Air Quality and Manufacturing Firm Productivity: Comprehensive Evidence from China

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Abstract

We provide comprehensive 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 sets of firms to ensure causality. To provide more comprehensive estimates necessary for policy analysis, we estimate effects for all but some small firms (90% of manufacturing output in China) 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 0.0084% (0.0572%) with an elasticity of -0.45 (-0.86). Lowering $PM_{2.5}$ (SO_2) by 1% nationwide through methods other than reducing manufacturing output would generate productivity increases of CNY 57.6 (110.5) thousand annually for the average firm and CNY 9.2 (17.6) billion annually or 0.06% (0.12%) of GDP across all firms. Accounting for output's contribution to $PM_{2.5}$ (SO_2) emissions leads to a net elasticity of -0.23 (-0.75).

Using air quality of a nearby city conditional on wind blowing toward a focal city as an alternative instrument, we find a one $\mu g/m^3$ decrease in PM_{10} increases productivity by 0.41% with an elasticity of -0.43 using a subsample of larger cities. Improving air quality generates substantial output and productivity benefits and these should be considered in evaluating environmental regulations and in evaluating their effect on firm competitiveness.

JEL Codes: D62; Q51; Q53; R11
Key words: 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 labor productivity. These papers significantly advance our understanding of how pollution affects productivity and convincingly demonstrate that air pollution causes labor productivity to decrease. However, because these studies rely on the exogeneity of air pollution as an identification strategy, they focus on narrow groups of workers in particular occupations such as fruit picking (Graff Zivin and Neidell, 2012), pear packing (Chang *et al*., 2016a), call center services (Chang *et al*., 2016b), garment assembly (Adhvaryu *et al*., 2014a) or a few firms in textile assembly (He, Liu *et al.,* 2016). Air pollution has also been found to negatively impact short-run productivity of outdoor sports personnel including soccer players (Lichter *et al*., 2015), marathon runners (Fu and Guo, 2016), and baseball umpires (Archsmith *et al*., 2016). While these estimates are useful for evaluating narrowly-targeted environmental policies or evaluating the costs and benefits for small groups of people, their external validity is of concern in evaluating broad-based pollution reduction policies.

We provide comprehensive, nationwide estimates of the effect of air pollution on short-run labor productivity for manufacturing firms in China encompassing all channels of effects. Using satellite data for pollution measures 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 sample captures 90% of China's manufacturing output[1] (Brandt *et al.*, 2012) making our estimates useful for analyses of broad-based, nationwide environmental policies.

We estimate an elasticity of labor productivity with respect to pollution of -0.45 for $PM_{2.5}$ and -0.86 for 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 CNY 54.8 (USD 7.2)[2] thousand and increase output across all firms by CNY 8.73 (USD 1.15) billion annually (0.06% of China's average GDP over the sample period). Adjusting for manufacturing's role in $PM_{2.5}$ creation leads to a net elasticity of -0.21. Therefore, lowering $PM_{2.5}$ by 1% nationwide proportionally across all its sources would increase the average firm's output by CNY 26.9 (USD 3.54) thousand annually and increase total output across all firms by CNY 4.29 (USD 0.56) billion annually (0.03% of average GDP). Similar calculations for SO_2 yield a per-firm increase of CNY 65.4 (USD 8.60) thousand and an aggregate increase of CNY 10.34 (USD 1.36) billion (0.07% of average GDP). These are significant effects which should be considered in any cost-benefit analysis of environmental policies.

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

The primary obstacle to overcome in estimation is reverse causality bias. If estimated by ordinary least squares (OLS), pollution's effect on labor productivity will be biased upward toward or even above zero because more output per employee in a region leads to both more output and more pollution. To overcome this endogeneity problem while achieving comprehensive estimates we employ as our primary instrument the number of thermal inversions (Arceo *et al*., 2015; 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 air pollution, the instrumented estimates display more negative effects on productivity than OLS estimates. Our secondary instrument for a focal city's air pollution is the air quality of a nearby city conditional on wind blowing from the nearby to the focal city. When wind blows toward the focal city the nearby city's pollution degrades focal city air quality exogenously. This instrument allows us to estimate the effects of a different pollutant, PM_{10}, but only for a subset of major cities. This instrument is also powerful and attenuates the simultaneity bias resulting in more negative effects of pollution on productivity.

This paper makes three primary contributions. First, we provide nearly exhaustive measures for the causal effect of pollution on the 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. 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 have positive or negative effects on 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 innovations in processes that are both cleaner and more cost effective. We identify another channel that influences this debate. Environmental regulations that decrease air pollution will in turn increase productivity and offset compliance costs. For example, Greenstone *et al.* (2012) find that the US Clean Air Act significantly decreased firm productivity because it imposed additional costs on firms such as installing scrubbing and gas reclamation equipment. Our findings suggest that these cost estimates are biased toward zero since they are confounded by improvements in labor productivity realized indirectly through improved air quality. Because of the offsetting productivity improvements a country's firms are not as uncompetitive when complying with environmental measures as they would be absent the productivity gains.

Third, estimates for China are important in and of themselves. China is the world's most populous country and is a large source of manufacturing and resulting pollution. In 2015, China represented almost 25% of the world's manufacturing output.[3] The findings also have implications for the global economy as China incurs a disproportionate fraction of the world's pollution because of its significant exports. Depending on the type of pollutant, 17 to 36% of China's pollution is attributable to exports (Lin *et al.*, 2014). Our estimates imply that policies that reduce China's air pollution can generate a substantial increase in labor productivity in addition to the health benefits previously substantiated 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 (Ostro, 1983; Matus *et al*., 2012; Chen *et al*., 2013a; Bombardini and Li, 2016; He, Fan *et al*., 2016).

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 the results using our primary instrument and a set of robustness checks while Section 6 does the same for our secondary instrument. Section 7 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 (Chay and Greenstone, 2003) and elderly morbidity resulting from air pollution (Deryugina *et al*., 2016) can require working adults to miss work to care for them (Aragon *et al*., 2016; Hanna and Oliva, 2015). Long-term exposure can also reduce life expectancy (Chen *et al*., 2013a) 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 (Lavy, *et al*., 2014; Pun *et al*., 2016) which would affect the

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[3] "Global Manufacturing: Made in China?" *Economist*, March 14, 2015.

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

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, fine particulates such as $PM_{2.5}$ can seep into buildings (Thatcher and Layton, 1995), 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 units of time measured. In our context, time is measured as a worker-year. 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 the two. We separately estimate the labor supply effects on number of workers (another type of extensive margin).

Most extant studies of air pollution's effect on short-run labor productivity measure time as worker-hours and therefore capture productivity effects on per-hour productivity (intensive margin) although many separately estimate labor supply effects on hours worked (extensive margin). $PM_{2.5}$ 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 productivity of garment factory workers in India with no effects on absences (Adhvaryu *et al*., 2014a). $PM_{2.5}$ 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 ensure exogeneity of pollution, all of these studies focus on a small group of firms or a particular type of worker for which pollution is exogenous. Although this establishes a causal link, the results may not generalize raising a concern of external validity. A few other papers examine pollution's effect on performance in other environments. Air pollution has been found to increase 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, 2016), and baseball umpires (Archsmith *et al*., 2016).

3. Primary data

Our primary estimation is of 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. China is an ideal setting for estimating the effects of air pollution on productivity. Not only is it a large country that produces a significant portion of the world's pollution but its vastness also offers significant geographic and time-series variation in output and pollution levels.

Our main pollution measure is 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 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 providing us with 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. We use the kriging interpolation method (Oliver, 1990)[6] to convert this to the county level, which is the smallest administrative unit in China to which we can match firm locations.[7]

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

[5] The AOD data are obtained from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2). 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] See http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm for an explanation of the method.
[7] 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).

million) and contains detailed information on firm location,[8] 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 period yields 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.[9] We drop 2% of observations with unreliable data following the previous literature (Cai and Liu, 2009; Brandt *et al*., 2012; Yu, 2014).[10] In addition, six 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 in the survey 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. The final data includes 1,593,247 firm-year observations for 539,557 unique firms. Geographically, the sample includes 2,755 counties with an average of 57.8 firms per county-year. Because the large firms that are winsorized have a disproportionate effect on the total output included in estimation we check the robustness of our results to using the non-winsorized data and they are similar.

We obtain daily, station-level weather variables that could affect both air pollution and firm output including temperature, precipitation, humidity (inferred from temperature and dew point temperature), and wind speed from the National Climatic Data Center at the National Oceanic and Atmospheric Administration. We convert the station-level data to county level using the kriging interpolation method and then calculate annual means. 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. Following Arceo *et al.* (2016), we define a thermal inversion as the temperature of the second layer (320 meters) being higher than

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[8] 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.
[9] Their Stata programs are posted at: http://feb.kuleuven.be/public/N07057/CHINA/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] Specifically, we use product M2I6NPANA version 5.12.4 from MERRA-2.

that of the first layer (110 meters).[12] We determine this within each six-hour period of each day and then calculate the total number of six-hour periods in the year in which an inversion occurs in the grid. We then convert this data from the grid to the county level using the kriging interpolation method. We show that our results are robust to using the strength of thermal inversions, which is the temperature difference between the first and second layers as an instrument aggregated in the same way.

Table 1 presents the 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, thermal inversion, and weather 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 recommends a maximum annual mean of ten μg/m^3 for $PM_{2.5}$ and a maximum mean of 20 ug/m^3 within a 24-hour period for both $PM_{2.5}$ and SO_2 (World Health Organization, 2006). In the sample, the mean annual $PM_{2.5}$ level is 53.5 and reaches a high of 134.8 and the mean SO_2 is 15.1 and reaches a high of 54.7. The number and strength of thermal inversions display significant variation ranging from zero to 628 (almost two six-hour periods per day in which an inversion occurs). The mean number of inversions in the sample is about 246 or about 17% of the possible six-hour periods in a year.

[Insert Table 1 here]

4. Model specification and identification

We focus on labor productivity because there are no obvious channels by which pollution would affect capital productivity.[13] Our primary econometric model is:

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

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. P is a measure of pollution and W the vector of weather variables in county c in year t. We include a quadratic function of each weather variable to allow for nonlinearity in its effects (Adhvaryu *et al*., 2014b; Sudarshan *et al*., 2015; Zhang *et al*., 2016). The coefficient β_1 is the main coefficient of interest and captures the effect of pollution on labor productivity. Since L is measured in units of number of employees these estimates will capture the combined effects on productivity of output per hour worked and total hours worked including absences.

[12] Using temperatures in the first and third layers (540 meters) generates similar results.

[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.

Firm fixed effects (α_i) capture time-persistent firm attributes that affect labor productivity. Since very few firms switch counties (7%) and none switch industries over the time period of our sample, these also absorb any county- or industry-specific time-invariant unobservables that affect productivity. Year fixed effects (ρ_t) capture year-specific 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 which could be created by persistence in a firm's capital stock or technology.

Although our data is at the firm level, the effect of pollution on productivity is identified by variation at the county-year level. 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.

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 productivity. Our primary instrument, because it is available for all of China, is the annual number of thermal inversions at the county level. Normally, air temperature decreases with altitude above the Earth's surface. A thermal (or temperature) inversion is a deviation from this norm. 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 layers at 110 and 330 meters and conduct robustness checks using 110 and 550 meters.

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*., 2015; Hicks *et al*., 2016; Jans *et al*., 2016; Sager, 2016).[14] With this as our instrument we employ two-stage least squares (2SLS) with the first-stage equation:

[14] Arceo *et al.* (2015) estimates the effect on infant mortality in Mexico City, Hicks *et al.* (2016) on pro-cyclical mortality in the U.S., Jans *et al.* (2016) on child respiratory health in Sweden, and Sager (2016) on traffic accidents in the United Kingdom.

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

where I_{ct} is the number of thermal inversions in county c in year t. The quadratic functions of weather controls from the second stage are also included because these same variables affect the formation of inversions and are also needed to ensure exogeneity of instrumented pollution 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 level. Firms may choose to locate in cities with less severe pollution because it leads to higher productivity which would lead to a downward bias in estimating the effect of pollution on productivity. On the other hand, they may choose to locate in cities with more severe pollution because it reflects less stringent underlying local environmental regulations – the "pollution haven" effect (Becker and Henderson, 2000; Greenstone, 2002; Brunnermeier and Levinson, 2004). The bias induced here depends on the relationship between pollution output and productivity.

Regardless of the relationship, the inclusion of firm fixed effects means that only inter-temporal changes in pollution identify its effects on firm productivity and any initial sorting effects are absorbed in them if firms do not relocate over time.[15] Therefore, our estimates will be biased only by firms relocating during the sample period due to pollution. Few firms relocate for any reason meaning that any effect is small;[16] however, sorting by new firms could occur.

A second possible type of spatial sorting is due to workers choosing their location based on their willingness to pay for air quality. High-skilled workers generally prefer high-quality urban amenities and tend to work in industries or areas that produce low levels of pollution while low-skilled workers generally have lower willingness to pay for air quality and are more likely to work in polluting industries. This self-selection 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). This spurious correlation would induce a downward bias in estimating the effect of pollution 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 bias our estimates.

[15] Sorting could also occur by industry but since no firms switch industries this is also absorbed by the firm fixed effects.
[16] We perform a robustness check excluding relocating firms.

5. Results using AOD data

Our primary results use AOD pollution data because they are nationwide and available for a longer period (1998 to 2007). We use the annual mean concentration of $PM_{2.5}$ and SO_2 in each county-year as measures of air pollution. Following Arceo *et al.* (2015), we control for weather by including linear and squared terms of the annual means of daily average temperature, daily average humidity, daily wind speed, and annual cumulative precipitation in each county in each year.

5.1 OLS estimates using AOD data

We first present estimates not accounting for the simultaneity bias between productivity and pollution. Table 2 presents OLS estimates of Equation (1). Column 1 implies that $PM_{2.5}$ pollution has no effect on productivity. The lack of effect is perhaps due to the simultaneity bias. Results for SO_2 (Column 2) indicate that SO_2 pollution decreases productivity with an elasticity of -0.083 evaluated at the mean SO_2 in the sample.

[Insert Table 2 here.]

5.2 2SLS results using AOD data

Because of the simultaneity bias, OLS estimates will be biased upward toward or above zero. We use the number of thermal inversions as an instrument for pollution concentration. The first-stage results in the top panel of Table 2 (Columns 3 and 4) show that the number of thermal inversions is a powerful predictor of both $PM_{2.5}$ and SO_2 concentrations. The coefficient on thermal inversions is positive and highly significant for both pollutants and the Kleibergen Paap (KP) test for weak instruments is much larger than the Stock-Yogo weak identification test critical value of 16.38 (Stock and Yogo, 2005). One additional average daily inversion increases $PM_{2.5}$ by 0.016 and SO_2 by 0.0024 $\mu g/m^3$. These are big effects. A one standard deviation increase in daily thermal inversions increases $PM_{2.5}$ by 2.3 $\mu g/m^3$ (4.3%) and SO_2 by 0.34 $\mu g/m^3$ (2.3%).

The lower panel of Columns 3 and 4 show the second-stage results. Column 3 shows that instrumented $PM_{2.5}$ has a negative and very significant effect on labor productivity. Consistent with instrumenting addressing the simultaneity problem, the estimate for $PM_{2.5}$ moves from being insignificant in the OLS estimates to significantly negative here. Evaluating this at the mean $PM_{2.5}$ in the sample yields an elasticity of -0.45. Column 2 shows that instrumented SO_2 also has a negative and very significant effect on productivity. 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. Evaluated at the mean SO_2 in the sample implies an elasticity of -0.86.

How large are these effects? First, 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. This would increase value added for the average firm in our sample by CNY 57.6 (USD 7.58) thousand annually and increase total value added across all firms by CNY 9.18 (USD 1.21) billion annually.[17] This represents 0.06% of China's GDP.[18] Similar calculations for SO_2 imply an output increase for the average firm of CNY 110.5 (USD 14.5) thousand and CNY 17.6 (USD 2.3) billion annually across all firms (0.12% of GDP).

Since manufacturing output itself represents a major source of air pollution it is useful to calculate the effects assuming that pollution is reduced proportionally across all sources including output. Manufacturing output is estimated to generate about 45% of $PM_{2.5}$ in China.[19] Suppose that $PM_{2.5}$ were reduced by 1%. This would require pollution derived from manufacturing output to decline by 0.45%. The elasticity of pollution with respect to industrial output is estimated to be 2.1[20] implying that manufacturing output must decline by 0.22%. Using our estimated elasticity of -0.45, a pollution reduction of 1% will increase output by 0.45%. Therefore, the net gain in output from a 1% reduction in $PM_{2.5}$ is 0.23% implying a "net elasticity" of 0.23 if pollution is reduced across the board proportionally from all sources. Therefore, a one percent, across-the-board reduction in $PM_{2.5}$ would increase per-firm output by CNY 29.5 (USD 3.88) thousand and output across all firms by CNY 4.70 (USD 0.62) billion or 0.032% of GDP.

To adjust the SO_2 implications similarly, manufacturing output is estimated to generate about 30% of total SO2 emissions[21] and the elasticity of SO_2 with respect to industrial output is estimated to be 2.63.[22] This implies a "net elasticity" of -0.75 and a 1% across-the-board reduction in SO_2 would increase per-firm productivity by CNY 96.2 (USD

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[17] A 1% decrease in $PM_{2.5}$ increases annual output by 0.45%. The mean annual output per firm in our sample is CNY 12.82 million implying an annual increase of CNY 57.6 (USD 7.58) thousand. There is an average of 159,325 firms present in each year of our sample which implies an annual increase in output of CNY 9.18 (USD 1.21) billion annually.

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

[19] Guan *et al.* (2014) estimate that 45% of China's $PM_{2.5}$ is generated from "industrial processing" while Huang *et al.* (2011) estimate that 47% in China's Pearl River Delta Region is generated from "processing of mineral products" and "iron and steel processing" (eyeballed from Figure 3).

[20] "Cutting China's Smog Will Come at a Massive Cost," Fielding Chen and Tom Orlik, *Bloomberg*, March 26, 2015.

[21] Streets *et al.* (2006, Table 3) estimate that 39% of SO_2 in China's Pearl River Delta Region is generated from "industry" while Mohajan (2014, page 270) estimates that 20% of SO_2 is generated from "industrial facilities" throughout China.

[22] From Liu and Wang (2013, Table 2) the cumulative GDP change from 2004 to 2010 is -1.12 and the cumulative emissions change is -2.94. This is based on all output not just manufacturing.

12.65) thousand annually and aggregate productivity by CNY 15.32 (USD 2.02) billion or 0.103% of GDP.

China's most recent five-year plan sets a goal of reducing $PM_{2.5}$ from 60 to 35 $\mu g/m^3$. Using our elasticity of pollution with respect to output this implies a 20% reduction in output. Scaling our "net elasticity" estimate linearly, the productivity boost from this output reduction would be 4.6% so that output would fall by only 15.4%. This, however, assumes that our estimates extrapolate fairly far outside out 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 sometimes for different pollutants. Graff Zivin and Neidell (2012) estimate an elasticity of per-hour productivity with respect to ozone pollution of -0.073 for outdoor fruit pickers in California. Although lower than our elasticity, it is for a different pollutant and for a particular type of worker 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 estimate for $PM_{2.5}$ but it is again for a particular type of worker 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. Again, this is lower than our estimates but it applies to service workers in a specific industry and two specific locations in China. For garment factory workers in India, Adhvaryu *et al.* (2014a) 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 estimate, which is much greater, in that it applies to manufacturing workers and the same type of pollutant, it applies to a specific industry and measures effects conditional on being at work. He, Liu *et al.* (2016) examine textile workers in China and find no contemporaneous effect from $PM_{2.5}$ exposure but elasticities ranging from -0.035 to -0.30 in two provinces due to cumulative effects over 25 to 30 days. The upper range of this is close to our estimates for all locations and all manufacturing industries in China.

5.3 Robustness checks using AOD data

Columns 1 through 4 of Table 3 show various robustness checks of the 2SLS estimates for $PM_{2.5}$. Our main estimates weight all observations equally. Column 1 re-estimates weighting observations by value added per firm. The coefficient is slightly larger in magnitude than the baseline estimates (although not significantly so) consistent with larger firms' productivity being more affected by pollution or being located in dirtier counties. Column 2 allows for two-way clustering of errors by firm and county-by-year (Cameron and Miller, 2015). Clustering at the county-by-year level captures spatial correlation within counties which could result from county-level labor market conditions, agglomeration effects, and government policies (Greenstone *et al*., 2012). This is less critical in our context because our instrumented pollution measure should be orthogonal to these shocks. Moreover, it is a fairly demanding test because instrumenting pollution already absorbs a lot of its variation. Nonetheless, although some significance is lost the results remain significant. Column 3 tests the robustness to not winsorizing the data. The results are very similar to the baseline estimates. Column 4 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 test is well above the Stock-Yogo critical value while the second stage results are very close to the baseline estimates.

Columns 5 through 8 repeat the same robustness checks for SO_2. As with $PM_{2.5}$, weighting the observations by value added (Column 5) results in an effect which is larger in magnitude although not significantly so. Allowing for two-way clustering (Column 6) reduces the significance to 14% and the KP test indicates that the first-stage instruments are weak . Estimates using the non-winsorized data are very significant and similar to the baseline estimates. Finally, strength of thermal inversions is a powerful instrument and results in fairly similar second-stage estimates.

Appendix A shows robustness checks using log pollution rather than a linear function in the first stage. Column 1 shows estimates for $PM_{2.5}$. Pollution has a highly significant effect on productivity and the elasticity is larger (-0.96) than that estimated using a linear function. Results for SO_2 are shown in Column 2. The estimated elasticity (-1.00) is very significant and larger than that using a linear function.

5.4 Effect on number of workers

Our estimates capture the effect on labor productivity from all channels: any changes in per-hour productivity or changes in hours worked or absences. Pollution may also affect the number of workers employed. To assess this we estimate Equation (1) with log number of employees in each firm as the dependent variable using thermal inversions as the first-stage instrument. The survey data capture both permanent and contract employment thereby making it likely we can capture short-run, annual adjustments in response to pollution. In addition, the survey measures end-of-year employment so that short-run changes in employment due to pollution would be captured. We find a positive and significant effect on number of workers. A one $\mu g/m^3$ increase in $PM_{2.5}$ increases employment by 0.42% implying an elasticity of 0.21. Firms increase employment to compensate for the decreased labor productivity and this offsets about half of the labor productivity loss. The elasticity of the total effect on output with respect to $PM_{2.5}$ allowing labor supply to adjust is -0.24. Although the positive labor supply effects partially mitigate the negative labor productivity effects, employing additional workers imposes costs on firms. We also re-estimate Equation (1) with log capital as the dependent variable.[23] Consistent with pollution not affecting physical capital there is no significant effect.

6. Results using PM_{10} data

6.1 Air quality of nearby city as instrument

As a robustness check, we instrument for a focal city's pollution using pollution that drifts from a nearby city. A firm's productivity is affected by both locally-produced pollution and nearby cities' pollution that is transported to the focal city by wind. To ensure exogeneity, we condition on the wind blowing from the nearby to the focal city (when the wind blows toward the nearby city its pollution measure is not exogenous because greater focal city output would increase the nearby city's air pollution level) and show that the timing of this is random. Wind direction has been used as an instrument for air pollution in a few studies (Luechinger, 2009; Schlenker and Walker, 2011; Deryugina *et al*., 2016). Identification requires that the instrument be sufficiently correlated with the endogenous regressor and uncorrelated with any unobserved determinant of the dependent variable. The former is ensured as long as the nearby city is close enough that pollution can drift from it to the focal city. The latter is ensured as long as unobserved determinants of focal city production are uncorrelated with the nearby city's pollution in the time period measured.

Implementing this requires relating the two cities' pollution levels on a high-frequency basis in order to isolate time periods in which the wind is blowing toward the focal city. Averaging over long time periods risks mixing periods in which the wind blows toward the focal city with those in which it blows away destroying the instrument's exogeneity. High-frequency data also reduces the possibility that regional shocks to pollution, which might affect both the focal and nearby city, will introduce spurious correlation that biases the estimates. We therefore use daily data on pollution and wind direction in the first stage of 2SLS estimation. Daily data is frequent enough to capture wind direction shifts accurately. It is also likely immune to correlated shocks to pollution across cities. While output and therefore pollution is likely correlated across cities within a region over longer time periods it is unlikely that this is so on a daily basis.

The need for daily pollution data forces us to focus on a different pollutant and also reduces the coverage of the data. The satellite-based AOD data is available only on a monthly basis. We instead use PM_{10} data derived from daily API data. This is available at the city level and only for certain cities. A further constraint for this approach is that we can only consider focal cities that have a nearby city sufficiently close that pollution can drift far enough that it affects the focal city's air quality. Fine particulates such as

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

PM_{10} can travel from hundreds to thousands of kilometers (EPA, 1996, page IV-7). In our estimation we consider nearby cities that are within 100 to 250 kilometers of a focal city and test the robustness of the estimates within this range. There is a tradeoff in increasing the distance – it increases the available data but weakens the instrument's power.

6.2 PM_{10} model specification

To accommodate daily data for the pollution instrument and annual data for the firm productivity data, we employ mixed two-stage least squares (M2SLS) estimation. M2SLS estimates are consistent and asymptotically normal (Dhrymes and Lleras-Muney, 2006; Lleras-Muney, 2005). The first stage equation is:

$$P_{ftd} = \gamma_0 + \gamma_1 P_{N(f)td} + \gamma_2 W_{ftd} + \mu_{ft} + \varepsilon_{ftd}, \quad (3)$$

where P_{ftd} is pollution level of focal city f on day d of year t; $P_{N(f)td}$ is the pollution level of the nearby city to focal city f, denoted by $N(f)$, on day d of year t; and W_{ftd} are daily weather controls that affect pollution in the focal city. We define the nearby city as the closest city to a focal city within a certain distance and test the sensitivity of our results to different distances. Focal city-by-year fixed effects (μ_{ft}) allow for different mean levels of pollution in each focal city-year and also control for the exogenous variables in the second stage to ensure that instrumented pollution is uncorrelated with the second-stage error.[24] Every nearby city in our data set is also a focal city although it might be paired with a different nearby city that is closer to it than the original focal city. The first stage is estimated using only days when the wind blows from the nearby to the focal city.

After estimating Equation (3), we compute predicted values $\widehat{P_{ftd}}$ and average them over days within each city-year to obtain instrumented pollution for the second-stage: $\overline{P_{ft}}$. The second stage equation is:

$$\ln\left(Y_{ift}/L_{ift}\right) = \beta_0 + \beta_1 \overline{P_{ft}} + \alpha_i + \rho_t + \varepsilon_{ict}. \quad (4)$$

Standard errors are clustered at the firm and city-year levels and are adjusted for the error introduced in the first stage following the procedure in Cameron, *et al*. (2011) for two-way clustering. We do not include weather variables in this second-stage equation because they are nearly collinear with the firm and year fixed effects (since no firms move cities during the sample period).

[24] Although second-stage variables vary by firm within city-year these do not vary at the daily level and are absorbed by the city-by-year fixed effect since no firms move cities during the sample period.

6.3 API dataset

We use city-level, daily API data published by China's Ministry of Environmental Protection (MEP) from 2001 to 2007. The API ranges from 0 to 500 with higher numbers indicating stronger pollution concentrations and more harmful health effects. A city's daily API is the worst of three pollutants (PM_{10}, nitrogen dioxide (NO_2), and sulfur dioxide (SO_2)) that are measured at multiple monitoring stations within the city and rescaled to make them comparable.[25] By far, the pollutant that is most frequently the worst is PM_{10}. PM_{10} are particulates that are less than 10 microns in diameter. To relate physical levels of pollution to labor productivity we back out PM_{10} measures from the API based on the piecewise linear function of PM_{10} as shown in Appendix B. As we noted earlier, the API is potentially subject to manipulation by those who collect and report the data; however, the API and AOD data have been shown to produce similar results (Chen *et al.*, 2013b).

Since the firm output data is annual we require each city-year to have at least 280 days of PM_{10} data to ensure that seasonality of air pollution is properly captured. In earlier years fewer cities released API data so that the number of cities available increases over time in the sample. Summary statistics for the main variables are shown in Table 4 for the minimum (100 kilometers) and maximum (250 kilometers) distance cutoffs. The top panel summarizes the first-stage data which is at the city-day level. The summary statistics are fairly similar across the two distances. The PM_{10} levels in the sample are high enough to reasonably affect productivity with an annual mean of 104.6 $\mu g/m3$ for the 100-kilometer sample compared to a WHO recommended guideline of 20 $\mu g/m3$ and a daily maximum of 600 or greater compared to a guideline of 25 (WHO, 2006). The second-stage data, which is at the firm-year level, is summarized in the bottom panel. Because of the more limited availability of API data and the necessity to have a nearby city close enough to the focal city, the coverage of this data is much less than that of the AOD even using the 250-kilometer distance.

[Insert Table 4 here]

To construct our instrument, we use daily wind direction data from the World Weather Records Clearinghouse collected by the National Oceanic and Atmospheric Administration.[26] The data provides a direction from which the wind is blowing stated in degrees clockwise from true North in each three-hour period of each day. We use a

[25] Each monitoring station in a city records the concentrations of the three pollutants multiple times each day. Each of these intra-day measurements is rescaled to an API index for comparability. A daily mean API for each pollutant across all stations in a city is then calculated and the maximum of these three means is the city-level API for that day. Data from MEP website (in Chinese). Viard and Fu (2015) provide more detail on the calculation of API.

[26] Data available at: http://www.ncdc.noaa.gov/data-access.

“unit-vector” average method defined by the NOAA to arrive at an average daily wind direction.[27]

For each focal city we find the nearest nearby city, if available, within a given radius distance. If none is available for a focal city it is dropped from the estimation. We then calculate the bearing in degrees (from true North) from the nearby to the focal city using each city's latitude and longitude.[28] Finally, to determine whether the wind is blowing toward the focal city on a given day we subtract this bearing from the wind's direction. If this angle difference is between 281.25° and 78.75° with true North defined as 0° (i.e., within the top seven of 16 quadrants) we assume the wind is blowing toward the focal city.

To ensure that this instrument is exogenous we must exclude days in which the wind blows toward the nearby city. If wind direction is not random across days of the year, this may bias the coefficients because air quality is not randomly distributed across days of the year. For example, in northern regions of China air quality is worse in the winter than in other seasons. To test whether wind direction is random within a year we regress an indicator variable for whether the wind blows from the nearby to the focal city each day on city fixed effects, week-of-year dummies, month-of-year dummies, and within-year time trends. The results are shown in Appendix C. F-tests reveal that the coefficients on these time controls are highly significant but the difference in R^2's is extremely small (never greater than 0.5% for any radius distance) consistent with wind direction being primarily random.

6.4 OLS and M2SLS results using PM_{10} data

Panel A of Table 5 shows OLS results for the samples of focal cities with a nearby city applying radius distances in 50 kilometer increments from 100 to 250 kilometers. The estimated coefficients on PM_{10} are negative and significant above a 100-kilometer distance and tightly clustered (-0.0025 to -0.0024). The OLS estimates are potentially biased due to reverse causality. Panel B shows the results of estimating the first-stage equation (Equation (3)) at the different distances using PM_{10} of nearby cities as an instrument conditional on wind blowing toward the focal city. This estimation is at the city-day level and the wind blows toward the focal city on approximately 50% of the days. The results reveal a strong instrument. A 1% increase in a nearby city's PM_{10} increases the focal city's PM_{10} by between 0.63 and 0.68 with a high level of significance.

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[27] This is method 1 described at: http://www.ndbc.noaa.gov/wndav.shtml. In each three-hour period, the direction is converted to a unit vector with coordinates $\langle u, v\rangle$. The u-component is the North-South wind direction and v the East-West. The coordinates are separately averaged as $\bar{u}$ and $\bar{v}$ and the average wind direction translated into a 0 to 360 degree scale depending on the signs of u and v: $180-\theta$ if $u<0$ and $v>0$, $\theta-180$ if $u<0$ and $v<0$, $360-\theta$ if $u>0$ and $v<0$, and θ if $u<0$ and $v>0$ where $\theta=(180/\pi)*arctan(\bar{u}/\bar{v})$.

[28] A formula and calculator for this are at: http://www.movable-type.co.uk/scripts/latlong.html.

Panel C shows the second-stage estimates of Equation (4) at the firm-year level. The estimated coefficients of PM_{10} are all negative and greater in absolute value than the OLS estimates consistent with the instrument attenuating the reverse causality bias. The results are very significant at all radiuses and decrease in absolute value as the radius becomes bigger (from -0.0041 to -0.0024). The bias correction is not as great here as in the AOD data perhaps because these are larger geographic areas so that output and pollution are not as highly correlated. The correction also narrows as the radius distance increases likely indicating that the instrument is less informative when nearby cities are further away. The estimated elasticities decline with the radius distance: from -0.43 at 100 kilometers to -0.26 at 250 kilometers. Given the greater statistical significance and likely higher power of the instrument at 100 kilometers our preferred estimate is an elasticity of -0.43.

These estimates imply a significant economic impact. Using the preferred elasticity, a 1% reduction in PM_{10} increases per-firm productivity for the average firm by CNY 126.9 (USD 16.7) thousand. The Clean Air Act of China sets a goal by 2017 to reduce urban concentrations of PM_{10} by 10% relative to 2012.[29] Scaling our estimates linearly this would increase productivity by 4.3% although this is extrapolating well outside our sample range.

[Insert Table 5 here]

6.5 Validation test of wind as an instrument

As a falsification test of our wind instrument we use PM_{10} of nearby cities conditional on wind blowing from the focal to the nearby city. This should further bias the estimates upward relative to OLS because this strengthens the reverse causality. The M2SLS results are reported in Table 6. Panel A shows the first stage-results which, as expected, are very similar to the first stage results in Table 5. Panel B reports the second-stage results. The estimated coefficients are close to zero and insignificant. This is consistent with the upward bias from reverse causality and the validity of our instrument when wind blows toward the focal city.

[Insert Table 6 here]

6.6 Effect on number of workers

To assess the effect of PM_{10} on number of workers we estimate Equation (4) with log labor as the dependent variable using PM_{10} of nearby cities as the instrument. We find a positive and highly significant effect on number of workers at all radiuses. Using the 100-kilometer radius as our preferred estimate, a one $\mu g/m^3$ increase in PM_{10} increases

[29] "Air Pollution Prevention and Control Action Plan," Clean Air Alliance of China (State Council), October 2013 (English translation).

employment by 0.13% with an elasticity of 0.14. The elasticity of output with respect to PM_{10} allowing labor supply to adjust is therefore -0.29. We also re-estimate Equation (4) with log capital as the dependent variable and using a radius of 100 kilometers. Consistent with pollution not affecting physical capital there is no significant effect.

7. 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 two instrumental variables approaches: thermal inversions, which are meteorologically determined, and air pollution of nearby cities conditional on wind blowing from the nearest to the focal city. Both approaches attenuate the bias due to reverse causality and indicate a significant negative effect of air pollution on productivity.

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 total output and labor productivity. Our study contributes to the small emerging literature on air pollution's effect on short-run labor productivity by providing empirical evidence that captures all channels through which pollution can affect productivity and is comprehensive and nationwide. These estimates can be used directly in cost-benefit analyses of broad-based environmental policies and our approach can be employed in any country with sufficient variation in pollution and thermal inversions.

Since our identification relies on yearly variation we are unable to estimate long-run effects of pollution on productivity. In the longer 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.

Although we can capture all channels by which pollution can influence productivity, we are unable to decompose the exact channels by which pollution lower 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 for AOD sample

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	30,782	64	350,801
Labor productivity (1,000 CNY/worker)	88	160	0.13	16,248
County-year sample				
Air pollution				
Particular matter ($PM_{2.5}$) (ug/m^3)	53.52	25.46	2.62	134.84
Sulphur dioxide (SO_2) (ug/m^3)	15.07	10.7	0.04	54.68
Thermal inversion				
Number of thermal inversion	245.54	142.07	0.00	628.00
Thermal inversion strength (celsius)	324.55	283.92	0.00	1788.87
Weather				
Temperature (degrees fahrenheit)	57.75	9.18	24.29	80.57
Accumulative precipitation (cm)	161.93	102.24	0.15	2146.48
Humidity (%)	66.53	13.92	10.79	99.93
Wind speed (km/h)	8.00	2.65	0.90	26.88

Firm-year sample size: 1,593,247. County-year sample size: 25,359. There are 356,179 firms and 2,755 counties in the sample. Sample period: 1998-2007.

Table 2 2SLS estimates – effect of pollution on labor productivity using number of thermal inversions as instrument

	(1)	(2)	(3)	(4)
	OLS		2SLS	
Dependent Variable:			$PM_{2.5}$	SO_2
#thermal inversions			0.0162***	0.0024***
			(0.0002)	(0.0001)
KP Test			6028	560
Dependent variable:	ln(Value added/worker)			
$PM_{2.5}$	0.00004		-0.0084***	
	(0.0002)		(0.0016)	
SO_2		-0.0055***		-0.0572***
		(0.0005)		(0.0109)
R^2	0.7343	0.7343	0.1260	0.1067
	1,593,247	1,593,247	1,593,247	1,593,247

All models include firm fixed effects, year fixed effects, and weather controls. There are 356,179 firms and 2,755 counties (districts) in the sample. Sample size: 1,593,247. Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses.

Table 3 2SLS estimates – effect of pollution on labor productivity (robustness)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First stage								
Dependent variable:	**$PM_{2.5}$**				**SO_2**			
Number of thermal inversions	0.0167***	0.0162***	0.0167***		0.0023***	0.0024***	0.0025***	
	(0.0004)	(0.0019)	(0.0002)		(0.0002)	(0.0010)	(0.0001)	
Strength of thermal inversions				0.0068***				0.0010***
				(0.0001)				(0.00004)
KP test	1,599	74	6,623	5,692	132	5	661	518
Second stage								
Dependent variable:	**Dependent variable: log(Valued added per worker)**							
$PM_{2.5}$	-0.0120***	-0.0084*	-0.0088***	-0.0086***				
	(0.0025)	(0.0047)	(0.0017)	(0.0018)				
SO_2					-0.0865***	-0.0572	-0.0585***	-0.0589***
					(0.0197)	(0.0383)	(0.0114)	(0.0123)
Weighting	Y	N	N	N	Y	N	N	N
Two-way clustering	N	Y	N	N	N	Y	N	N
R^2	0.1257	0.1260	0.0943	0.1259	0.0624	0.1067	0.0793	0.1053
# of firms	356,179	356,179	379,349	356,179	356,179	356,179	379,349	356,179
Sample size	1,593,247	1,593,247	1,746,850	1,593,247	1,593,247	1,593,247	1,746,850	1,593,247

All models include firm fixed effects, year fixed effects, and weather controls. Sample period: 1998-2007. Standard errors are clustered at the firm level for columns 1, 3-5, 7-8 and at the firm and county-by-year level in Columns 2 and 4 and reported in parentheses.

Table 4: Summary statistics for PM_{10} data

	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
First-stage sample (city-day)								
	100 kilometers proximity (N = 12,238)				**250 kilometers proximity (N = 27,369)**			
Focal city PM_{10} (ug/m^3)	104.6	55.7	10	600	108.2	61.6	10	600
Nearby city PM_{10} (ug/m^3)	98.0	52.6	11	600	100.2	57.9	11	600
Temperature (celsius)	14.2	10.8	-22	36	14.1	11.3	-26	36
Humidity (%)	62.4	20.3	4	100	62.7	20.0	4	100
Windspeed (km/h)	8.7	5.4	0	48	8.0	4.7	0	48
Precipitation (mm)	1.3	5.7	0	145	1.2	5.8	0	233
# of city-years	69				156			
# of cities	24				51			
Second-stage sample (firm-year)								
	100 kilometers proximity (N = 123,526)				**250 kilometers proximity (N = 229,632)**			
Value added (CNY1,000)	29,514.2	149,640.3	35.1	19,400,000.0	30,000.8	166,031.9	11.5	28,200,000.0
Total workers	212.0	543.3	8.0	31,458.0	227.0	719.8	8.0	98,190.0
Value added per worker (CNY1,000)	113.2	137.4	0.0	3,207.5	109.0	134.6	0.0	3,207.5
# of firms	44,776				82,820			

Table 5: OLS and M2SLS results using wind direction of nearby city within different radius distances as instrument

	100 km	150 km	200 km	250 km
Panel A: OLS (firm-year sample)				
Dependent variable:	**ln(Value added/worker)**			
Mean annual PM_{10}	-0.0035	-0.0025**	-0.0025**	-0.0024**
	(0.0022)	(0.0013)	(0.0012)	(0.0012)
R^2	0.0412	0.0355	0.0399	0.0395
Sample size	123,526	199,838	219,305	229,632
Panel B: 2SLS first stage (city-day sample)				
Dependent variable:	**Focal city PM_{10}**			
Nearby city PM_{10}	0.6774***	0.6657***	0.6357***	0.6279***
	(0.0372)	(0.0309)	(0.0283)	(0.0268)
Fraction of days wind toward focal city	0.49	0.48	0.48	0.48
Average distance between cities (km)	701	89.3	109.2	119.6
R^2	0.5434	0.5558	0.5346	0.5219
Sample size	12,224	19,007	24,831	27,369
Panel C: 2 SLS second stage (firm-year sample)				
Dependent variable:	**ln(Value added/worker)**			
Predicted focal city PM_{10}	-0.0041***	-0.0028*	-0.0026*	-0.0024**
	(0.0015)	(0.0015)	(0.0014)	(0.0014)
R^2	0.0419	0.0357	0.0399	0.0395
Sample size	123,526	199,838	219,305	229,632

First stage models include city-year fixed effects, linear and quadratic terms of weather controls. The second stage models include firm and year fixed effects. Standard errors are clustered at the firm and city-year levels and reported in parentheses. Standard errors in Panels 2 and 3 are to be adjusted by bootstrapping.

Table 6: Falsification test using PM_{10} of nearby city conditional on wind blowing away from focal city as instrument

	100 km	150 km	200 km	250 km
Panel A: First stage (city-day sample)				
Dependent variable:	**Focal city PM_{10}**			
Nearby city PM_{10}	0.6668***	0.6401***	0.6017***	0.5891***
	(0.0351)	(0.0384)	(0.0328)	(0.0305)
Fraction of days wind away from focal city	0.51	0.52	0.52	0.52
Average distance between cities (km)	72.1	91.1	110.7	121.0
R^2	0.5675	0.5717	0.5475	0.5362
Sample size	9,983	15,862	20,837	22,896
Panel B: Second stage (firm-year sample)				
Dependent variable:	**ln(Value added/worker)**			
Predicted focal city PM_{10}	0.0018	0.0002	0.0000	-0.0001
	(0.0023)	(0.0009)	(0.0007)	(0.0007)
R^2	0.0409	0.0351	0.0393	0.0390
Sample size	123,526	199,838	219,305	229,632

The first stage models include city-year fixed effects, linear and quadratic terms of weather controls. The second stage models include firm and year fixed effects. Standard errors are clustered at the firm and city-year levels and reported in parentheses. Standard errors are to be adjusted by bootstrapping.

Appendix A 2SLS estimates – effect of pollution on labor productivity using number of thermal inversions as instrument (log-log specification)

	(1)	(2)
First stage		
Dependent variable:	**ln($PM_{2.5}$)**	**ln(SO_2)**
ln(#thermal inversions)	0.0439***	0.0422***
	(0.0007)	(0.0015)
KP Test	4,448	782
Second stage		
Dependent variable:	**ln(Value added per worker)**	
ln($PM_{2.5}$)	-0.9611***	
	(0.1018)	
ln(SO_2)		-0.9987***
		(0.1098)
Firm fixed effects	Y	Y
Year fixed effects	Y	Y
Weather controls	Y	Y
R^2	0.1242	0.1205
Sample size	1,592,626	1,592,626

Standard errors are clustered at the firm level and reported in parentheses.

Appendix B: Conversion of API to PM_{10}

API	PM_{10}	Conversion Formula
0 – 50	0 – 50	API = PM_{10}
50 – 200	50 – 350	API = (1/2)*PM_{10} + 25
200 – 300	350 – 420	API = (10/7)*PM_{10} – 300
300 – 400	420 – 500	API = (5/4)*PM_{10} – 225
400 – 500	500 – 600	API = PM_{10} – 100

Based on Andrews (2008).

Appendix C: Tests for randomness of wind direction

	1 Linear Trend/Month Dummies	2 Cubic Trend/Month Dummies	3 Linear Trend/Week Dummies	4 Cubic Trend/Week Dummies
	100-Kilometer Radius (N = 22,237)			
R^2 With Time Controls	0.1156	0.1157	0.1169	0.1169
R^2 Without Time Controls	0.1119	0.1119	0.1119	0.1119
Difference	0.0037	0.0037	0.0049	0.0050
F-Statistic	7.67	6.70	2.37	2.32
Prob > F (Time Controls)	0.0000	0.0000	0.0000	0.0000
	150-Kilometer Radius (N = 34,93)			
R^2 With Time Controls	0.0970	0.0970	0.0976	0.0976
R^2 Without Time Controls	0.0952	0.0952	0.0952	0.0952
Difference	0.0019	0.0019	0.0025	0.0025
F-Statistic	5.99	5.17	1.83	1.78
Prob > F (Time Controls)	0.0000	0.0000	0.0003	0.0004
	200-Kilometer Radius (N = 45,783)			
R^2 With Time Controls	0.0957	0.0957	0.0964	0.0965
R^2 Without Time Controls	0.0940	0.0940	0.0940	0.0940
Difference	0.0016	0.0017	0.0024	0.0024
F-Statistic	6.93	6.04	2.34	2.28
Prob > F (Time Controls)	0.0000	0.0000	0.0000	0.0002
	250-Kilometer Radius (N = 50,380)			
R^2 With Time Controls	0.1021	0.1021	0.1029	0.1029
R^2 Without Time Controls	0.1010	0.1010	0.1010	0.1010
Difference	0.0011	0.0012	0.0019	0.0019
F-Statistic	5.18	4.70	2.05	2.02
Prob > F (Time Controls)	0.0000	0.0000	0.0000	0.0000
Week Dummies	No	No	Yes	Yes
Month Dummies	Yes	Yes	No	No
Linear Time Trend	Yes	No	Yes	No
Cubic Time Trend	No	Yes	No	Yes