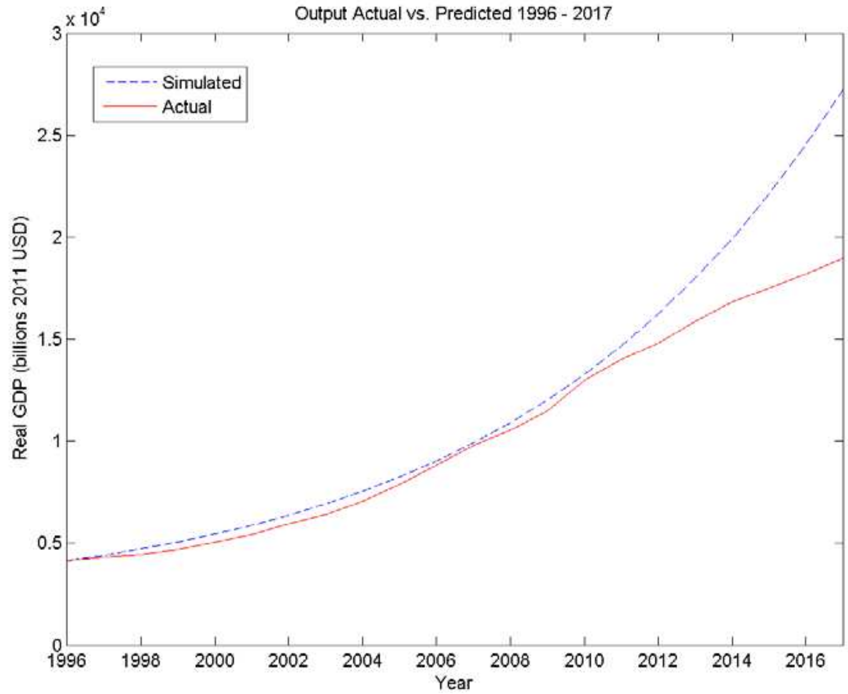
Now substituting this for $C(t)$ in Equation (A1) we can transform the optimization problem to a choice of investment period-by-period:

$$\underset{I(t)\geq 0}{max} \sum_{t=1}^{T} P(t) ln\left[\frac{\Gamma(I(t))}{P(t)}\right](1+\rho)^{-t}, \text{(A10)}$$

where $\Gamma[I(t)] = \left\{\tilde{A}(t)[(1-\delta)K(t-1) + I(t)]^{\gamma}P(t)^{(1-\gamma)}\right\}^{\eta(t)} - I(t)$.

We use the Matlab function *fmincon* to solve Equation (A10) over 100 periods (1996 to 2096) choosing the optimal investment path given the initial capital stock (in 1995). We simulate 100 years to ensure that endpoint conditions do not unduly impact the outcome over the sample period. As in Nordhaus (1993), the parameter values described below allow us to match actual output and pollution reasonably well. The plot below compares actual and simulated values of output over the sample period (actual values are based on the variable "real GDP at constant 2011 national prices" from the Penn World Tables (Zeileis, 2019 and Feenstra *et al.*, 2015)). Average annual emissions in the data are 135,721 $\mu g/m^3$ compared to an average simulated value of 152,672 $\mu g/m^3$ per year.

To simulate the general-equilibrium effects of a change in non-manufacturing pollution we adjust $\mu(t)$ slightly and re-optimize the model to obtain a derivative of output with respect to pollution. We then compute the average change in output and pollution over the sample period to calculate an elasticity. The estimate was similar for a range of variations in both directions ($\mu(2002)$ ranging from 1.2 to 1.6).



Parameter calibration

To calibrate the model from 1996 to 2017 taking 1995 capital stock as given we follow the approach in Nordhaus (1992) adapted to China's economy during our sample period:

1) The consumer's rate of time preference (ρ) is set to 0.04 which is a value commonly used in macroeconomic simulations (*e.g.*, Chang *et al.*, 2015).
2) The labor share ($1-\gamma$) is set to 0.575 based on the average labor share in China from 1995 to 2017 based on the variable "share of labor compensation in GDP at current national prices" in the Penn World Tables (Zeileis, 2019 and Feenstra *et al.*, 2015).
3) The elasticity of output with respect to pollution (θ) is set to our partial-equilibrium estimate of -0.17.
4) The depreciation rate (δ) is set to 0.09 based on Brandt *et al.* (2012) from which our firm productivity data is taken.
5) The elasticity of pollution with respect to output (μ) is set to 1.43 in 2002 based on our differences-in-differences estimates as described in the paper. We assume that this value changes smoothly from 1996 to 2096 (the last year of our simulation) passing through this value in 2002 and ending at 1.0. This is to account for China's projected improvements in emissions control over time.
6) The share of total output comprised of manufacturing (λ) is set year-by-year based on the share of GDP in first, second, and tertiary industries (*China Statistical Yearbook*, 2018) from 1996 to 2017. After 2017 we assume that it remains constant at that value.

Exogenous data

Population (P): actual and projected population by the United Nations from 1996 to 2096 (https://population.un.org/wpp/).

Augmented TFP $(\tilde{A})$: the 1996 value is based on the variable "residual TFP" in the Penn World Tables (Zeileis, 2019 and Feenstra *et al.*, 2015). We assume that it grows at 7.96% per annum based on estimates in Brandt *et al.* (2012) using manufacturing sector data from 1998 to 2007.

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Appendix 15: Derivations of estimates for pollution reduction costs

Chay and Greenstone (2005): The first stage of the paper's 2SLS estimation implies that total suspended particulates (TSPs)[2] declined by 12% more in non-attainment than in attainment counties in response to the US Clean Air Act. The estimates use data from 1970 and 1980.

Chen *et al.* (2013): Estimates that the Air Pollution Index (API) dropped 33% due to the regulations implemented during the 2008 Beijing Olympics.[3] The API is primarily attributable to PM_{10}[4] in 2008.

Fu and Gu (2017): Estimates the elasticity of the API with respect to toll rates across Chinese cities. Using data from 2011 to 2012 they find an elasticity of -0.15. The API is primarily attributable to PM_{10} during this time. To reduce the API by 1% the toll rate needs to increase on average from CNY 0.40 to 0.437.

Gendron-Carrier *et al.* (2017): Finds that particulate concentrations (measured by AOD) drop by 4% in a 10-kilometer radius around a city center following a subway system opening. The paper uses a sample of 171 cities across Asia, Europe, North America, South America, Australia, and Africa between August 2001 and July 2013.

Li *et al.* (2019): Estimates the effects on the API and Air Quality Index (AQI)[5] of all subway expansions in Beijing from 2008 to 2017. A one-standard deviation increase in subway density (by their measure) decreases the API/AQI by 2%. The API is primarily attributable to PM_{10} during this time period and the AQI to $PM_{2.5}$.

Greenstone (2002): From 1972 to 1987, non-attainment counties that were subject to regulation under the US Clean Air Act lost approximately $75 billion of output (in 1987 dollars) in pollution-intensive industries relative to attainment counties. This is a lower bound on the costs since it is a partial-equilibrium estimate ignoring output's effect on pollution. Adjusting this for inflation using the Consumer Price Index this is $118.8 billion in 2002 dollars (roughly the midpoint of our sample). This is $7.9 billion annually on average over the fifteen years. The pollutants include carbon monoxide (CO), O3, sulfur dioxide (SO_2), and total suspended particulates (TSP).

He *et al.* (2016): The first-stage of the paper's 2SLS estimation estimates that the air quality regulations during the 2008 Beijing Olympic Games[6] reduce PM_{10} concentrations by 24 to 26%.

Viard and Fu (2015): Beijing's API, which is primarily due to PM_{10} during the sample period, falls 21% in response to restricting 20% of cars one-day-a-week in the short run. This suggests reducing pollution by 1% requires restricting 1% of vehicles one-day-per week.

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[2] TSP was a cruder measure of suspended particulates before the PM_{10} and $PM_{2.5}$ measures were introduced later; and is the closest to the pollutant measure we examine during our sample period.

[3] These measures included plant closures and relocations, furnace replacements, introduction of new emission standards, and stringent traffic controls.

[4] This is particulate matter smaller than ten micrometers in diameter.

[5] China reported the API through 2013 after which it began reporting the more sophisticated AQI. The primary pollutant in the AQI index is PM_{10} and in the API index $PM_{2.5}$.

[6] These were wide-ranging and included installation of abatement equipment on power plants, replacement of all high-emissions public transit vehicles, shutdown of many factories, increase in vehicle gas prices, and relocation of a major steel plant.

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