Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China

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Abstract

We provide nationwide estimates of air pollution's effect on short-run labor productivity for manufacturing firms in China from 1998 to 2007. An emerging literature estimates air pollution's effects on labor productivity but only for small groups of workers of particular occupations or firms. To provide more comprehensive estimates necessary for policy analysis, we estimate effects for all but some small firms (90% of China's manufacturing output) and capture all channels by which pollution influences productivity. We instrument for reverse causality between pollution and output using thermal inversions.

Our causal estimates imply that a one $\mu g/m^3$ decrease in $PM_{2.5}$ (SO_2) increases labor productivity by 0.011% (0.036%) with an elasticity of -0.58 (-0.54). Lowering $PM_{2.5}$ (SO_2) by 1% nationwide through methods other than reducing manufacturing output would generate annual productivity increases of CNY 74.1 (69.7) thousand for the average firm and CNY 11.8 (11.1) billion or 0.079% (0.075%) of GDP across all firms. Improving air quality generates substantial productivity benefits and these should be considered in evaluating environmental regulations and their effect on firm competitiveness.

JEL Codes: Q51; Q53; D62; R11
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1 Introduction

An emerging literature documents the effect of air pollution on short-run labor productivity. These papers significantly advance our understanding of how pollution affects productivity and convincingly demonstrate that air pollution can decrease labor productivity. However, because these studies utilize detailed measures of hourly or daily output, they focus on narrow groups of workers in particular occupations such as fruit picking (Graff Zivin and Neidell, 2012), garment assembly (Adhvaryu *et al.*, 2014b), pear packing (Chang *et al.*, 2016a), call center services (Chang *et al.*, 2016b) or a few firms in textile assembly (He, Liu *et al.*, 2016). 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 estimates of air pollution's effect on short-run labor productivity for manufacturing firms in China encompassing all channels of effects. Using satellite data to measure pollution we are able to include all firms in China's manufacturing survey in our estimates. Since the survey includes all state-owned enterprises (SOEs) and all non-SOEs with more than CNY 5 million in annual sales, our estimates capture 90% of China's manufacturing output[1] (Brandt *et al.*, 2012) making them useful for evaluating nationwide environmental policies.

We estimate an elasticity of labor productivity with respect to pollution of -0.58 for particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$) and -0.54 for sulfur dioxide (SO_2). Holding number of workers constant, lowering $PM_{2.5}$ by 1% nationwide through methods other than reducing manufacturing output would increase the average firm's output by USD 9.7 (CNY 74.1)[2] thousand and increase output across all firms by USD 1.6 billion annually (0.079% of China's average GDP over the sample period). Similar calculations for SO_2 yield a per-firm increase of USD 9.2 thousand and an aggregate increase of USD 1.5 billion (0.075% of average GDP). These are significant effects and should be considered in any cost-benefit analysis of environmental policies.

The primary obstacle in estimation is reverse causality. Ordinary least squares (OLS) estimates will bias pollution's effect on labor productivity upward toward or above zero because more output per employee in a region leads to both more output and more pollution. Previous papers in this literature maintain exogeneity by focusing on one or a few firms which do not materially impact overall pollution levels. Estimating with a national sample no longer affords this condition. To overcome this endogeneity problem while achieving comprehensive estimates we employ the number of days with

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

thermal inversions (Arceo *et al*., 2016; Hicks *et al*., 2016; Jans *et al*., 2016; Sager, 2016) in geographic areas corresponding to counties. Thermal inversions form due to exogenous meteorological factors yet trap pollutants such as $PM_{2.5}$ and SO_2 near the ground degrading air quality. The instrument is highly predictive and, consistent with the simultaneity bias between output and pollution, 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 based on pollution. Using education as a proxy for skill we find no significant evidence of sorting by workers and pollution's effect on productivity is similar for firms with high- and low-education workforces. 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 exit consistent with survival bias having limited effect on our estimates.

This paper makes three primary contributions. First, we provide nearly exhaustive measures for the causal effect of pollution on the short-run labor productivity of a country's manufacturing sector. Previous studies examine only small sets of workers in particular occupations or a small set of firms. Cost-benefit analyses of national environmental policies require comprehensive estimates of pollution's effects 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, 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 are 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. For example, Greenstone *et al.* (2012) find that the US Clean Air Act significantly decreased firm productivity because it induced firms to employ inputs that are not necessarily useful for producing commercial outputs but are for meeting regulatory requirements – such as installing scrubbing and gas reclamation equipment and hiring environmental compliance officers. Our findings suggest that these estimates capture the net of two effects: reduced productivity due to compliance activities and increased productivity due to cleaner air. Therefore, an estimate of the productivity cost of compliance would require subtracting the productivity gains from cleaner air from the net effect. Put another way, firms are not made as uncompetitive when complying with environmental measures as they would be absent the productivity gains.

Third, there is relatively little evidence concerning pollution's effect on high-skilled workers (Chang *et al*. (2016b) is an exception using call center workers). We estimate the effects of $PM_{2.5}$ and SO_2 on labor productivity separately for firms likely to have high-versus low-skilled workers. We find very similar effects for these two subsets for both $PM_{2.5}$ and SO_2. This suggests that the results for call center service workers likely extend to high-skilled workers in manufacturing consistent with the fact that both $PM_{2.5}$ and SO_2 can penetrate buildings.

Finally, 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 labor 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; He, Fan *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). Our finding of significant labor productivity gains from such measures provides additional impetus to implement these measures. Because of China's severe pollution, the central government has designed many policies to reduce air pollution but these often go unenforced because local governments lack incentives to do so or incentives emphasize alternative goals such as economic growth (Li and Zhou, 2005; Chen *et al*., 2016; Jia, 2017). Our findings reveal that local governments may underestimate the benefits to local economic growth of reducing air pollution.

[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).

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 results and Section 6 concludes.

2. Pollution and Productivity

How does air pollution affect short-run labor 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) 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 psychological effects (Levinson, 2012; Lavy *et al*., 2014; Pun *et al*., 2016) 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, particulates such as $PM_{2.5}$ (Thatcher and Layton, 1995) and SO_2 (Vardoulakis *et al.*, 2010) can seep into buildings, 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 the effect of all possible channels.

Pollution can affect output through labor productivity, the intensive margin, and labor supply, the extensive margin. 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 workers (another type of extensive margin).

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

To illustrate this, suppose per-hour productivity is A, each worker's annual hours is H, number of workers is L and annual output is Q. Then, $Q = A * H * L$. In the data we observe L but not A or H. Consider, as we do in our estimates, the effect of pollution (p) on annual labor productivity holding the number of workers constant: $d(Q/L)/dp = dA/dp * H + A * dH/dp$. 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.

Extant studies observe worker hours (H) and therefore measure effects on per-hour productivity (dA/dp); although many separately estimate effects on hours worked (dH/dp) 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*., 2016a). $PM_{2.5}$ also reduces per-hour productivity of garment factory workers in India with no effect on absences (Adhvaryu *et al*., 2014b). $PM_{2.5}$ and SO_2 reduce per-hour output of textile workers at two sites in China but has little effect on hours worked (He, Liu *et al*., 2016). 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 API affects call center workers (Chang *et al*., 2016b) 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 also establishes 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 (Lavy *et al*., 2014). It also has negative effects on short-run performance of outdoor athletic participants including soccer players (Lichter *et al*., 2015), marathon runners (Fu and Guo, 2017), and baseball umpires (Archsmith *et al*., 2016).

3. Primary data

We estimate firm-level labor productivity combining comprehensive data on firm characteristics with air pollution data for highly-specific geographic areas across all of China from 1998 to 2007. Our pollution measures are monthly concentrations of $PM_{2.5}$ and SO_2 derived from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by the National Aeronautics and Space Administration (NASA).[5] We use

[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

the AOD data because it provides the most comprehensive measures 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). The SO_2 concentrations are reported in the data and the $PM_{2.5}$ concentrations are calculated following Buchard *et al.* (2016).

The AOD data has several advantages compared to ground-based pollution data. First, it begins in 1980 while ground-based pollution data is available only beginning in 2000 enabling us to use two more years of data. Second, it covers the whole country while ground-based pollution data covers only 42 cities in 2000 increasing to 113 in 2010. Third, ground-based pollution data is potentially subject to human manipulation (Andrews, 2008; Ghanem and Zhang, 2014) while the satellite data is not. The AOD pollution data is 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 $PM_{2.5}$ and SO_2 in each county-year.

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 during our sample period (Brandt *et al*., 2012). The sample includes 2,223,406 firm-year observations and 568,888 unique firms.

Following the matching algorithm described in Brandt *et al.* (2012) we match firms over time to form an unbalanced panel, and convert nominal into real values using industry-level price indices.[8] We drop 2% of observations with unreliable data following the previous literature (Cai and Liu, 2009; Brandt *et al*., 2012; Yu, 2014).[9] In addition, six

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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).

[7] 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). 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] 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

percent of observations are firms appearing in only one year and dropped with the inclusion of firm fixed effects. We also winsorize the top and bottom 0.5% of data based on the values of output, value added, employment, and capital for two reasons. First, to be consistent with the previous literature (Cai and Liu, 2009). Second, the largest firms are likely to have multiple plant locations making it impossible to match them with local pollution measures because we observe only the firm's headquarters. Because the large firms that are winsorized have a disproportionate effect on total output we show that the results are similar using the non-winsorized data. The final data includes 1,593,247 firm-year observations for 356,179 unique firms. Geographically, the sample includes 2,755 counties with an average of 57.8 firms per county-year.

One issue with obtaining broad-based measures of productivity effects is how to measure productivity. 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. Firms report value added directly in the data and it 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. This approach is typical in aggregate studies such as ours since output is not directly observed (Syverson, 2011) although 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 firm output including temperature, precipitation, relative humidity (inferred from temperature and dew point temperature), and wind speed from the National Climatic Data Center at the National Oceanic and Atmospheric Administration.[10] We convert the

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violating accounting identities such as the components of net assets exceeding total assets or current depreciation exceeding cumulative depreciation.

[10] The data is available at: ftp://ftp.ncdc.noaa.gov/pub/data/noaa/.

station-level data to county level using the inverse-distance weighting method (Deschenes and Greenstone, 2011) and then calculate annual means for temperature, humidity, and wind speed and annual cumulative precipitation. These are then matched to the firm data by county and year.

For our instrument, we obtain thermal inversion data from NASA.[11] The data reports 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 main instrument, we calculate for each county the annual number of days that have at least one inversion. We show that our results are robust to using two alternative instruments: the annual cumulative number of six-hour periods with an inversion and the annual cumulative strength of thermal inversions across all six-hour periods where strength is defined as the temperature difference between the first and second layers.

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 labor 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 for both $PM_{2.5}$ and SO_2 (WHO, 2006). In the sample, the mean annual $PM_{2.5}$ level is 53.5 with a high of 134.8 and the mean SO_2 is 15.1 with a high of 54.7. 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. The annual cumulative number of inversions also displays significant variation ranging from zero to 628 (almost two six-hour periods per day).

[Insert Table 1 here]

[11] 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.

4. Model specification and identification

We focus on labor productivity because there are no obvious channels by which pollution would affect capital productivity.[12] Our primary econometric model is:

$$ln(Y_{ict}/L_{ict}) = \beta_0 + \beta_1 P_{ict} + \beta_2 W_{ict} + \alpha_i + \rho_t + \varepsilon_{ict}, \quad (1)$$

where i indicates firm, c county, and t year. For firm i in year t located in county c, Y is value added and L is the number of workers.[13] P is a measure of pollution and W the vector of weather variables faced by firm i in county c in year t. We include a quadratic function of each weather variable to allow for non-linearity in its effects (Adhvaryu *et al.*, 2014a; Sudarshan *et al.*, 2015; Zhang *et al.*, 2016). The coefficient β_1 captures the effect of pollution on labor productivity. Since L is measured in number of employees, this captures the combined effects on productivity of output per hour worked and total hours worked including absences.

Firm fixed effects (α_i) capture time-persistent firm attributes that affect labor 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 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_{ict}) captures time-varying, firm-specific unobservables that affect labor productivity. In our baseline estimation we cluster standard errors by firm to allow for serial correlation in productivity within firm over time. In robustness checks we allow for two-way clustering by firm and county-by-year that allows separately for serial correlation of unobservables over time within firm and spatial correlation of unobservables within each county-year. In other robustness checks we cluster at the county-by-year level which allows unobservables to be spatially correlated within each county-year and at the county level which allows unobservables to be correlated over time and spatially within each county.

Identification requires that, conditional on the control variables, pollution is independent of the error in Equation (1). There are two separate causal identification issues that are specific to our context: reverse causality and spatial sorting.

[12] In Section 5 we directly test whether pollution affects capital productivity and find insignificant effects.
[13] Estimating labor productivity 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.

4.1 Causal identification issue – reverse causality

Reverse causality results from the fact that production itself produces air pollution. The more output a county's firms produce the worse its pollution. Estimated using OLS, this simultaneity will bias estimates upward toward or above zero. This is the main identification issue, which we address using instrumental variables.

A valid instrument is correlated with a county's air pollution but uncorrelated with its resident firms' productivity. Our primary instrument is the annual number of days with a 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 on top of a cooler, denser air mass trapping dust and pollutants near the ground and increasing air pollution. We calculate thermal inversions using the first and second layers (110 and 330 meters respectively).

Since thermal inversions are a meteorological phenomenon and, after conditioning on weather variables, are unrelated to production except via pollution it is a valid instrument for addressing the simultaneity bias of output and air pollution. 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*., 2016; Sager, 2016). With this as our instrument we employ two-stage least squares (2SLS) with the first-stage equation:

$$P_{ict} = \gamma_0 + \gamma_1 I_{ict} + \gamma_2 W_{ict} + \alpha_i + \rho_t + \varepsilon_{ict}, \quad (2)$$

where I_{ict} is the number of thermal inversion days faced by firm i in county c in year t. The quadratic functions of weather controls from the second stage are included because these same variables affect the formation of inversions and are also needed to ensure exogeneity of instrumented pollution in the second stage (Arceo *et al*., 2016).

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 bias the results.[14] Only 7% of firms relocate counties during the sample period. Excluding these reveals some evidence of firm sorting and suggests even larger productivity effects absent sorting. Firm exit during the sample period could introduce bias through endogenous selection. To check for this possibility we estimate the effect of pollution on the probability of exit (controlling for endogeneity) and find no significant effect.

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, but we check for evidence of this occurring. We utilize China's 2000 and 2005 population censuses (the only available during the sample period) to compute the college share of manufacturing workers in each county (six-digit administrative code) in these two years as a proxy for high-skilled labor. Significant geographic migration of workers by education level in response to air pollution should result in a weak correlation of this fraction within each county across the two years. We find a correlation of 0.81 significant at better than the 0.01% level suggesting that spatial sorting of workers is not a major concern. In addition, we estimate pollution's effect separately on firms whose workforces are above and below the median in the fraction of college-educated workers and find similar results across the two subsets.

5. Results

5.1 OLS estimates

We first present estimates not accounting for the simultaneity bias between productivity and pollution. Table 2 presents OLS estimates of Equation (1). $PM_{2.5}$

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

pollution (Column (1)) has no effect on productivity, perhaps due to the simultaneity bias. SO_2 pollution decreases productivity (Column (2)) with an elasticity of -0.083 evaluated at the mean SO_2 level in the sample.

[Insert Table 2 here.]

5.2 2SLS results

Because of the simultaneity bias, OLS estimates will be biased upward toward or above zero. We use the annual number of days with a thermal inversion as an instrument for pollution concentration. The first-stage results in the top panel of Table 2 show that the instrument is a powerful predictor of both $PM_{2.5}$ (Column (3)) and SO_2 (Column (4)) concentrations. The coefficient on annual days with thermal inversions is positive and highly significant for both pollutants 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.[15] One additional day with an inversion increases $PM_{2.5}$ by 0.032 and SO_2 by 0.0097 $\mu g/m^3$. These are big effects. A one standard deviation increase in the annual number of days with inversions increases $PM_{2.5}$ by 2.5 $\mu g/m^3$ (4.8%) and SO_2 by 0.76 $\mu g/m^3$ (5.1%).

The lower panel of Table 2 shows the second-stage results. In Column (3), instrumented $PM_{2.5}$ has a negative and very significant effect on labor productivity. Consistent with the instrument correcting for simultaneity, the coefficient on $PM_{2.5}$ moves from being insignificant in the OLS estimates to significantly negative. A one $\mu g/m^3$ increase in $PM_{2.5}$ decreases labor productivity by 1.08%. Evaluating this at the mean $PM_{2.5}$ in the sample (53.5) yields an elasticity of -0.58. Instrumented SO_2 (Column (4)) also has a negative and very significant effect on productivity. A one $\mu g/m^3$ increase in SO_2 decreases labor productivity by 3.60%. Although the effect was negative and significant in the OLS estimates it is now more negative consistent with an upward bias due to reverse causality. Evaluating at the mean SO_2 in the sample (15.1) yields an elasticity of -0.54.

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. This would increase the average firm's value added by CNY 74.1 (USD 9.7) thousand annually and increase total value added across

[15] 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.

all firms by CNY 11.8 (USD 1.6) billion annually.[16] This represents 0.079% of China's GDP.[17] Similar calculations for SO_2 imply an output increase for the average firm of CNY 69.7 (USD 9.2) thousand and CNY 11.1 (USD 1.5) billion annually across all firms (0.075% of GDP).[18]

China's Air Pollution Prevention and Control Action Plan stipulates 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[19] 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 12% (1.6% 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.

We can compare our estimates to previous ones although these apply only to particular types of workers or small sets of firms and are often for different pollutants. Also, all of these studies measure effects on per-hour productivity and hours worked separately while our estimates include both. Graff Zivin and Neidell (2012) estimate an elasticity of per-hour productivity with respect to ozone pollution of -0.26 for outdoor fruit pickers in California. Although lower than our elasticity, it is for a different pollutant and for a particular worker type in a much less polluted environment. For indoor pear packers in California, Chang *et al.* (2016a) estimate a per-hour productivity elasticity of -0.062 for $PM_{2.5}$. This is lower than our $PM_{2.5}$ estimate but it is again for a particular worker type in a much less polluted environment. In China, Chang *et al.* (2016b) estimate an elasticity of per-hour labor productivity with respect to the API of -0.023 for call center workers. This is again lower than our estimates but it applies to service workers in two specific locations of a specific industry.

For garment factory workers in India, Adhvaryu *et al.* (2014b) estimate an elasticity of -0.052 for per-hour productivity with respect to $PM_{2.5}$ pollution. While this is most directly comparable to our higher estimate, in that it applies to manufacturing workers

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[16] A 1% decrease in $PM_{2.5}$ increases annual output by 0.58%. The mean annual output per firm in the sample is CNY 12.82 million implying an annual increase of CNY 74.1 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 11.8 billion annually.

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

[18] Since manufacturing output is itself a major source of air pollution it would be useful to calculate the effects assuming that pollution is reduced proportionally across all sources including manufacturing output. However, this would require estimates of the relationship between pollution and manufacturing output and an assumption about how much, and whether, productivity increases brought about by reduced air pollution will generate more emissions.

[19] Issued by the State Council on September 10, 2013 (http://www.gov.cn/zwgk/2013-09/12/content_2486773.htm).

and the same pollutant, it applies to a specific firm and measures effects conditional on being at work indoors. He, Liu *et al.* (2016) examine textile workers in two firms in two Chinese provinces and find no contemporaneous effect from $PM_{2.5}$ exposure but elasticities ranging from -0.035 to -0.30 due to cumulative effects over 25 to 30 days. The upper end of this range is about half of our estimate for all locations and all manufacturing industries in China. Overall, we find a larger effect than these previous papers although these studies measure daily or monthly effects while we capture annual cumulative effects.

5.3 Robustness checks

Table 3 shows robustness to different assumptions about the model's standard errors 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, Gelbach, and Miller, 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 very 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 as expected but the results remain significant at better than the 5% level for both pollutants.

[Insert Table 3 here.]

Panel A of Table 4 show additional robustness checks of the 2SLS estimates for $PM_{2.5}$. Our baseline estimates (reproduced in Column (1)) weight all observations equally. Column (2) re-estimates weighting observations by value added per firm. The coefficient yields a higher elasticity (-0.83) than the baseline estimates. Column (3) shows that not winsorizing the data leads to very similar results as the baseline estimates (an elasticity of -0.53). Column (4) uses the annual cumulative number of six-hour periods with inversions as the instrument. Our baseline estimates assume all days with inversions are the same. This alternative instrument weights their severity by the number of six-hour periods within a day that have inversions. The instrument is very significant and the KP *F*-statistic is well above the Stock-Yogo critical value while the second-stage results yield a slightly lower elasticity (-0.45). Column (5) uses strength of thermal inversions as an alternative instrument. The severity of an inversion depends on its temperature differential and counties with the same number of inversions may differ in severity. The alternative instrument is very significant and the KP *F*-statistic is well above the Stock-Yogo critical value while the second stage results are somewhat below the baseline estimates (elasticity of -0.46).

[Insert Table 4 here.]

Panel B of Table 4 repeats the same robustness checks for SO_2. As with $PM_{2.5}$, weighting the observations by value added (Column (2)) results in an effect which is larger in magnitude (elasticity of -0.82) than the baseline estimates reproduced in Column (1). Estimates using the non-winsorized data (Column (3)) are very significant and yield a somewhat lower elasticity (-0.50) than the baseline estimates. Finally, both cumulative number (Column (4)) and cumulative strength of thermal inversions (Column (5)) are powerful instruments and result in larger elasticity estimates (-0.86 and -0.89) than the baseline estimates.

Table A1 in the Appendix shows robustness checks using log pollution rather than linear pollution in the first stage. Column (1) shows estimates for $PM_{2.5}$. Pollution has a highly significant effect on productivity and the elasticity is very close to that estimated using a linear function. Results for SO_2 are shown in Column (2). The coefficient is very significant and the elasticity is only slightly larger (0.60) than that using linear pollution.

5.4 Tests for firm and worker sorting

Firms may relocate to places with better air quality to improve labor productivity or to places with lax environmental regulation to lower costs. Table 5 shows tests for this potential spatial sorting. Column (2) estimates excluding firms that relocated across counties (about 7% of firms) during the sample period. The estimated elasticities (-0.89 for $PM_{2.5}$ and -1.02 for SO_2) are larger for both pollutants than the baseline estimates 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. 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 (3) tests whether instrumented pollution significantly increases the probability of firm exit in the following year. The effect of pollution on an indicator variable set to one in the last year in which a firm appears is not significant for either pollutant suggesting that exit bias is not a major concern.[20]

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. We use the fraction of workers with a college degree as a proxy for skill and divide firms into those above and below the median in fraction of college-educated workers. Columns (4) and (5) show the results of separately estimating Equation (1) on these two subsamples. These estimates include only firms that appear in 2004 – the only year for which education data is available during our sample period – and at least one other year. The results show some evidence of sorting with the effects being slightly greater for firms below the median. However, the difference is not large and the effects for firms with high skilled workers are large and statistically significant.

[Insert Table 5 here.]

5.5 Multiple pollutants models

In our baseline model, we estimate the effect of each pollutant separately. Since air pollutants are typically highly correlated, our single-pollutant estimates may capture both its effect as well as the effect of the other. To estimate the joint effects, we apply the two methods in Arceo *et al.* (2016). The first is to estimate $PM_{2.5}$ and SO_2 together. For the two instruments we use annual number of days with an inversion and annual cumulative strength of inversions. The second approach is to combine the two into an index and construct our own AQI based on the definition of China's Ministry of Environmental Protection (MEP).[21] This is a piece-wise linear transformation of the worst of the two air pollutants in each month.

Column (1) of Table A2 in the Appendix presents the estimates when both $PM_{2.5}$ and SO_2 are included in the same model. The first stage performs well. The Sanderson-Windmeijer *F*-statistics (Sanderson and Windmeijer, 2016) for both first instruments are

[20] Year 2007 data is dropped in this estimation since we cannot observe whether firms present in 2007 exit in the following year. Estimates using a balanced panel could be used to address this issue as well as any selection effects by entering firms. However, only 7% of firms are present in all years due to significant firm turnover. For this small sample, the estimates are very significant and the estimated elasticities are much greater presumably due to exposure levels that differ from those in the full sample.

[21] See detailed formula at http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/W020120410332725219541.pdf (in Chinese). Our calculation differs from the MEP's in two ways. First, ours is a monthly index rather than daily. Second, ours depends only on SO_2 and $PM_{2.5}$, while the MEP formula depends on two additional pollutants (CO, and O_3). However, the worst daily pollutants are predominantly SO_2 and $PM_{2.5}$ in the MEP calculations.

well above the Stock-Yogo critical value of 8.68. The KP *F*-statistic for the joint strength of the instruments is also much greater than the Stock-Yogo critical value of 7.03. The *p*-value of the under-identification test indicates that we can reject the hypothesis that the model is under-identified. In the second-stage, the $PM_{2.5}$ effects are significant but lower in magnitude than the baseline results while the SO_2 effects are not significant. This is likely due to the very high correlation (0.95 with a significance level below 0.01%) between $PM_{2.5}$ and SO_2.

Using annual number of days with a thermal inversion as an instrument, Column (2) shows that the AQI index has significant negative effects on labor productivity. A one-unit increase in AQI decreases labor productivity by 0.88%. The mean API is 72.6 implying an elasticity of -0.64 – above the standalone elasticities for $PM_{2.5}$ and SO_2.

5.6 Effect by worker skill level

We are aware of only one paper that considers the effect of pollution on labor productivity of high-skilled workers: Chang *et al*. (2016b) find a significant productivity decrease for call center workers in China. 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. $PM_{2.5}$ and SO_2 can permeate indoors making it possible for them to affect indoor workers. Our data allows us to offer some evidence by skill level for manufacturing firms in China. We categorize firms based on the NBS' definitions of high- and low-technology firms.[22] The results are shown in Columns (2) and (3) of Table 6 along with the estimates for the full sample in Column (1). For $PM_{2.5}$, the estimates for the high- and low-technology groups are significant, virtually identical, and almost the same as those for the full sample. For SO_2 the effects are significant for both groups and the estimate for the high-technology firms is only slightly lower than those for the low-technology group and the full sample. Thus, the previous evidence for call center workers appears to extend 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.

[Insert Table 6 here.]

[22] See http://www.stats.gov.cn/tjsj/tjbz/201310/P020131021347576415205.pdf for the definitions. The high-technology industries are medicine manufacturing, aviation and aerospace manufacturing, electronic and telecommunication manufacturing, computer manufacturing, medical equipment manufacturing, and information chemicals manufacturing.

5.7 Effect on number of workers

Our estimates capture the effect on labor productivity from all channels: changes in per-hour productivity, hours worked, or absences. Pollution may also affect the number of workers employed. To assess this, we estimate Equation (1) with log number of workers in each firm as the dependent variable using annual number of days with a thermal inversion as the first-stage 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 during the course of a year would be captured. The results are shown in Column (2) of Table 7. A one $\mu g/m^3$ increase in $PM_{2.5}$ (SO_2) increases employment by 0.72% (2.40%) implying an elasticity of 0.39 (0.36). Although firms increase employment to compensate for some of the labor productivity loss it is not enough to offset the negative effect on labor productivity shown in Column (1). Column (3) estimates the effect of pollution on log product. The effects are significant and the elasticity of log product with respect to pollution is -0.19 for $PM_{2.5}$ and -0.18 for SO_2. These equal the summed effect of pollution's effect on labor productivity (-0.58 for $PM_{2.5}$ and -0.54 for SO_2) and its effect on labor supply (0.39 for $PM_{2.5}$ and 0.36 for SO_2).

As a placebo test, we re-estimate Equation (1) with log capital as the dependent variable.[23] Consistent with pollution not affecting physical capital there is no significant effect for either $PM_{2.5}$ or SO_2 (Column (4) of Table 7). This also implies that firms are not adjusting their capital-labor ratios.

Although the positive labor supply effects partially mitigate the negative labor productivity effects, 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 0.39%, or 0.80 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 10,087 (USD 1,327). Aggregated across all firms this equals CNY 1.61 billion (USD 0.21 billion) annually or 14% of the productivity loss from the 1% increase in $PM_{2.5}$. Similar calculations for SO_2 yield an increase in employment of 0.36% or 0.75 workers. This implies an additional annual cost per firm of CNY 9,490 (USD 1,249) and an aggregate cost of CNY 1.51 (USD 0.20) billion or 13% of the associated productivity loss.

[Insert Table 7 here.]

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

6. Conclusion

Using a large micro dataset on manufacturing firms in China, we estimate the effect of air pollution on labor productivity. To deal with the reverse causality of output and pollution we take an instrumental variable approach using thermal inversions, which are meteorologically determined. The approach attenuates the bias due to reverse causality and indicates a significant negative effect of air pollution on productivity. Our approach can be employed in any country with sufficient variation in thermal inversions.

Our study shows a significant economic loss in labor 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 labor productivity and total output. Our study contributes to the emerging literature on air pollution's effect on short-run labor productivity by providing comprehensive, nationwide empirical evidence that captures all channels through which pollution can affect productivity. These estimates can be used directly for short-run effects in cost-benefit analyses of broad-based environmental policies.

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 no 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 while 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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Table 1: Summary statistics

Variables	Mean	Standard deviation	Minimum	Maximum
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
Labor productivity (1,000 CNY/worker)	88	160	0.13	16,248
County-year sample				
Air pollution				
Particular matter ($PM_{2.5}$) ($\mu g/m^3$)	53.52	25.46	2.62	134.84
Sulphur dioxide (SO_2) ($\mu g/m^3$)	15.07	10.70	0.04	54.68
Thermal inversions				
Annual days with thermal inversions	156.9	78.7	0.0	333.0
Annual cumulative number of thermal inversions	245.5	142.1	0.0	628.0
Annual cumulative thermal inversion strength (^oC)	324.5	283.9	0.0	1,788.9

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.

Table 2 OLS and 2SLS estimates – effect of pollution on labor productivity using annual number of days with thermal inversions as instrument

	(1)	(2)	(3)	(4)
	OLS		**2SLS**	
			First stage	
Dependent variable:			**$PM_{2.5}$**	**SO_2**
Annual days with inversions			0.0323***	0.0097***
			(0.0004)	(0.0002)
KP *F*-statistic			5,938	2,287
# counties			2,755	2,755
Dependent variable:	**ln(Value added per worker)**			
			Second stage	
$PM_{2.5}$	0.00004		-0.0108***	
	(0.0002)		(0.0015)	
SO_2		-0.0055***		-0.0360***
		(0.0005)		(0.0050)
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

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 3 2SLS estimates – effect of pollution on labor productivity using annual number of days with thermal inversions as instrument (robustness checks for clustering of standard errors)

	(1)	(2)	(3)	(4)
Dependent variable:	**ln(value added per worker)**			
Panel A: $PM_{2.5}$	-0.0108***	-0.0108**	-0.0108**	-0.0108**
	(0.0015)	(0.0044)	(0.0043)	(0.0049)
KP *F*-statistic	5,938	98	99	53
Panel B: SO_2	-0.0360***	-0.0360**	-0.0360**	-0.0360**
	(0.0050)	(0.0148)	(0.0146)	(0.0164)
KP *F*-statistic	2,287	35	35	23
Cluster by firm	Y	N	N	N
Cluster by firm and county-year	N	Y	N	N
Cluster by county-year	N	N	Y	N
Cluster by county	N	N	N	Y
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	379,349	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247

Panel A shows second-stage results for $PM_{2.5}$ and Panel B for SO_2. 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 in Column 1, 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).

Table 4 2SLS estimates – effect of pollution on labor productivity (robustness checks on firm weighting, sample, and instruments)

	(1)	(2)	(3)	(4)	(5)
Panel A:					
Dependent variable:			**$PM_{2.5}$**		
Instrument	0.0323***	0.0322***	0.0335***	0.0162***	0.0068***
	(0.0004)	(0.0009)	(0.0004)	(0.0002)	(0.0001)
KP *F*-statistic	5,938	1,353	6,589	6,028	5,692
Dependent variable:			**ln(value added per worker)**		
	-0.0108***	-0.0155***	-0.0100***	-0.0084***	-0.0086***
	(0.0015)	(0.0025)	(0.0016)	(0.0016)	(0.0018)
Panel B:					
Dependent variable:			**SO_2**		
Instrument	0.0097***	0.0092***	0.0101***	0.0024***	0.0010***
	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0000)
KP *F*-statistic	2,287	456	2,573	560	518
Dependent variable:			**ln(value added per worker)**		
	-0.0360***	-0.0546***	-0.0333***	-0.0572***	-0.0589***
	(0.0050)	(0.0091)	(0.0053)	(0.0109)	(0.0123)
First-stage instrument:					
Annual days with inversions	Y	Y	Y	N	N
Cumulative number inversions	N	N	N	Y	N
Cumulative inversion strength	N	N	N	N	Y
Weighting by value added	N	Y	N	N	N
Winsorized	Y	Y	N	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
# firms	356,179	356,179	379,349	356,179	356,179
Sample size	1,593,247	1,593,247	1,746,850	1,593,247	1,593,247

Panel A shows second-stage results for $PM_{2.5}$ and Panel B for SO_2. For first-stage instruments, Columns 1 through 3 use annual number of days with thermal inversions; Column 4 annual cumulative number of inversions; and Column 5 annual cumulative strength of inversions. 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 in all models 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).

Table 5: 2SLS estimates – effect of pollution on labor productivity using annual number of days with thermal inversions as instrument (tests for firm and worker sorting based on pollution)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**ln(value added per worker)**		**Exit**	**ln(value added per worker)**	
				(Number skilled workers/employment)	
	Baseline	**Exclude relocating firms**	**Exit probability**	**Below median**	**Above median**
Panel A: $PM_{2.5}$	-0.0108***	-0.0166***	0.0023	-0.0228***	-0.0160***
	(0.0015)	(0.0020)	(0.0014)	(0.0026)	(0.0025)
KP *F*-statistic	5,938	7,284	5,938	2,008	1,673
Panel B: SO_2	-0.0360***	-0.0675***	0.0070	-0.0720***	-0.0543***
	(0.0050)	(0.0081)	(0.0043)	(0.0083)	(0.0086)
KP *F*-statistic	2,287	2,389	1,530	802	638
Firm fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
# firms	356,179	329,858	129,338	88,307	88,792
Sample size	1,593,247	1,432,765	469,734	505,924	490,238

Sample period: 1998 - 2007 in Columns 1, 2, 4, and 5; 1998 - 2006 in Column 3 to measure exit in the following year. Columns 1 through 3 include all firms; Columns 4 and 5 include only firms that are present in 2004 (when education data is available) and at least one other year. Panel A shows second-stage results for $PM_{2.5}$ and Panel B for SO_2. 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. 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 – effect of pollution on labor productivity distinguishing high- and low-technology firms using annual number of thermal inversions as instrument

	(1)	(2)	(3)
Dependent variable:	**ln(value added per worker)**		
	Full sample	**High technology**	**Low technology**
Panel A: $PM_{2.5}$	-0.0108***	-0.0107**	-0.0107***
	(0.0015)	(0.0054)	(0.0015)
KP *F*-statistic	5,938	315	5,6593
Panel B: SO_2	-0.0360***	-0.0300**	-0.0362***
	(0.0050)	(0.0151)	(0.0053)
KP *F*-statistic	2,287	171	2,123
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Weather controls	Y	Y	Y
# firms	356,179	24,220	331,959
Sample size	1,593,247	111,121	1,482,126

Panel A shows second-stage results for PM2.5 and Panel B for SO2. 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 pollution on labor, output, and capital using annual number of days with thermal inversions as instrument

Dependent variable:	(1) **ln(value added per worker)**	(2) **ln(number workers)**	(3) **ln(value added)**	(4) **ln(capital)**
Panel A: $PM_{2.5}$	-0.0108***	0.0072***	-0.0036**	0.0013
	(0.0015)	(0.0011)	(0.0016)	(0.0013)
KP *F*-statistic	5,938	5,938	5,938	5,938
Panel B: SO_2	-0.0360***	0.0240***	-0.0120**	0.0043
	(0.0050)	(0.0037)	(0.0052)	(0.0045)
KP *F*-statistic	2,287	2,287	2,287	2,287
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

Panel A shows second-stage results for $PM_{2.5}$ and Panel B for SO_2. 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 A1: 2SLS estimates – effect of pollution on labor productivity using annual number of days with thermal inversions as instrument (log-pollution specification)

	(1)	(2)
First stage		
Dependent variable:	**ln($PM_{2.5}$)**	**ln(SO_2)**
Annual days with inversions	0.0006***	0.0006***
	(0.0000)	(0.0000)
KP *F*-statistic	7,894	2,012
Second stage		
Dependent variable:	**ln(value added per worker)**	
ln($PM_{2.5}$)	-0.5835***	
	(0.0798)	
ln(SO_2)		-0.6002***
		(0.0829)
Firm fixed effects	Y	Y
Year fixed effects	Y	Y
Weather controls	Y	Y
# firms	356,179	356,179
Sample size	1,592,626	1,592,626

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 A2: 2SLS estimates – multiple-pollutant models of effects of pollution on labor productivity

	(1)	(2)
Dependent variable:	**ln(value added per worker)**	
$PM_{2.5}$	-0.0065**	
	(0.0029)	
SO_2	-0.0144	
	(0.0102)	
API		-0.0088***
		(0.0012)
Firm fixed effects	Y	Y
Year fixed effects	Y	Y
Weather controls	Y	Y
SW F - $PM_{2.5}$	4,298	
SW F - SO_2	2,368	
First-stage KP *F*-statistic	902	5,728
Under-identification test (p-value)	0.000	0.000
# firms	356,179	356,179
Sample size	1,593,247	1,593,247

Column 1 first-stage instruments are annual number of days with thermal inversions and annual cumulative strength of thermal inversions. Column 2 first-stage instrument is annual number of days with thermal inversions. 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. SW F are Sanderson-Windmeijer *F*-statistics for test of weak instruments for each endogenous variable. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006). The underidentification test is p-value for the Kleibergen-Paap rk LM statistic.