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. To address the endogeneity of air pollution, we use thermal inversions as an instrument.

Our causal estimates imply that a one $\mu g/m^3$ decrease in $PM_{2.5}$ increases labor productivity by 0.85% with an elasticity of -0.45. Lowering $PM_{2.5}$ by 1% nationwide through methods other than reducing manufacturing output would generate annual productivity increases of CNY 57.7 thousand for the average firm and CNY 9.2 billion or 0.062% 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
Keywords: air pollution; productivity; environmental costs and benefits; firm competitiveness

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1 Introduction

An emerging literature documents the effect of air pollution on short-run labor productivity, an important driver of economic growth. These papers significantly advance our understanding of how pollution affects productivity and convincingly demonstrate that air pollution can decrease labor productivity. However, because these studies utilize detailed measures of hourly or daily output per worker, they focus on narrow groups of workers in particular occupations such as fruit picking (Graff Zivin and Neidell, 2012), garment assembly (Adhvaryu *et al*., 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 -0.45 for particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$). 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 7.7 (CNY 57.7)[2] thousand and increase output across all firms by USD 1.2 billion annually (0.062% of China's average GDP over the sample period). These are significant effects and should be considered in any cost-benefit analysis of environmental policies.

The primary obstacles in estimation are simultaneity and omitted-variable biases. Simultaneity bias in OLS estimates could result from the production process itself in the absence of any effect of pollution on productivity or from compensating actions taken by firms in the presence of such effects. In the absence of any effects the more output a region's firms produce the worse its pollution, biasing OLS estimates upward towards or above zero. If pollution lowers labor productivity, bias may result if firms compensate by using more alternative inputs. This could bias OLS estimates upward, if these other inputs are low-polluting, or downward, if they are high-polluting. Omitted variable bias could result from region-specific, time-varying correlations between

[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.

pollution and output induced by production decisions, industrial policies, or regulations.[3] These could bias OLS estimates upward or downward depending on whether low-productivity regions adopt cleaner or dirtier technologies over time in response to these actions.

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

A second estimation obstacle is potential spatial sorting across regions of low- versus high-skilled workers or low- versus high-polluting firms based on pollution. Using OECD (2011)'s criteria, we classify firms by technology intensiveness and find that pollution is not predictive of the year-by-year fraction of employment in low- versus high-technology firms suggesting that the migration of workers is limited in the short run. Few firms move during the sample period consistent with no significant sorting by extant firms. Excluding firms that relocate results in greater effects on productivity indicating that pollution's effect may be even greater if these are representative of the full sample. Pollution is not predictive of firm exit or entry consistent with survival bias and endogenous choice of entry locations 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.

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

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 is offset by process innovations that are both cleaner and of lower cost. Our results confirm another channel that influences this debate. Environmental regulations that decrease air pollution will in turn increase productivity and at least partially offset the decreased productivity due to complying. 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 $PM_{2.5}$ on labor productivity separately for firms in high- and low-technology industries based on the OECD (2011) classification and find significant effects for both. This suggests that the results apply not just to older, traditional manufacturing firms but also to those employing newer, more advanced technologies.

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.[4] 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; Ebenstein *et al*., 2016).

[4] "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).

Many developing countries are hesitant to implement measures to reduce air pollution for fear of hindering growth (Hanna and Oliva, 2015). Figure 1 illustrates the environmental cost of China's development. It plots the average concentration of $PM_{2.5}$ across all regions of China over the sample period against annual value added for all firms in our sample. The rapid increase in output has resulted in accompanying rapid increases in air pollution, especially after China joins the World Trade Organization (WTO) in 2001. Our finding of significant labor productivity gains from reducing pollution provides additional impetus to implement pollution control measures. Because of China's severe pollution, the central government has designed many policies to reduce air pollution but these often go unenforced because local governments lack incentives to do so or their incentives emphasize alternative goals such as economic growth (Li and Zhou, 2005; Chen *et al*., 2016; Jia, 2017). Our findings suggest local governments may underestimate the benefits to local economic growth of reducing air pollution.

[Insert Figure 1 here.]

The rest of the paper is organized as follows. The next section discusses related literature. Section 3 describes the data; Section 4 specifies the econometric models and discusses identification issues and strategies. Section 5 presents our 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.[5] These short-run effects can result in decreased physical stamina at work and missed work days. Long-run exposure may lead to cardiopulmonary diseases, respiratory infections, lung cancer (EPA, 2004), and asthma (Neidell, 2004). These long-run health problems can manifest themselves in the short run if high levels of pollution trigger conditions resulting from previously accumulated exposure. Infant and elderly morbidity resulting from air pollution (Chay and Greenstone, 2003; Deryugina *et al*., 2016) can require working adults to miss work to care for them (Hanna and Oliva, 2015; Aragón *et al*., 2017). Long-term exposure can also reduce life expectancy (Chen *et al*., 2013; Ebenstein *et al*., 2017) which can result in experienced workers being replaced by new, inexperienced ones.

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

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

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 of pollution and productivity observe worker hours (H) and therefore measure effects on per-hour productivity (dA/dp); many also 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 air pollution index (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 (Ebenstein *et al*., 2016). 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. While several different pollutants' effects on productivity have been studied we focus on $PM_{2.5}$ because of its severe effects. Due to its small size it can enter the lungs and bloodstream causing severe health problems and reduced stamina. $PM_{2.5}$ can also penetrate buildings allowing it to affect indoor manufacturing workers (Thatcher and Layton, 1995; Vette *et al*., 2001). Our pollution measure is monthly concentration of $PM_{2.5}$ derived from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by the National Aeronautics and Space Administration (NASA).[6] 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). Chen *et al.* (2017) validate the AOD data using ground-based, station data in China, and find that the difference between them is statistically insignificant conditional on geographic and year fixed effects. The $PM_{2.5}$ concentrations are calculated following Buchard *et al.* (2016).

The AOD data have several advantages compared to ground-based pollution data. First, it begins in 1980 while ground-based pollution data are 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 cover only 42 cities in 2000 increasing to 113 in 2010. Third, ground-based pollution data are potentially subject to human manipulation (Andrews, 2008; Ghanem and Zhang, 2014) while the satellite data are not. The AOD pollution data are reported in grids of 50 by 60 kilometers which we aggregate to the county level

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

– the smallest administrative unit in China to which we can match firm locations.[7] We then average by year to obtain annual mean concentrations of $PM_{2.5}$ 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,[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 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.[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 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 include 1,593,247 firm-year observations for 356,179 unique firms. Geographically, the sample includes 2,755 counties with an average of 58 firms per county-year.

One issue with obtaining broad-based measures of productivity effects is how to measure them. 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.

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[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).

[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.

Pooling all manufacturing firms, as we do, requires an alternative measure. Since we abstract from intermediate inputs we use value added as the measure of output. Value added per worker is commonly used as a measure of labor productivity in the general productivity literature (Syverson, 2011; Brandt *et al.*, 2012) and in the temperature-productivity literature (Hsiang, 2010; Dell *et al.*, 2012). 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 labor productivity including temperature, precipitation, relative humidity, wind speed, sunshine duration, and pressure from the National Meteorological Information Center of China. We convert the daily station data to daily-county level using the inverse-distance weighting method (Deschenes and Greenstone, 2011) and then calculate annual cumulative precipitation and annual means for relative humidity, wind speed, sunshine duration, and pressure. To allow for a non-linear effect of temperature, we construct bins for below 0° Celsius, 5° Celsius intervals from 0 to 30°, and above 30° Celsius and then calculate the number of days with daily average temperature in each bin (Deschênes and Greenstone, 2011). The weather measures are then matched to the firm data by county-year.

For our instrument, we obtain thermal inversion data from NASA.[11] The data report air temperatures every six hours at 42 vertical layers from 110 meters to 36 thousand meters within 50- by 60-kilometer grids. We aggregate from the grid to the county level

[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.

within each six-hour period and for each layer. Following Arceo *et al.* (2016), we define a thermal inversion as the temperature of the second layer (320 meters) being higher than that of the first layer (110 meters). We determine this within each six-hour period of each day for each county. Since thermal inversions are short-lived (on the order of a few weeks) relative to the annual output measure, we use a cumulate annual measure of inversions to make them temporally consistent. For our instrument, we calculate for each county the annual number of days that have at least one inversion.

Table 1 presents summary statistics of the key variables. The firm characteristics are at the firm-year level and reflect a high degree of variation in 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 (WHO, 2006). In the sample, the mean annual $PM_{2.5}$ level is 53.5 with a high of 134.8. The annual number of days with thermal inversions displays significant variation ranging from zero to 333 days per year with a mean equal to a little under one-half year.

[Insert Table 1 here.]

4. Model specification and identification

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

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

where i indicates firm and t year. For firm i in year t, 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 year t. We aggregate the annual pollution and weather measures to the county level because the location of most firms is known only at the county level and not finer. Because of this, we also check the robustness to clustering the standard errors at the county-year level. Temperature is included in the flexible, non-parametric function of bins described earlier. For the other weather variables, we include a quadratic function of each to allow for non-linearity in its effects (Adhvaryu *et al.*, 2014a; Sudarshan *et al.*, 2015; Zhang *et al.*, 2018). The coefficient β_1 captures the effect of pollution on labor productivity. Since L is measured in number of employees, this

[12] In Section 5 we directly test whether pollution affects capital 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.

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_{it}) 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). The causal identification issues that are specific to our context include simultaneity bias, omitted variable bias, and spatial sorting.

4.1 Causal identification issue – simultaneity and omitted variable biases

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

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

A valid instrument is correlated with a county's air pollution but uncorrelated with its resident firms' productivity. Our instrument is the annual number of days with at least one thermal inversion for each county. Normally, air temperature decreases with altitude above the Earth's surface. A thermal (or temperature) inversion is a deviation from this. It occurs when a mass of warmer, less dense air moves above a cooler, denser air mass trapping dust and pollutants near the ground and increasing air pollution. We follow previous literature and calculate thermal inversions using the first and second layers (110 and 330 meters respectively) (Chen *et al.*, 2017).

Since thermal inversions are a meteorological phenomenon and, after conditioning on weather variables, are unrelated with production except via pollution, it is a valid instrument. Figure 2 provides visual evidence that the instrument is exogenous with respect to output. It plots value added over the sample period for all the firms in the sample against the average number of days with thermal inversions across all regions. In contrast to value added, the inversions display no clear time trend suggesting our instrument is not correlated with economic activity. 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; Chen *et al.*, 2017). With this as our instrument we employ two-stage least squares (2SLS) with the first-stage equation:

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

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

[Insert Figure 2 here.]

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 from estimation suggests some sorting effects and even larger productivity effects absent sorting. Firm entry and exit during the sample period could introduce bias through endogenous selection. To check for this possibility we estimate the effect of pollution on the fraction of firms exiting and entering each county in each year (controlling for endogeneity) and find no significant effect for either.

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

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

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

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

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

5. Results

5.1 OLS estimates

We first present estimates not accounting for any endogeneity bias between productivity and pollution. Table 2 presents OLS estimates of Equation (1). Without weather controls (Column (1)), $PM_{2.5}$ pollution has no effect on productivity. Including weather controls (Column (2)), reveals a positive effect of pollution on productivity. A one $\mu g/m^3$ increase in $PM_{2.5}$ increases productivity by 0.04% implying an elasticity of 0.021 evaluated at the mean level of $PM_{2.5}$ in the sample.

A positive effect of pollution on productivity could result from either simultaneity or omitted variable bias. Even absent any effect of pollution on productivity, counties with more output will generate more pollution leading to a positive coefficient. Even if pollution reduces labor productivity, firms may respond by utilizing other inputs which are dirtier biasing the OLS coefficient upward above zero. Omitted variables could also create county-specific, time-varying correlations between pollution and output which could lead to a positive OLS coefficient. This would occur if firms in low-productivity counties adopt cleaner technologies over time in response to their own decisions or due to industrial planning or environmental regulation efforts by the government.

[Insert Table 2 here.]

5.2 2SLS results

Because of the simultaneity and omitted-variable biases, OLS estimates produce inconsistent estimates. 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 $PM_{2.5}$ concentrations either without (Column (3)) or with (Column (4)) weather controls. The coefficient on annual days with thermal inversions is positive and highly significant in both cases and the Kleibergen-Paap Wald rk F-statistic (KP) (Kleibergen and Paap, 2006) for weak identification is much larger than the Stock-Yogo critical value of 16.38.[16] One additional day with an inversion increases $PM_{2.5}$ by 0.030 and 0.037 $\mu g/m^3$ depending on whether weather is controlled for. These are big effects. Using the results with weather controls, a one standard deviation increase in the annual number of days with inversions increases $PM_{2.5}$ by 2.9 $\mu g/m^3$ (5.4%).

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

The lower panel of Table 2 shows the second-stage results. Without weather controls, instrumented $PM_{2.5}$ has a negative and very significant effect on labor productivity. Consistent with the instrument correcting for endogeneity, the coefficient moves from being insignificant in the OLS estimates to being significantly negative. A one $\mu g/m^3$ increase in $PM_{2.5}$ decreases labor productivity by 0.80%. Evaluating this at the mean $PM_{2.5}$ in the sample (53.5) yields an elasticity of -0.43. Controlling for weather changes increases the estimate somewhat and makes it even more significant. A one $\mu g/m^3$ increase in $PM_{2.5}$ decreases labor productivity by 0.85% implying an elasticity of -0.45. Again consistent with the instrument correcting for bias, the effect moves from being positive and significant in the OLS estimates to negative and very significant. Since controlling for weather is preferred we do so throughout the remainder of the paper.

How large are these effects? Consider lowering $PM_{2.5}$ by one percent nationwide through means other than lowering manufacturing output. This could include reducing other pollution sources like road dust, automobile exhaust, and power generation or by decreasing pollution per unit of manufacturing output via pollution abatement equipment that does not reduce output.[17] The resulting labor productivity improvement would increase the average firm's value added by CNY 57.7 (USD 7.6) thousand annually and increase total value added across all firms by CNY 9.2 (USD 1.2) billion annually.[18] This represents 0.062% of China's GDP.[19]

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[20] 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 9.1% (1.3% 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.

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[17] 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.

[18] A 1% decrease in $PM_{2.5}$ increases annual output by 0.45%. The mean annual output per firm in the sample is CNY 12.82 million implying an annual increase of CNY 57.7 thousand. There is an average of 159,325 firms present in each year of the sample implying an annual increase in output across all firms of CNY 9.2 billion annually.

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

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

Since our estimates capture pollution's effect on both per-hour productivity and working hours, it is useful to disentangle the two for comparisons to previous estimates of per-hour productivity effects.[21] We borrow estimates from Aragón *et al*. (2017) which finds an elasticity of working hours with respect to $PM_{2.5}$ of -0.21 in Lima, Peru. Assuming $PM_{2.5}$'s effect on working hours is the same in China, our estimated elasticity of per-hour productivity with respect to pollution is -0.24. This is similar to the estimate in Graff Zivin and Neidell (2012), which finds an elasticity of -0.26 for per-hour productivity with respect to ozone for outdoor fruit pickers in California. It is also similar to the upper end of estimates by He, Liu *et al.* (2016) for textile workers in two firms in two Chinese provinces. They find elasticities ranging from -0.035 to -0.30 from $PM_{2.5}$ exposure if effects are accumulated over 25 to 30 days.

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

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

[21] This makes use of the fact that the elasticity of labor productivity equals the elasticity of labor productivity per hour plus the elasticity of hours worked.

5.3 Robustness checks

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

Our baseline estimates weight all observations equally. Column (5) re-estimates weighting observations by value added per firm. The coefficient yields a slightly higher elasticity (-0.48) than the baseline estimates. Column (6) shows that not winsorizing the data leads to very similar results as the baseline estimates (an elasticity of -0.46 evaluated at the mean $PM_{2.5}$ of 53.3). Column (7) uses log rather than linear pollution. The elasticity is very close to that estimated using a linear function (-0.50).

[Insert Table 3 here.]

5.4 Tests for firm 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 4 shows tests for this potential spatial sorting. Column (2) estimates exclude firms that relocated across counties (about 7% of firms) during the sample period. The estimated elasticity (-0.69) based on a mean $PM_{2.5}$ of 53.7 is larger than that of the baseline estimate (-0.45) using all firms (replicated in Column (1)) consistent with either firms avoiding pollution to increase their productivity or a "pollution haven" effect and high-polluting firms being more productive. This also means that our baseline estimates may understate pollution's effect on productivity to the extent that the non-relocating firms are representative of the full sample.

[Insert Table 4 here.]

Although the inclusion of firm fixed effects in our main results controls for any initial sorting of firms based on pollution levels, new firms who enter during the sample period may choose locations endogenously based on pollution. To see if this might affect the results, Column (3) of Table 4 tests whether a county's instrumented pollution significantly affects the fraction of new firms entering the county in the following year. We aggregate to the county-level for this analysis because we do not observe firms prior to entry and therefore cannot create an entry variable at the firm level. In addition to the weather controls we include county and year fixed effects so that identification derives from within-county variation over time. We cluster standard errors at the county level to allow spatial correlation in unobserved factors within counties and intertemporal variation across years within counties. Year 1998 data is dropped because it is the first year of our sample period and thus we cannot determine the level of entry.

The estimated effect of entry is close to zero and insignificant consistent with pollution not affecting firm location choice on entry. Since the sample censors non-SOE firms with less than CNY 5 million in annual revenues, this may confound measures of entry in this full sample. To minimize this possibility, Columns (4) and (5) restrict the entry regression to include firms that have at least CNY 10 and 15 million in average annual sales respectively. This makes it much less likely that firms in existence but below the CNY 5 million threshold will be coded as having "entered" when they exceed the threshold in a later year. The coefficients remain close to zero and insignificant.

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 (6) tests whether a county's instrumented pollution significantly affects the fraction of firms exiting the county in the following year. This county-level regression is analogous to the entry regression and includes the same control variables and uses the same clustering of standard errors. Year 2007 data is dropped in this estimation since we cannot observe whether firms present in 2007 exit in 2008. The estimate is close to zero and insignificant suggesting that exit bias is not a major concern.[22] This also suggests that any actions taken by the government to shut down firms in high-polluting areas are minimal. To see whether the censoring of non-SOE firms with less than CNY 5 million in annual revenues confounds the exit measure, Columns (7) and (8) restrict the exit regression to include firms with more than CNY 10 and 15 million in average annual sales respectively. The coefficients remain close to zero and insignificant.

[22] Estimates using a balanced panel could address this issue as well as any selection effects by entering firms. However, only 7% of firms are present in all years due to 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.

5.4 Tests for worker sorting

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

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

[Insert Table 5 here.]

5.5 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. $PM_{2.5}$ can permeate indoors making it possible for it to affect indoor workers. Our data allow us to offer some evidence by skill level for manufacturing firms in China. We categorize firms' technological intensity based on the four industry categories in OECD (2011) and estimate the effect of pollution on productivity separately splitting the sample into the four categories.

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

[Insert Table 6 here.]

5.6 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 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 $PM_{2.5}$ increases employment by 0.44% implying an elasticity of 0.24. 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). Moreover, employing additional workers imposes costs on firms. We can use the average wage in the sample to produce a ballpark estimate of these costs. A one percent increase in $PM_{2.5}$ increases employment by 0.24%, or 0.49 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 6,199 (USD 816). Aggregated across all firms this equals CNY 0.99 billion (USD 0.13 billion) annually or 10.6% of the productivity loss from the 1% increase in $PM_{2.5}$.

Column (3) estimates the effect of pollution on log value added. The effect is significant and the elasticity of value added with respect to pollution is -0.21. This equals the summed effect of pollution's effect on labor productivity (-0.45) and its effect on labor supply (0.24).

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.

[Insert Table 7 here.]

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 and other potential endogeneity issues we take an instrumental variable approach using thermal inversions, which are meteorologically determined. The approach attenuates the endogeneity bias 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 little evidence of such sorting in our short-run results but this may occur over longer periods and would attenuate the productivity effects. Future work on these long-run effects would be useful.

Although we can capture all channels by which pollution can influence productivity, we are unable to decompose the exact channels by which pollution lowers productivity. Significant effects on productivity per hour would indicate that there are large benefits

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

from protecting workers from air pollution while at work. Effects on hours worked might indicate exposure to pollution by a worker's family members in addition to workplace exposure. These would be useful avenues for future research.

References:

Adhvaryu, A., N. Kala, and A. Nyshadham. (2014a). "The Light and the Heat: Productivity Co-Benefits or Energy-Saving Technology," working paper.

Adhvaryu, A., N. Kala, and A. Nyshadham. (2014b). "Management and Shocks to Worker Productivity: Evidence from Air Pollution Exposure in an Indian Garment Factory," working paper.

Andrews, S. Q. (2008). "Inconsistencies in Air Quality Metrics: 'Blue Sky' Days and PM_{10} Concentrations in Beijing," *Environmental Research Letters*, 3, 1 – 14.

Aragón, F., J. J. Miranda, and P. Oliva. (2017). "Particulate Matter and Labor Supply: The Role of Caregiving and Non-Linearities," *Journal of Environmental Economics and Management*, 86, 295 – 309.

Arceo, E., R. Hanna, and P. Oliva. (2016). "Does the Effect of Pollution on Infant Mortality Differ between Developing and Developed Countries?: Evidence from Mexico City," *Economic Journal* 126, 257 – 280.

Archsmith, J., A. Heyes, and S. Saberian. (2016). "Air Quality and Error Quantity: Pollution and Performance in a High-Skilled, Quality Focused Occupation," working paper.

Arnott, R., T. Rave, and R. Schöb. (2005). *Alleviating Urban Traffic Congestion*, MIT Press: Cambridge, MA.

Becker, R. and J. Henderson. (2000). "Effects of Air Quality Regulations on Polluting Industries," *Journal of Political Economy* 108, 379 – 421.

Bishop, K., J. Ketcham, and N. Kuminoff. (2017). "Hazed and Confused: Air Pollution, Dementia, and Financial Decision Making", working paper.

Bombardini, M. and B. Li. (2016). "Trade, Pollution and Mortality in China," working paper.

Brandt, L., J. Van Biesebroeck, and Y. Zhang. (2012). "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97, 339 – 351.

Brunnermeier, S. and A. Levinson. (2004). "Examining the Evidence on Environmental Regulations and Industry Location," *Journal of Environment & Development* 13, 6 – 41.

Buchard, V., A. M. da Silva, C. A. Randles, P. Colarco, R. Ferrare, J. Hair, C. Hostetler, J. Tackett, and D. Winker. (2016). "Evaluation of the Surface $PM_{2.5}$ in Version 1 of the NASA MERRA Aerosol Reanalysis over the United States," *Atmospheric Environment*, 125, 100 – 111.

Cai, H. and Q. Liu. (2009). "Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms," *The Economic Journal*, 119, 764 – 795.

Cameron, A. C., J. Gelbach, and D. Miller. (2011). "Robust Inference with Multi-Way Clustering," *Journal of Business and Economic Statistics*, 29, 238 – 249.

Cameron, C. and D. Miller. (2015). "A Practitioner's Guide to Cluster-Robust Inference," *Journal of Human Resources* 50, 317 – 372.

Chang, T., J. G. Zivin, T. Gross and M. Neidell. (2016a). "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy*, 8, 141 – 169.

Chang, T., J. G. Zivin, T. Gross and M. Neidell. (2016b). "The Effect of Pollution on Worker Productivity: Evidence from Call-Center Workers in China," NBER working paper 22328.

Chay, K. Y. and M. Greenstone. (2003). "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *Quarterly Journal of Economics*, 118, 1121 – 1167.

Chen, S., P. Oliva, and P. Zhang. (2017). "The Effect of Air Pollution on Migration: Evidence from China," NBER working paper 24036.

Chen, S., P. Oliva, and P. Zhang. (2018). "The Effect of Air Pollution on Mental Health: Evidence from China," SSRN working paper.

Chen, Y., A. Ebenstein, M. Greenstone and H. Lie. (2013). "Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy," *Proceedings of the National Academy of Sciences of the United States of America*, 110, 12936 – 12941.

Chen, Y. J., P. Li, and Y. Lu. (2016). "Accountability, Career Incentives, and Pollution — The Case of Two Control Zones in China," working paper.

Currie, J., E. A. Hanushek, E. M. Kahn, M. Neidell, S. G. Rivkin. (2009). "Does Pollution Increase School Absences?" *Review of Economics and Statistics* 91, 682 – 694.

Dell, M., B. F. Jones, and B. A. Olken. (2012). "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, 4, 66 – 95.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor and J. Reif. (2016). "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction," NBER Working Paper 22796.

Deschênes, O., and M. Greenstone. (2011). "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, 3, 152-185.

Ebenstein A, M. Fan, M. Greenstone, G. He, and M. Zhou. (2015). "Growth, Pollution, and Life Expectancy: China from 1991-2012," *American Economic Review Papers and Proceedings*, 105, 226 – 231.

Ebenstein, A., Lavy, V., and Roth, S. (2016). "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution," *American Economic Journal: Applied Economics*, 8, 36 – 65.

Ebenstein, A., Fan, M., Greenstone, M., He, G., and Zhou, M. (2017). "New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy," *Proceedings of the National Academy of Sciences*, *114*(39), 10384 – 10389.

EPA (U.S. Environmental Protection Agency). (2004). "Air Quality Criteria for Particulate Matter."

Fu, S. and M. Guo. (2017). "Running with a Mask? The Effect of Air Pollution on Marathon Runners' Performance," working paper, https://ssrn.com/abstract=2978302.

Ghanem, D. and J. Zhang. (2014). "Effortless Perfection: Do Chinese Cities Manipulate Air Pollution Data?" *Journal of Environmental Economics and Management*, 68, 203 – 225.

Graff Zivin, J. and M. Neidell. (2012). "The Impact of Pollution on Worker Productivity," *American Economic Review*, 102, 3652 – 3673.

Greenstone, M. (2002). "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and Census of Manufactures," *Journal of Political Economy*, 110, 1175 – 219.

Greenstone, M., J. A. List and C. Syverson. (2012). "The Effects of Environmental Regulation on the Competitiveness of US Manufacturing," NBER working paper 18392.

Gupta, P., S. A. Christopher, J. Wang, R. Gehrig, Y. C. Lee and N. Kumar. (2006). "Satellite Remote Sensing of Particulate Matter and Air Quality Assessment over Global Cities," *Atmospheric Environment*, 40, 5880 – 5892.

Hanna, R. and P. Oliva. (2015). “The Effect of Pollution on Labor Supply: Evidence from a Natural Experiment in Mexico,” *Journal of Public Economics*, 122, 68 – 79.

He, G., M. Fan and M. Zhou. (2016). “The Effect of Air Pollution on Mortality in China: Evidence from the 2008 Beijing Olympic Games,” *Journal of Environmental Economics and Management*, 79, 18 – 39.

He, J., H. Liu and A. Salvo. (2016). “Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China,” IZA Working Paper 8916.

Hicks, D., P. Marsh and P. Oliva. (2016). “Air Pollution and Procyclical Mortality: Causal Evidence from Thermal Inversions,” working paper.

Hsiang, S. M. (2010). “Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America,” *Proceedings of the National Academy of Sciences*, 107, 15367 – 15372.

Ito, K. and Zhang, S. (2016). “Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China,” working paper.

Jaffe, A., S. Peterson and P. Portney. (1995). “Environmental Regulation and the Competitiveness of US Manufacturing: What does the Evidence Tell Us?” *Journal of Economic Literature*, 33, 132 – 163.

Jans, J., P. Johansson and J. P. Nilsson. (2016). “Economic Status, Air Quality, and Child Health: Evidence from Inversion Episodes,” working paper.

Jia, R. (2017). “Pollution for Promotion,” UCSD School of Global Policy & Strategy working paper.

Kleibergen, F. and Paap, R. (2006). “Generalized Reduced Rank Tests Using the Singular Value Decomposition,” *Journal of Econometrics*, 133, 97 – 126.

Kloek, T. (1981). “OLS Estimation in a Model Where a Microvariable Is Explained by Aggregates and Contemporaneous Disturbances Are Equicorrelated,” *Econometrica*, 49, 205 – 207.

Kumar, N., A. D. Chu, A. D. Foster, T. Peters and R. Willis. (2011). “Satellite Remote Sensing for Developing Time and Space Resolved Estimates of Ambient Particulate in Cleveland, OH,” *Aerosol Science and Technology*, 45, 1090 – 1108.

Lavy, V., A. Ebenstein, S. Roth. (2014). “The Impact of Short Term Exposure to Ambient Air Pollution on Cognitive Performance and Human Capital Formation,” NBER Working Paper No. 20648.

Levinson, A. (2012). “Valuing Public Goods using Happiness Data: The Case of Air Quality,” *Journal of Public Economics*, 96, 869 – 880.

Li, H and L. Zhou. (2005). "Political Turnover and Economic Performance: The Incentive Role of Personnel Control in China," *Journal of Public Economics*, 89, 1743 – 1762.

Lichter, A., N. Pestel and E. Sommer. (2015). "Productivity Effects of Air Pollution: Evidence from Professional Soccer," IZA discussion paper 8964.

Lin, Y. (2017). "The Long Shadow of Industrial Pollution: Environmental Amenities and the Distribution of Skills," working paper.

Lin, J. *et al.* (2014). "China's International Trade and Air Pollution in the United States," *Proceedings of the National Academy of Sciences of the United States of America*, 111, 1736 – 1741.

Matus, K., K. Nam, N. Selin, L. Lamsal, J. Reilly and S. Paltsev. (2012). "Health Damages from Air Pollution in China," *Global Environmental Change*, 22, 55 – 66.

Moulton, B. (1986). "Random Group Effects and the Precision of Regression Estimates," *Journal of Econometrics*, 32, 385 – 397.

Neidell, M. J. (2004). "Air Pollution, Health, and Socio-Economic Status: The Effect of Outdoor Air Quality on Childhood Asthma," *Journal of Health Economics*, 23, 1209 – 1236.

OECD Directorate for Science, Technology and Industry. (2011). "ISIC Rev. 3 Technology Intensity Definition, https://www.oecd.org/sti/ind/48350231.pdf.

Pun, V. C., J. Manjouride and H. Suh. (2016). "Association of Ambient Air Pollution with Depressive and Anxiety Symptoms in Older Adults: Results from the NSHAP Study, Environmental Health Perspectives," working paper.

Sager, L. (2016). "Estimating the Effect of Air Pollution on Road Safety using Atmospheric Temperature Inversions," Grantham Research Institute on Climate Change and the Environment working paper 251.

Stock, J. H. and M. Yogo. (2005) "Testing for Weak Instruments in Linear IV Regression," in *Andrews DWK Identification and Inference for Econometric Models*. New York: Cambridge University Press, 80 – 108.

Sudarshan, A., E. Somanathan, R. Somanathan, and M. Tewari. (2015). "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing," working paper.

Syverson, C. (2011). "What Determines Productivity," *Journal of Economic Literature*, 49, 326 – 365.

Thatcher, T. L. and D. W. Layton. (1995). "Deposition, Resuspension, and Penetration of Particles within a Residence," *Atmospheric Environment*, 29, 1487 – 1497.

van Donkelaar, A., R. V. Martin, M. Brauer, R. Kahn, R. Levy, C. Verduzco and P. J. Villeneuve. (2010). "Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-Based Aerosol Optical Depth: Development and Application," *Environmental Health Perspectives*, 118, 847 – 855.

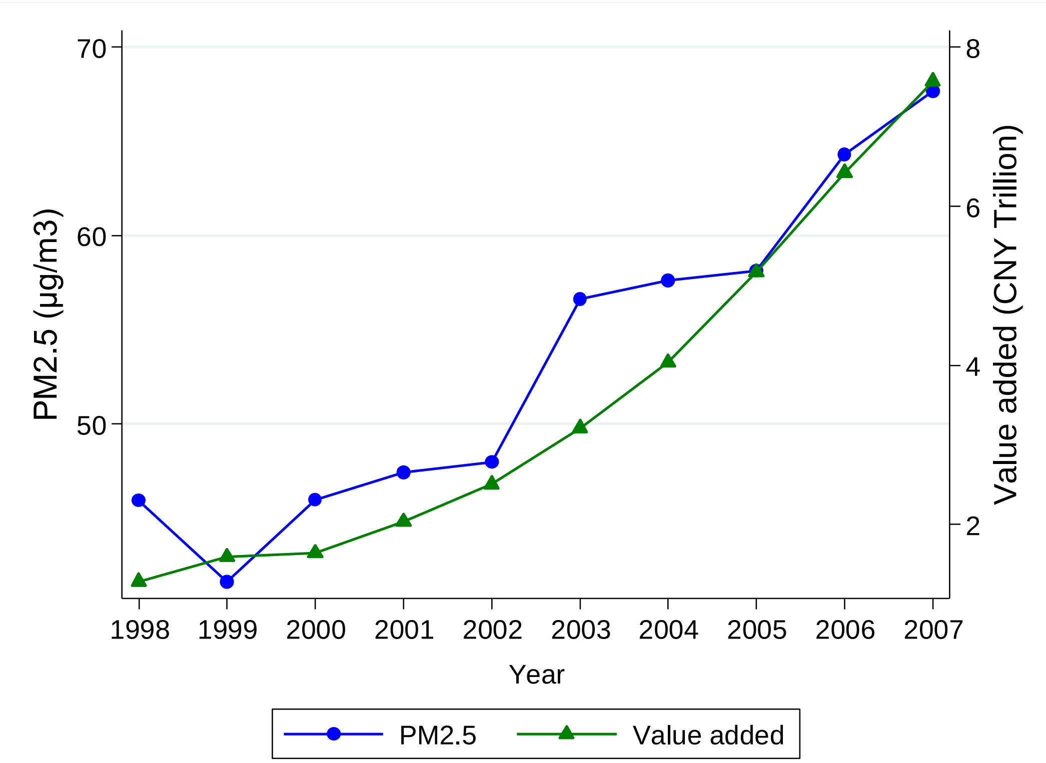
Vette, A. F., Rea, A. W., Lawless, P. A., Rodes, C. E., Evans, G., Highsmith, V. R., & Sheldon, L. (2001). "Characterization of Indoor-Outdoor Aerosol Concentration Relationships during the Fresno PM Exposure Studies," *Aerosol Science & Technology*, 34, 118 – 126.

World Health Organization. (2006). *WHO Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide: Global Update 2005*, Geneva, Switzerland.

Yu, M. (2014). "Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms," *The Economic Journal*, 125, 943 – 988.

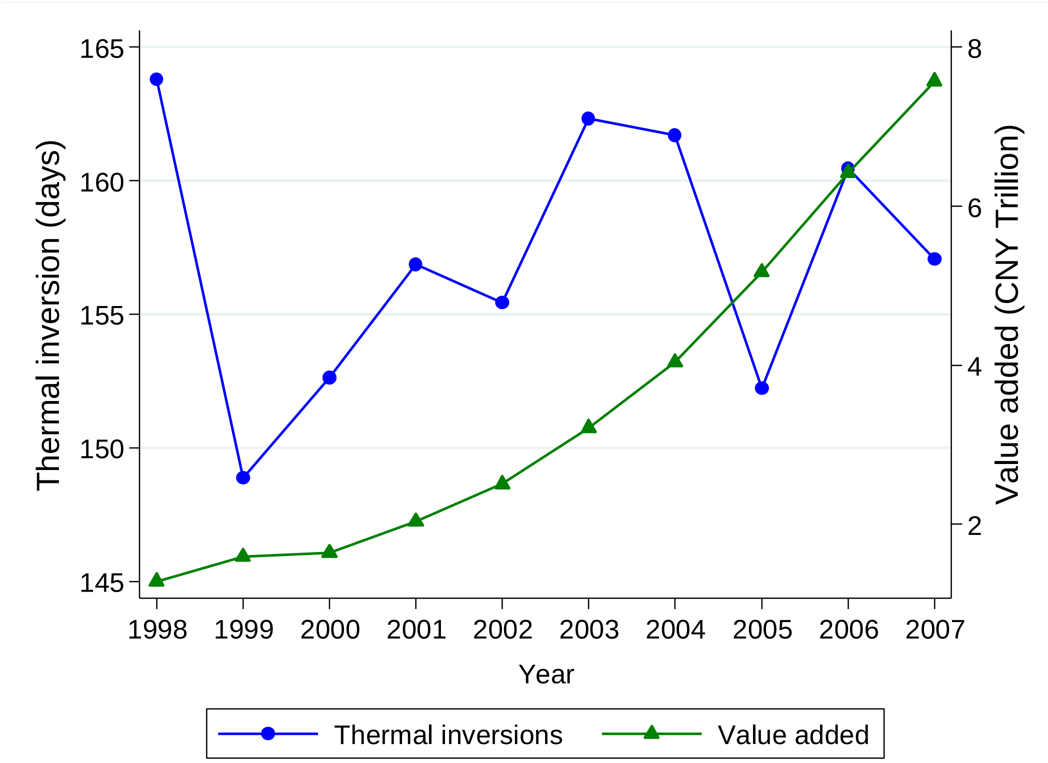
Zhang, P., J. Zhang, O. Deschênes, and K. Meng. (2018). "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants," *Journal of Environmental Economics and Management*, 88, 1 – 17.

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



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

Figure 2: Time trend of thermal inversions and aggregate value added in China (1998 to 2007)



Notes: This graph displays aggregate value added of China's manufacturing sector and national average of county-level annual cumulative days with thermal inversion in China from 1998 to 2007. Value added includes all state-owned enterprises (SOEs) and all non-SOEs with sales above CNY 5 million.

Table 1: Summary statistics

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
Thermal inversions				
Annual days with thermal inversions	156.95	78.75	0.00	333.00

Notes: Firm-year sample size: 1,593,247 including 356,179 firms. County-year sample size: 25,359 including 2,755 counties. Sample period: 1998-2007.

Table 2 OLS and 2SLS estimates – effect of air pollution on labor productivity

	(1)	(2)	(3)	(4)
	OLS		**2SLS**	
			First stage	
Dependent variable:			**$PM_{2.5}$**	
Annual days with inversions			0.0300***	0.0368***
			(0.0004)	(0.0004)
KP *F*-statistic			5,520	8,784
Dependent variable:	**ln(value added per worker)**			
			Second stage	
$PM_{2.5}$	0.0003	0.0004**	-0.0080***	-0.0085***
	(0.0002)	(0.0002)	(0.0016)	(0.0013)
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Weather controls	N	Y	N	Y
# firms	356,179	356,179	356,179	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247

Notes: All models include firm fixed effects and year fixed effects 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 air pollution on labor productivity (robustness checks)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**ln(value added per worker)**						
		Clustering of standard errors					
	Baseline	Firm and county-year	County-year	County	Weighted	Non-winsorized	Functional form (log)
$PM_{2.5}$	-0.0085***	-0.0085**	-0.0085**	-0.0085**	-0.0089***	-0.0087***	
	(0.0013)	(0.0037)	(0.0037)	(0.0038)	(0.0022)	(0.0014)	
Log $PM_{2.5}$							-0.4999***
							(0.0773)
KP *F*-statistic	8,784	123	124	84	1,923	9,547	9,768
Cluster by firm	Y	N	N	N	Y	Y	Y
Cluster by firm and county-year	N	Y	N	N	N	N	N
Cluster by county-year	N	N	Y	N	N	N	N
Cluster by county	N	N	N	Y	N	N	N
Weighting by value added	N	N	N	N	Y	N	N
Winsorized	Y	Y	Y	Y	Y	N	Y
# firms	356,179	356,179	356,179	356,179	356,179	379,349	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247	1,593,247	1,746,850	1,593,247

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm-year sample		**County-year sample**					
Dependent variable:	**ln(value added per worker)**		**Fraction of firms entering**			**Fraction of firms exiting**		
	Baseline	**Exclude relocating firms**	**Full sample**	**Sales above CNY 10 million**	**Sales above CNY 15 million**	**Full sample**	**Sales above CNY 10 million**	**Sales above CNY 15 million**
$PM_{2.5}$	-0.0085***	-0.0129***	0.0023	0.0035	0.0027	0.0020	-0.0009	-0.0011
	(0.0013)	(0.0017)	(0.0028)	(0.0023)	(0.0019)	(0.0017)	(0.0011)	(0.0009)
KP *F*-statistic	8,784	12,398	179	167	166	328	314	309
Firm fixed effects	Y	Y	N	N	N	N	N	N
County fixed effects	N	N	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y
Clustering	Firm	Firm	County	County	County	County	County	County
Sample size	1,593,247	1,432,765	23,091	22,224	21,706	22,684	21,680	21,137

Notes: Sample period: 1998 - 2007 in Columns 1 and 2; 1999 to 2007 in Columns 3 through 5 to measure entry from the prior year; 1998 - 2006 in Columns 6 through 8 to measure exit in the following year. Columns 1 and 2 are firm-year data; Column 1 includes all firms and Column 2 all firms that did not relocate during the sample period. Columns 3 through 8 are county-year data; Columns 3 and 6 aggregate all firms to the county level; Columns 4 and 7 (5 and 8) aggregate firms with annual sales above CNY 10 (15) million respectively to the county level. All models use annual number of days with thermal inversions as instruments. All models include year fixed effects and weather controls in both stages. Models in Columns 1 and 2 include firm fixed effects and models in Columns 3 through 8 county fixed effects. Standard errors are clustered at the firm level in Columns 1 and 2 and at the county level in Columns 3 through 8 and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 5: 2SLS estimates – tests for worker sorting based on pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Fraction of employment**					
	Four categories				**Two categories**	
	High technology	**Medium-high technology**	**Medium-low technology**	**Low technology**	**High technology**	**Low technology**
$\mathbf{PM_{2.5}}$	0.0000	-0.0010	-0.0023	0.0033*	-0.0010	0.0010
	(0.0009)	(0.0016)	(0.0020)	(0.0019)	(0.0017)	(0.0017)
KP *F*-statistic	171	171	171	171	171	171
County fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y
Clustering	County	County	County	County	County	County
Sample size	2,753	2,753	2,753	2,753	2,753	2,753

Notes: All models use annual number of days with thermal inversions as instruments. All models include county fixed effects, year fixed effects, and weather controls in both stages. The technology intensiveness definition in Columns 2 through 5 is from OECD (2011). We combine high and medium-high technology into high technology in Column 5 and combine low and medium-low technology into low technology in Column 6. Sample period: 1998-2007. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 6: 2SLS estimates – effect of air pollution on labor productivity by firm technology level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**ln(value added per worker)**						
		Four categories				**Two categories**	
	Full sample	**High technology**	**Medium-high technology**	**Medium-low technology**	**Low technology**	**High technology**	**Low technology**
$PM_{2.5}$	-0.0085***	-0.0091*	-0.0133***	-0.0073***	-0.0060***	-0.0121***	-0.0065***
	(0.0013)	(0.0048)	(0.0026)	(0.0025)	(0.0020)	(0.0023)	(0.0016)
KP *F*-statistic	8,784	429	1,835	2,672	4,171	2,276	6,821
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y
# firms	356,179	24,652	102,699	97,918	130,910	127,351	228,828
Sample size	1,593,247	112,792	467,768	435,842	576,845	580,560	1,012,687
Share of sample size (%)	100	7.08	29.36	27.36	36.21	36.44	63.56

Notes: All models use annual number of days with thermal inversions as instruments. All models include firm fixed effects, year fixed effects, and weather controls in both stages. The technology intensiveness definition in Columns (2) through (5) is from OECD (2011). We combine high and medium-high technology into high technology into Column (6) and combine low and medium-low technology into low technology into Column (7). Sample period: 1998-2007. Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The KP *F*-statistic is the Kleibergen-Paap Wald rk *F*-statistic for weak identification in the first stage (Kleibergen and Paap, 2006).

Table 7: 2SLS estimates – effects of air pollution on labor productivity, employment, value added, and capital

Dependent variable:	(1) **ln(value added per worker)**	(2) **ln(number workers)**	(3) **ln(value added)**	(4) **ln(capital)**
$PM_{2.5}$	-0.0085***	0.0044***	-0.0040***	-0.0008
	(0.0013)	(0.0010)	(0.0014)	(0.0012)
KP *F*-statistic	8,784	8,784	8,784	8,784
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
# firms	356,179	356,179	356,179	356,179
Sample size	1,593,247	1,593,247	1,593,247	1,593,247

Notes: All models use annual number of days with thermal inversions as 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).