THE
ECONOMIC
JOURNAL

The Economic Journal, 1–33 https://doi.org/10.1093/ej/ueab033
Advance Access Publication Date: 27 April 2021

AIR POLLUTION AND MANUFACTURING FIRM PRODUCTIVITY: NATIONWIDE ESTIMATES FOR CHINA*

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We provide nationwide causal estimates of air pollution's effect on short-run productivity for China's manufacturing sector from 1998 to 2007. Using thermal inversions as an instrument, a 1 $\mu g/m^3$ decrease in $PM_{2.5}$ increases productivity by 0.82% (elasticity of −0.44). Increased hiring attenuates the elasticity to −0.17. Differential effects of a trade shock on coastal versus inner regions imply a pollution elasticity of output of 1.43. Simulating a dynamic general-equilibrium model yields an output elasticity of −0.28 with respect to $PM_{2.5}$. An exogenous 1% decrease in $PM_{2.5}$ nationwide increases gross domestic product by 0.039%.

An emerging literature documents the effect of air pollution on short-run productivity, an important driver of economic growth. These papers significantly advance our understanding of how pollution affects productivity and convincingly demonstrate that air pollution can decrease productivity. However, because these studies utilise 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.*, 2019), pear packing (Chang *et al.*, 2016), call centre services (Chang *et al.*, 2019) or textile assembly (He *et al.*, 2019). While these estimates are useful for evaluating narrowly targeted environmental policies or evaluating the costs and benefits for certain groups, their external validity is of concern in evaluating broad-based pollution reduction policies.

We provide comprehensive, nationwide causal estimates of the effect of air pollution on short-run productivity for manufacturing firms in China encompassing all channels of effects. Using satellite data to measure pollution, we are able to consider all firms in China's manufacturing survey. The survey includes all state-owned enterprises (SOEs) and all non-SOEs with more than CNY 5 million in annual sales, rendering evaluations of nationwide environmental policies feasible. For our partial-equilibrium estimates, we find an elasticity of productivity with respect to pollution of −0.44 for particulate matter less than 2.5 μg in diameter ($PM_{2.5}$). Holding inputs constant, an exogenous 1% increase in $PM_{2.5}$ nationwide decreases the average firm's output

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This paper was received on 25 May 2018 and accepted on 15 April 2021. The Editor was Estelle Cantillon.

The authors were granted an exemption to publish their data because access to the data is restricted. However, the authors provided the Journal with temporary access to the data, which allowed the Journal to run their codes. The codes are available on the Journal website. The data and codes were checked for their ability to reproduce the results presented in the paper.

All authors contributed equally and are ordered alphabetically. We thank the editor, two referees, Richard Arnott, Michael Bates, Tom Chang, Olivier Deschênes, Joshua Graff Zivin, Sarojini Hirshleifer, H. Allen Klaiber, Matthew Neidell, Paulina Oliva, Paul Oyer, Alberto Salvo, Carolyn Sloane, Yang Xie, Linyi Zhang and Shuang Zhang; seminar participants at UC Riverside, Shanghai Jiaotong University and Wuhan University; and conference participants at the 2017 China Meeting of the Econometric Society, the 2017 International Conference on Industrial Economics, the 2017 China India Insights Conference and the 2018 American Economic Association Meeting for helpful comments. Quanyun Song, Jianghao Wang, Castiel Zhuang and Shihan Shen provided excellent research assistance. Shihe Fu acknowledges financial support from the National Natural Science Foundation of China (Grant #71773096; Basic Scientific Center Project #71988101).

by USD 7.4 (CNY 56.3) thousand and decreases output across all firms by USD 1.2 billion annually (0.060% of China's average gross domestic product (GDP) over the sample period).[1] Firms partially offset for this productivity loss by hiring more workers. The combined effect of the productivity loss and additional hiring is an elasticity of -0.17 for output with respect to pollution. We do not find significant differences in these effects between China's major manufacturing centres and elsewhere.

Since previous papers focus on small sets of firms or workers, general-equilibrium effects could be ignored. To obtain general-equilibrium effects, we combine this estimate with an estimate of the effect of output on pollution to simulate an integrated assessment model (IAM) of China's economy that combines a standard growth model with a pollution-damage function. To obtain a causal estimate of the effect of output on pollution, we use China joining the World Trade Organization (WTO) in 2001 as an exogenous shock to output for firms in China's coastal regions relative to that in its inner regions—an approach widely used in the trade literature. This yields an elasticity of $PM_{2.5}$ with respect to output of 1.43. This estimate is useful in and of itself as there are few causal estimates of the effect of output on pollution.

We combine these partial-equilibrium estimates and other realistic parameters to calibrate the IAM to economy-wide data during our sample period. From this we simulate counterfactuals quantifying how pollution affects output, incorporating both productivity and labour supply responses. A 1% increase in $PM_{2.5}$ over the sample period decreases total output by 0.28% on average over the sample period. Exogenously reducing $PM_{2.5}$ by 1% increases the average firm's output by CNY 35.9 (USD 4.7) thousand annually and increases output across all firms by CNY 5.7 (USD 0.75) billion annually or 0.039% of China's GDP. The dynamic effects exceed the static, partial-equilibrium effects because consumers favour current consumption relative to future consumption and sacrifice capital investment. The diminished capital accumulation results in a larger percentage drop in output relative to a static setting in which all current output is consumed. These are significant effects and can be used in cost-benefit analyses of nationwide environmental policies.

The primary obstacles in estimating the effect of pollution on output are simultaneity and omitted-variable biases. Simultaneity bias in ordinary least square (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. The more output a region's firms produce, the worse its pollution, biasing OLS estimates upward towards or above zero. If pollution lowers productivity, this will lower output and pollution biasing OLS estimates downward. Bias may also result if firms compensate by substituting to other inputs: upward if these are low polluting or downward if high polluting. Omitted-variable bias could result from region-specific, time-varying correlations between pollution and output induced by production decisions, industrial policies or regulations.[2] These could bias OLS estimates upward or downward depending on whether low-productivity regions adopt cleaner or dirtier technologies than high-productivity regions 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 that do not materially impact overall pollution levels. Estimating with a national sample over a longer period no longer affords this. To overcome the simultaneity and

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

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

omitted-variable biases while achieving comprehensive estimates, we employ the number of days with thermal inversions in geographic areas (roughly counties) to instrument pollution. Thermal inversions form due to exogenous meteorological factors yet trap pollutants such as $PM_{2.5}$ near the ground, degrading air quality. Previous papers using thermal inversions as an instrument include Arceo *et al.* (2016), Hicks *et al.* (2016), Chen *et al.* (2017), Dechezleprêtre *et al.* (2018), Jans *et al.* (2018) and Sager (2019). The instrument is highly predictive and, when applied, reveals more negative productivity effects than OLS estimates.

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

Estimating the effect of output on $PM_{2.5}$ concentrations also raises endogeneity issues. Most directly, pollution deters production that will bias OLS estimates. Estimates are also affected by all the same simultaneity and omitted-variable biases as the estimates for the effect fo pollution on productivity. Using China's joining the WTO to instrument for regional output addresses this because WTO accession is orthogonal to these firm and worker decisions.

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

Second, we provide general-equilibrium estimates of the effect of pollution on output, including effects on both productivity and labour supply. Previous papers avoided this complication because they considered only small sets of workers or firms, so it was unnecessary to consider the effect of output on pollution. This also distinguishes our work from Dechezleprêtre *et al.* (2018), who examined only partial-equilibrium effects. We do so by simulating these effects in a dynamic, general-equilibrium model of China's economy. Calibrating the model to observed economic values, we find that the general-equilibrium effects exceed the partial-equilibrium effects. We believe ours is the first paper to provide general-equilibrium estimates relating productivity and air pollution. The simulation approach is general and can be applied to evaluate policy

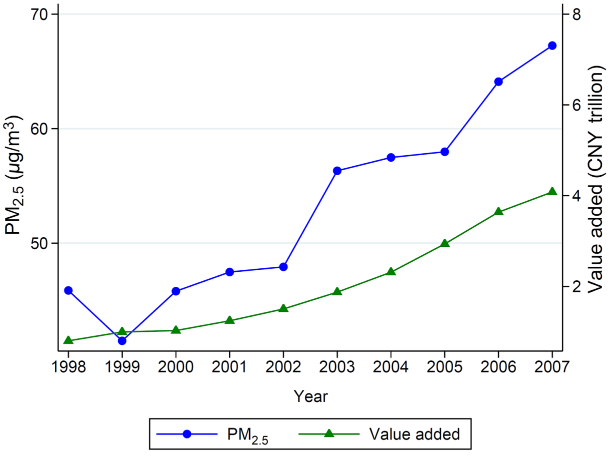

Fig. 1. *Time Trend of Air Pollution and Value Added in China (1998 to 2007).*
Notes: This graph displays the national average of county-level $PM_{2.5}$ and the aggregate value added of China's manufacturing sector from 1998 to 2007. Value added includes all SOEs and all non-SOEs with sales above CNY 5 million winsorised as described in the paper.

counterfactuals in any setting in which partial-equilibrium estimates of the effect of pollution on output and output's effect on pollution are available.

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

Estimates for China are important in and of themselves. China is the world's most populous country and a large source of manufacturing and the resultant pollution. China represented 29% of the world's manufacturing output in 2019.[3] The findings also have implications for the global economy as China incurs a disproportionate fraction of the world's pollution because of its substantial exports. Depending on the type of pollutant, 17% to 36% of China's air pollution is attributable to exports (Lin *et al.*, 2014). Our estimates imply that policies that reduce China's air pollution can generate substantial increases in productivity in addition to health benefits and, given China's extensive exports, benefit other countries via trade. Our estimates complement the literature that estimates the social costs of reduced health due to China's air pollution (Matus *et al.*, 2012; Chen *et al.*, 2013a; Ebenstein *et al.*, 2015; 2016; He *et al.*, 2016; Bombardini and Li, 2020; Ito and Zhang, 2020).

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 pollution resulting from China's development. It plots the average concentration of $PM_{2.5}$ across all regions of China over the sample period against annual value added for all firms in our sample. The rapid output increase has resulted in accompanying rapid air pollution increases, especially after China

[3] 'China Is the World's Manufacturing Superpower', Statista, 4 May 2021 (https://www.statista.com/chart/20858/top-10-countries-by-share-of-global-manufacturing-output/).

joins the WTO in 2001. Our finding of significant productivity gains from reducing pollution provides additional impetus to implement pollution control measures. Because of China's severe pollution, the central government has designed many policies to reduce air pollution, but these have often gone unenforced or under-enforced because local governments lack incentives to do so or their incentives emphasise alternative goals such as economic growth (Li and Zhou, 2005; Chen *et al.*, 2016; Jia, 2017). Our findings suggest that local governments may underestimate the benefits to local economic growth of reducing air pollution.

The rest of the paper is organised as follows. In the next section we discuss related literature in the context of a motivating model. In Section 2 we describe the data; in Section 3 we specify the econometric models and discuss identification issues and strategies. In Section 4 we present our partial-equilibrium results and in Section 5 the general-equilibrium analysis. In Section 6 we conclude.

1. Pollution, Output and Productivity

Air pollution affects a firm's short-run output through its effect on the health of workers and their families. 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, non-fatal heart attacks and angina.[4] These short-run effects can result in decreased physical stamina at work and missed work days. Long-run exposure may lead to cardiopulmonary diseases, respiratory infections, lung cancer (EPA, 2004) and asthma (Neidell, 2004). These long-run health problems can manifest themselves in the short run if high levels of pollution trigger conditions resulting from previously accumulated exposure. Infant and elderly morbidity resulting from air pollution (Chay and Greenstone, 2003; Deryugina *et al.*, 2018) 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.*, 2013a; Ebenstein *et al.*, 2017) that can result in experienced workers being replaced by new, inexperienced ones.

Air pollution can also lower cognitive ability, alter emotions, increase anxiety and have other negative psychological effects (Levinson, 2012; Lavy *et al.*, 2014; Pun *et al.*, 2017; Chen *et al.*, 2018) that 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, ch. 4). Moreover, $PM_{2.5}$ can seep into buildings (Thatcher and Layton, 1995; Vette *et al.*, 2001), making avoidance behaviour costly or impossible for workers unless their employer provides proper filtration equipment. While our estimates are unable to distinguish between these various channels, they capture all of them.

Pollution can affect output through productivity, the intensive margin, and labour 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 labour supply effects on the number of worker years (another type of extensive margin). Pollution can also affect capital productivity through firms investing in pollution-reduction measures, either in response to regulation or to offset decreases in productivity that arise from pollution.

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

To illustrate this, consider a constant-returns-to-scale, Cobb-Douglas production function in capital (K) and labour (L) in which the $PM_{2.5}$ pollution concentration (Ω) affects capital productivity (A_K), labour productivity (A_L) and labour supply (we assume here and later confirm that pollution does not affect capital supply):

$$Q = [A_K(\Omega)K]^{\gamma}[A_L(\Omega)L(\Omega)]^{1-\gamma}. \tag{1}$$

Here γ is the elasticity of output with respect to capital. Logging both sides yields

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

The first term in brackets on the right-hand side is also total factor productivity, $\text{TFP} = \{\gamma \ln[A_K(\Omega)] + (1-\gamma)\ln[A_L(\Omega)]\}$. The effects of pollution are given by

$$\frac{d\ln(Q)}{d\ln(\Omega)} = \left[\gamma \frac{d\ln(A_K)}{d\ln(\Omega)} + (1-\gamma)\frac{d\ln(A_L)}{d\ln(\Omega)}\right] + (1-\gamma)\frac{d\ln(L)}{d\ln(\Omega)}. \tag{2}$$

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

How do these partial-equilibrium effects (general-equilibrium effects are not previously considered) compare to those previously estimated in the literature? In our setting L is measured in worker years and Q annually. Suppose that per-hour labour productivity is a and that each worker's annual hours is H; then $A_L = a \times H$. In the data we observe L but not a or H. Our productivity estimates (both TFP and output per worker) hold the number of worker years constant, so that

$$\frac{d(\text{TFP})}{d\ln(\Omega)} = \left.\frac{d\ln(Q/L)}{d\ln(\Omega)}\right|_L = \gamma \frac{d\ln(A_K)}{d\ln(\Omega)} + (1-\gamma)\left[\frac{d\ln(a)}{d\ln(\Omega)} \times H + a \times \frac{d\ln(H)}{d\ln(\Omega)}\right]. \tag{3}$$

Our estimates therefore capture both the intensive (per-hour productivity) and one type of extensive margin (hours worked) effect on productivity. We also separately estimate the effect on labour supply (L) (another extensive margin) to determine the effects on total output given by (2).

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

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

The previous literature considers only partial-equilibrium effects of pollution on output consistent with their focus on a single industry or firm. To simulate nationwide, general-equilibrium effects, we supplement the production function with a pollution-damage function. We assume that $PM_{2.5}$ is created only by the manufacturing sector and specify (where t indexes years in the simulation)[5]

$$\Omega_t = B(\lambda_t Q_t)^{\mu_t}, \tag{4}$$

where λ_t is the fraction of national output produced by the manufacturing sector in year t, μ_t is the elasticity of pollution with respect to manufacturing output in year t and B is the baseline $PM_{2.5}$ concentration across all years.

For our general-equilibrium simulations, in (1) we set $A_{Kt}(\Omega_t) = \Omega_t^{\theta_K} A_{1t}$, $A_{Lt}(\Omega_t) = \Omega_t^{\theta_L} A_{2t}$, and $L(\Omega_t) = \Omega_t^{\kappa/(1-\gamma)} L_t$ (pollution determines effectiveness of each unit of labour):

$$Q_t = \Omega_t^{\theta} A_t K_t^{\gamma} [L(\Omega_t)]^{1-\gamma}. \tag{5}$$

Here $\theta = \gamma\theta_K + (1-\gamma)\theta_L$ and $A_t = A_{1t}^{\gamma} A_{2t}^{1-\gamma}$. The total-factor productivity in year t is $\Omega_t{}^{\theta} A_t$, where θ is the partial-equilibrium effect of pollution on output holding labour supply constant. The partial-equilibrium effect of pollution on labour supply is given by κ.

Using estimates of the parameters θ, κ and μ, we simulate a dynamic IAM calibrated to data on China's economy to obtain economy-wide general-equilibrium effects (see Section 5 for details).

2. Primary Data

We estimate firm-level productivity combining comprehensive data on firm characteristics with air pollution data for highly-specific geographic areas across all of China from 1998 to 2007. While several different pollutants' effects on productivity have been studied we focus on $PM_{2.5}$ because of its severe effects. Our pollution measure is the 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 they provide the most comprehensive measure of air pollution across China's geography and over time. AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution even in areas lacking ground-based monitoring stations (Gupta *et al.*, 2006; van Donkelaar *et al.*, 2010; Kumar *et al.*, 2011). Chen *et al.* (2017) validated the AOD data using ground-based station data in China and found 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, the AOD data predate the beginning of our firm sample in 1998 while ground-based pollution data are

[5] The services sector produces little $PM_{2.5}$. Our manufacturing data do not include power plants, so we implicitly assume that $PM_{2.5}$ from power plants scales proportionally with manufacturing output.

[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 utilise M2TMNXAER version 5.12.4 that reports monthly AOD data within each 0.5° latitude by 0.625° longitude (corresponding to a 50 km by 60 km) grid.

available beginning only in 2000, giving us two more years of data. Second, the AOD data cover 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 satellite data are not. The AOD pollution data are reported in grids of 50 km by 60 km, which we aggregate to the county level—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.

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

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 are from annual surveys of manufacturing firms conducted by China's National Bureau of Statistics (NBS). The survey includes all 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, accounting measures and firm characteristics.[8] This captures 90.7% of China's total manufacturing output in the later years (Brandt *et al.*, 2012). During our sample period this includes 2,082,823 firm-year observations and 544,308 unique firms.

Following Brandt *et al.* (2012) we match firms over time to form an unbalanced panel.[9] This matching process is careful and avoids interpreting name changes as different firms (see Online Appendix Section A.2 of Brand *et al.,* 2012). The panel is very unbalanced due to China's rapid growth during this period that leads to a large number of new firms surpassing the CNY 5 million revenue threshold year by year.[10] We also follow Brandt *et al.* (2012) in converting nominal values into real values using industry-level price indices. We drop observations with missing or unreliable data following the previous literature (Cai and Liu, 2009; Brandt *et al.*, 2012; Yu, 2015).[11] These represent 10.3% of observations and 7.9% of total manufacturing output. The biggest loss of data in estimation is due to firms appearing in only one year and dropped with

[7] The six-digit administrative code is published by the NBS' Administrative Division: http://www.mca.gov.cn/article/sj/xzqh/2020/. (in Chinese). In constructing the pollution and thermal inversion measures based on the satellite data, we take spatially weighted averages across a county of all pixels based on the proportion of the county that each pixel represents. Specifically, we interpolate within the original 50 km by 60 km grids using the bilinear method (Hijmans *et al.*, 2015) to obtain 10 km by 12 km grids to better accommodate counties that are smaller than 50 km by 60 km. For counties that span more than one 10 km by 12 km grid, we use a weighted average (by area) across all grids that it spans.

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

[11] 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.

the inclusion of firm fixed effects. These represent 16.1% of observations and 30.5% of total manufacturing output.[12]

Finally, we winsorise the top and bottom 0.5% of data based on each of the values of output, value added, employment and capital to be consistent with the previous literature (Cai and Liu, 2009) and because of the risk that these involve data entry or reporting errors. However, we show that the results are similar using the non-winsorised data. The results are also robust to excluding the few multi-plant firms in the data that cannot be uniquely matched to a single location. The final data include 1,593,247 firm-year observations for 356,179 unique firms. Geographically, the sample includes 2,755 counties with an average of 58 firms per county year.

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

First, using value added requires that prices do not reflect market power in either the primary or downstream input markets. If they do not, monetary-based measures are preferred over quantity based 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 the effect of pollution on productivity via instrumented values. The second issue concerns multi-product firms. Their product mix is not discernible from the firm's value added and may be correlated with pollution levels. However, our instrumenting strategy addresses this: thermal inversions are uncorrelated with a firm's decision of product mix, thereby removing any bias.

We obtain daily, station-level weather variables that could affect both air pollution and productivity, including temperature, precipitation, relative humidity, wind speed, sunshine duration and barometric pressure from the National Meteorological Information Centre of China. We convert the daily station data to the daily-county level using the inverse-distance weighting method (Deschênes and Greenstone, 2011) to give less weight to stations more distant from the geographic centroid. To allow for extreme weather events to have differential effects from more normal ones, we follow Deschênes *et al.* (2017) and calculate 20 quantiles for each weather variable based on the daily distribution and include the annual number of days within each quantile. The weather measures are then matched to the firm data by county year.

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

Table 1. *Summary Statistics for Firm-Level Productivity and County-Level Pollution Data.*

Variables	Mean	SD	Min	Max
Firm-year sample				
Firm				
Value added (CNY 1,000)	12,821	23,540	74	3,66,426
Employment (person)	207	299	10	3,013
Capital (CNY 1,000)	14,531	30,872	64	3,50,801
Output per worker (CNY 1,000)	88	160	0.13	16,248
Total factor productivity (OP estimates)	2.91	1.03	−3.23	8.44
Total factor productivity (LP estimates)	5.38	0.97	0.01	10.03
County-year sample				
Air pollution				
Particular matter ($PM_{2.5}$) ($\mu g/m^3$)	53.52	25.46	2.62	134.84
Thermal inversions				
Annual days with thermal inversions	156.95	78.75	0.00	333.00

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

For our instrument, we obtain thermal inversion data from NASA.[13] The data report air temperatures every 6 hours at 42 vertical layers from 110 to 36,000 m within 50 km by 60 km grids. We aggregate from the grid to the county level within each 6-hour period and for each layer. Following Arceo *et al.* (2016), we define a thermal inversion as the temperature of the second layer (320 m) being higher than that of the first layer (110 m).[14] We determine this within each six-hour period of each day for each county. Since thermal inversions are short lived (of 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 each county, we use the annual number of days that have at least one inversion.

Table 1 presents summary statistics of the key variables. The firm characteristics are at the firm-year level and reflect a high degree of variation in productivity. The pollution and thermal inversion data are at the county-year level. The pollution levels are such that they are likely to have an effect on mental and physical health and therefore productivity. The World Health Organization (WHO) recommends a maximum annual mean of 10 $\mu g/m^3$ for $PM_{2.5}$ and a maximum mean of 20 $\mu g/m^3$ 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.

3. Partial-Equilibrium Model Specification and Identification

To estimate the general-equilibrium effects of pollution on output, we proceed in three steps. We first estimate the partial-equilibrium effects of pollution on output by parameterising

[13] 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.

[14] The altitude used is referenced to sea level. There are missing values if layers are below the altitude for that grid. For example, if a grid's altitude is 400 m, the first and second layers (110 and 320 m) will be missing. In these cases, we use the two closest non-missing layers.

the model in Section 1. Second, we parameterise the pollution-damage function specified in Section 1 and estimate the partial-equilibrium effects of output on pollution. Third, we combine these two partial-equilibrium estimates in an IAM and simulate the general-equilibrium effects. In this section we discuss the specification and identification of the partial-equilibrium estimates.

3.1. *Partial-Equilibrium Effect of Pollution on Productivity*

To estimate the effect of pollution on productivity holding labour supply constant, we model total factor productivity in (5) in a log-linear form to be consistent with the previous literature that uses this functional form to relate productivity to physical pollution concentrations:

$$\ln(\text{productivity}_{it}) = \beta_0 \ + \beta_1 \Omega_{it} + \beta_2 \mathbf{W}_{it} + \alpha_i + \rho_t + \varepsilon_{it}. \tag{6}$$

Here i denotes the firm, the pollution elasticity $\theta = \beta_1 \bar{\Omega}$, where $\bar{\Omega}$ is mean $PM_{2.5}$ across all regions[15] and $\mathbf{W}$ contains the vector of weather variables faced by firm i in year t. We aggregate the annual pollution and weather measures to the county level because the location of most firms is known only at the county level and not finer. Because of this, we check the robustness to clustering the standard errrors (SEs) at the county-year level. Here θ captures the effect of pollution on productivity holding labour supply constant.

Firm fixed effects (α_i) capture time-persistent firm attributes that affect productivity. Since very few firms switch counties (7%) over the sample period, these also absorb most county-specific time-invariant factors that affect productivity. Similarly, no firms switch industries, so 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 effects. The error term (ε_{it}) captures time-varying, firm-specific unobservables that affect productivity. In our baseline estimation we cluster SEs by firm to allow for serial correlation in productivity within a firm over time but we show robustness to other clustering patterns.

We use two different measures for productivity: output per worker $\ln(Y_{it}/L_{it})$, where Y is the value added and L is the number of workers, and the total factor productivity TFP_{it} for firm i in year t.[16] In estimating TFP, we instrument for firms' endogenous choices of inputs using two different approaches: investment as an instrument (Olley and Pakes, 1996; OP) and intermediate inputs as an instrument (Levinsohn and Petrin, 2003; LP). Table 1 provides the summary statistics for TFP estimated under both approaches. The correlation between TFP (using the OP method) and output per worker is 0.71, significant at better than the 0.01% level. We use output per worker for our primary results to be consistent with the environmental economics literature, but the results are robust, although with somewhat smaller effects, using TFP. For TFP, we use a two-step approach as in Wang and Wang (2015), Yu (2015) and Brandt *et al.* (2017): in the first step we estimate TFP and in the second step we relate TFP to pollution including controls.

Identification requires that, conditional on the control variables, pollution is independent of the error in (6). The causal identification issues that are specific to our context include simultaneity

[15] As we show, estimation is robust to using the log-log form.

[16] Estimating output per worker has been criticised 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.

bias, omitted-variable bias and spatial sorting. We discuss these issues before introducing the pollution-damage function.

3.2. *Causal Identification Issue—Simultaneity and Omitted-Variable Biases*

Simultaneity bias can lead to OLS estimates of the effect of pollution on productivity to be biased either upward or downward. Absent any effect of pollution on productivity, higher productivity in a county leads to both more output and more pollution, biasing them upward toward or above zero. On the other hand, if pollution decreases productivity, this will lower output and therefore pollution biasing OLS estimates downward away from zero. If pollution lowers productivity, firms may also compensate by using more alternative inputs. If these inputs are high polluting, 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 the effect of pollution on productivity in OLS estimates (firm fixed effects capture time-invariant conditions). For example, counties with more productive firms may implement more advanced, lower-polluting technology over time, leading to an upward bias. Alternatively, firms that have older, higher-polluting technology may have low productivity and insufficient funds to upgrade their production technology over time, leading to a downward bias as technology degrades. Local trends in regulatory conditions may also bias OLS estimates. For example, counties with high-productivity workers may impose 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 technologies face environmental 'crises' and initiate more stringent regulations. We address these identification issues using instrumental variables.

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

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

$$\Omega_{it} = \tau_0 + \tau_1 I_{it} + \tau_2 \mathbf{W}_{it} + \alpha_i + \rho_t + \epsilon_{it}, \tag{7}$$

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 that the exclusion restriction is met in the second stage.

3.3. *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 that would bias estimates of the effect of pollution on productivity upward toward or above zero. Alternatively, firms may choose to locate in counties with more severe pollution because it reflects less stringent 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.

Firm fixed effects absorb any initial endogenous sorting of firms across counties so that only sorting that occurs during the sample period will introduce bias.[17] Only 7% of firms relocate counties during the sample period. Excluding these from estimation suggests some sorting effects and larger productivity effects absent sorting. Firm entry and exit during the sample period could introduce bias through endogenous selection. To check for this, 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 the negative effect of pollution on firm productivity.

Firm fixed effects absorb any initial endogenous sorting of workers, so that only movement of workers during the sample period will create bias. This effect is not likely large since we estimate annual effects and such migration would likely occur over longer periods, but we check for evidence of this occurring.[18] Based on OECD (2011) we categorise each firm as high, medium-high, medium-low or low technology and, based on their employment, compute the fraction of workers in each of the four categories in each county year. Changes in 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.

3.4. *Partial-Equilibrium Effect of Output on Pollution*

To estimate the effect of output on pollution (μ), we take logs and parameterise (4):

$$\ln(\Omega_{ct}) = \psi_0 + \mu \ln(Q_{ct}) + \alpha_c + \rho_t + \omega_{ct}. \tag{8}$$

Here c indexes counties, Ω_{ct} is the pollution concentration in county c in year t and Q_{ct} is the total output in county c in year t. County fixed effects (α_c) capture baseline concentrations in each county and year fixed effects (ρ_t) capture aggregate annual changes in concentrations. We assume that μ is constant over our sample period, but vary it outside that in our general-equilibrium simulations.

To instrument for the endogeneity of output with respect to pollution, we take advantage of China joining the WTO in late 2001 as an exogenous shock to output for firms in China's

[17] Sorting could occur by industry, but as no firms switch industries, firm fixed effects absorb this.
[18] Chen *et al.* (2017) found that people migrate in response to air pollution over a 5-year period.

coastal regions relative to that in its inner regions. This approach of comparing high- and low-exposure regions before and after trade liberalisation shocks has been widely used in the trade literature (e.g., Goldberg and Pavcnik, 2005; Verhoogen, 2008; Topalova, 2010). This provides a differences-in-differences estimator with counties in coastal regions as a treatment group and those in inner regions as a control group. With this as an instrument, we employ 2SLS with the first-stage equation

$$\ln(Q_{ct}) = \varsigma_0 + \varsigma_1 \mathbb{I}_{t>2001} \mathbb{I}_{c\in\text{Coast}} + \alpha_c + \rho_t + \nu_{ct}, \tag{9}$$

where $\mathbb{I}_{t>2001}$ is an indicator variable set to one in years after 2001 and zero otherwise, and $\mathbb{I}_{c\in\text{Coast}}$ is an indicator variable set to one if the county is on the coast and zero otherwise.

4. Partial-Equilibrium Results

4.1. *Effect of Pollution on Productivity*

We first present estimates not accounting for any endogeneity bias between productivity and pollution. Table 2 presents OLS estimates of (6) using output per worker. Without weather controls (column (1)), $PM_{2.5}$ pollution has no effect on productivity. Including weather controls (column (2)) reveals a positive effect of pollution on productivity.

In the presence of simultaneity or omitted-variable biases, OLS produces inconsistent estimates. We use (7) to produce instrumented values of pollution concentrations. We first check whether thermal inversions are predictive of productivity in a reduced-form estimate. Columns (3) and (4) of Table 2 show the results without and with weather controls. Both yield statistically significant results and the coefficient with weather controls implies that one additional day with an inversion annually decreases productivity by 0.03%.

The top panel of columns (5) and (6) of Table 2 show that the instrument is a powerful predictor of $PM_{2.5}$ concentrations. The coefficient on annual days with thermal inversions is positive and highly significant both with and without weather controls and the Kleibergen-Paap (KP) Wald rk *F*-statistic (Kleibergen and Paap, 2006) for weak identification is much larger than the Stock-Yogo critical value of 16.38.[19] One additional inversion day increases $PM_{2.5}$ by 0.036 $\mu g/m^3$ controlling for weather. This is a big effect. Using the results with weather controls, a one SD increase in the annual number of days with inversions increases $PM_{2.5}$ by 2.8 $\mu g/m^3$ (5.3%).

The lower panel of columns (5) and (6) show the second-stage results. Consistent with the instrument correcting for endogeneity, the coefficient moves to being significantly negative. Without weather controls, instrumented $PM_{2.5}$ has a negative and very significant effect on output per worker. A 1 $\mu g/m^3$ increase in $PM_{2.5}$ decreases productivity by 0.80%. Controlling for weather increases the estimate slightly and makes it even more significant. A 1 $\mu g/m^3$ increase in $PM_{2.5}$ decreases productivity by 0.82%. Evaluating this at the mean $PM_{2.5}$ in the sample (53.5) yields an elasticity of −0.44. Dechezleprêtre *et al.* (2018) found a lower elasticity (−0.11) for European regions that could be due either to lower levels of pollution in Europe or due to their data including both manufacturing and services. Using TFP as our productivity measure yields slightly lower estimates: an elasticity of −0.26 using the OP estimator and −0.19 using the LP estimator (columns (7) and (8)). Throughout the rest of the paper, we focus on results

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

Table 2. *OLS and 2SLS Estimates (Effect of Air Pollution on Productivity) and Reduced-Form Estimates (Effect of Thermal Inversions on Productivity).*

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

Notes: All models include firm and year fixed effects (in both stages for 2SLS). Sample period: 1998–2007. SEs 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).

using output per worker since previous papers estimating the effect of pollution have used this. However, the results are robust to, but somewhat lower, using TFP. Also, since controlling for weather is preferred, we do so throughout the remainder of the paper.

How large are these effects? Consider a nationwide exogenous decrease in $PM_{2.5}$ of 1%. 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 methods that do not reduce output. The resulting productivity improvement increases the average firm's value added by CNY 56.3 (USD 7.4) thousand annually and increases total value added across all firms by CNY 9.0 (USD 1.2) billion annually. This represents 0.060% of China's GDP.[20] In Online Appendix B we compare estimates for counties in China's three major economic centres (Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta) to the rest of the country.[21] The estimates for the two are fairly close to each other and significant, implying that air pollution affects productivity even outside the major manufacturing centres.

Since our estimates capture the effect of pollution 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.[22] We borrow estimates from Aragón *et al.* (2017), who found an elasticity of working hours with respect to $PM_{2.5}$ of -0.21 in Lima, Peru. Assuming that $PM_{2.5}$'s effect on working hours is the same in China, our estimated elasticity of per-hour productivity with respect to pollution is -0.23. It is similar to the upper end of estimates by He *et al.* (2019) for textile workers in two firms in two Chinese provinces. They found 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.* (2019), who found an elasticity of -0.052 for per-hour productivity with respect to $PM_{2.5}$ for garment factory workers in India. It is also larger than the elasticity of -0.062 for $PM_{2.5}$ found in Chang *et al.* (2016) for indoor pear packers in California and the elasticity of -0.023 with respect to the API for service workers (Chang *et al.*, 2019). The fact that we estimate elasticities that are at least as great as or greater than previous papers could be due to two factors. First, previous estimates apply only to particular worker types or small sets of firms. Second, previous studies measure daily or monthly effects while we capture annual cumulative effects.

We can also compare our estimates to studies that estimate the effect of $PM_{2.5}$ on economic outcomes besides productivity. To do so, we normalise results to the monetary impact of a 1% decrease in $PM_{2.5}$, which in our case increases productivity by USD 1.2 billion annually. Deryugina *et al.* (2018) estimated the short-run effect of $PM_{2.5}$ on mortality in the United States. They found that a 1% 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.* (2018) estimated the long-run effect of $PM_{2.5}$ on dementia in the United States. A 1% decrease in $PM_{2.5}$ concentration (0.09 $\mu g/m^3$) reduces medical expenditures on dementia by USD 0.11 billion annually, about one-tenth of our estimate. Chen *et al.* (2018) estimated the short-run effect of $PM_{2.5}$ on mental illness in China. A 1% decrease in $PM_{2.5}$ concentration (0.48 $\mu g/m^3$) reduces

[20] A 1% decrease in $PM_{2.5}$ increases annual output by 0.44%. The mean annual output per firm in the sample is CNY 12.82 million, implying an annual increase of CNY 56.3 thousand. There is an average of 159,325 firms present in each year of the sample, implying an annual increase in output across all firms of CNY 9.0 billion annually. China's average annual real GDP over the 10-year sample period is CNY 14.85 trillion.

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

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

expenditure on mental illness treatment by USD 0.60 billion annually—about one-half of our estimate.

4.2. *Robustness Checks*

In Online Appendix C we show 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 SEs may be biased downward (Kloek, 1981; Moulton, 1986). We check this in several different ways. Column (2) allows for two-way clustering of errors by firm and county by year (Cameron *et al.*, 2011). This allows for serial correlation in productivity within firms as well as spatial correlation within each county year. 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 SEs by county year, which allows unobservables to be spatially correlated within each county year. The SEs 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 SEs only slightly and the results remain significant.

Our baseline results use year fixed effects to control for nationwide time trends. We test for robustness to regional trends in four different ways: region-by-year fixed effects in column (5); province-by-year fixed effects in column (6); province-specific quadratic time trends in column (7); and year fixed effects along with province-specific quadratic time trends in column (8).[23] All four yield very significant results and all yield larger point estimates than our baseline except for province-specific quadratic time trends. We continue to use year fixed effects as the baseline because the province-specific time trends impose a specific functional form and the flexible year-by-province fixed effect results are less conservative.

Our baseline estimates weight all observations equally. Column (2) of Online Appendix D re-estimates weighting observations by value added per firm. The coefficient yields a slightly higher elasticity (−0.47) than the baseline estimates shown in column (1). Column (3) shows that not winsorising the data leads to results very similar to the baseline estimates (elasticity of −0.49 evaluated at the mean $PM_{2.5}$ of 53.3). Column (4) uses the raw data (before eliminating the unreliable observations as described in footnote 11 and without winsorising), yielding a somewhat lower elasticity (−0.39) using a mean $PM_{2.5}$ of 53.3. The survey is at the firm level and therefore it is possible that a firm has multiple plants in different locations, leading to an incorrect match with the pollution data. Column (5) eliminates the firms that have multiple plants (5% of our sample). The estimated elasticity (−0.43) is very similar to the baseline based on a mean $PM_{2.5}$ of 53.9. Finally, column (6) uses logarithmic rather than linear pollution. The elasticity (−0.52) is somewhat larger.

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

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

Table 3. *2SLS Estimates—Tests for Firm Sorting Based on Air Pollution.*

	(1)	(2)	(3)	(4)
	Firm-year sample		County-year sample	
Dependent variable:	ln(value added per worker)		Fraction of firms entering	Fraction of firms exiting
	Baseline	Exclude relocating firms		
$PM_{2.5}$	−0.0082***	−0.0124***	0.0033	0.0016
	(0.0014)	(0.0018)	(0.0027)	(0.0018)
KP F-statistic	8,249	12,377	218	322
Firm fixed effects	Y	Y	N	N
County fixed effects	N	N	Y	Y
Year fixed effects	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
Clustering	Firm	Firm	County	County
Sample size	15,93,247	1,432,765	23,091	22,684

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

4.3. *Tests for Firm Sorting*

Firms may relocate to places with better air quality to improve productivity or to places with lax environmental regulation to lower costs. Table 3 shows tests for this potential spatial sorting. Column (2) estimates excluding firms that relocated across counties (about 7% of firms) during the sample period. The estimated elasticity (−0.67) based on a mean $PM_{2.5}$ of 53.7 is larger than that of the baseline estimate (−0.44) using all firms (replicated in column (1)) consistent with either firms avoiding pollution to increase their productivity or a ‘pollution haven’ effect and high-polluting firms being more productive than low-polluting firms. This also means that our baseline estimates may understate the effect of pollution on productivity to the extent that the non-relocating firms are representative of the full sample.

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

If the effect of pollution on productivity is strong enough, firms may exit the market. Estimates using the full sample are conditional on survival, potentially understating the productivity effect.

To see if this might be a major factor, column (4) of Table 3 tests whether a county's instrumented pollution significantly affects the fraction of firms exiting the county in the following year. This regression is analogous to the entry regression and includes the same control variables and uses the same clustering of SEs. Year 2007 data are 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.[24] This also suggests that any actions taken by the government to shut down firms in high-polluting areas and induced by thermal inversions are minimal.

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

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

For example, suppose that 9% of firms nationwide appeared for the first time in a given year. Consider a county that had 0.04% of the nation's 'below-scale' firms in 2004, 0.05% of the nation's total firms in 2004 and that 8% of its firms appeared for the first time in that year. For r equal to 10% (fraction of firms that appeared nationwide that we assume moved from 'below scale' to 'above scale' rather than entering), we would adjust this county's entry rate to be $8\% - 9\% \times 0.1 \times (0.0004/0.0005) = 0.0728$. Having adjusted these rates for all years and counties, we re-run the entry regression varying r from 0 to 1 but bounding the entry rate to be non-negative. In Online Appendix G we describe the procedure in more detail and in Online Appendix H we show the results for increments of 0.1 for r. Instrumented pollution has no significant effect on entry over the entire range of r, providing suggestive evidence that censoring does not affect the results.

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

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

Table 4. *2SLS Estimates—Tests for Worker Sorting Based on Pollution.*

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

Notes: All models use the annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects and weather controls in both stages. The technology intensity definition in columns (2) through (6) is from https://www.oecd.org/sti/ind/48350231.pdf. We group high technology and medium-high technology into high technology in column (5), and we group low technology and medium-low technology into low technology in column (6). Sample period: 1998–2007. SEs 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).

results are shown in Online Appendix I. The results are again insensitive to the value of r over the entire range—instrumented pollution has no significant effect on exit.

4.4. *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, the effect of pollution on productivity is attenuated for firms with high-skilled workers. To test for worker sorting based on pollution levels, we see whether a county's instrumented pollution in a year affects the fraction of the county's workers employed by high- versus low-technology firms in that year. We classify a firm's technological intensity based on its industry following OECD (2011), which classifies industries as high, medium-high, medium-low or low technology. We then compute the fraction of workers employed in each of these categories in each county year using each firm's employment. 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 SEs by county to allow for intertemporal correlation of unobservables within each county.

Columns (1) through (4) of Table 4 show the results of estimating how instrumented pollution affects the fraction of employment in each of these four categories. The effects are all insignificant except for the fraction in low-technology industries, which air pollution increases. This is consistent with low-productivity workers sorting to more polluted areas although the effects are small. A 1 $\mu g/m^3$ 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 is 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.

4.5. *Effect by Worker Skill Level*

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

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

4.6. *Effect on Labour Supply, Capital and Output*

Estimates so far capture the effect on productivity conditional on the number of workers. Pollution may also affect the number of workers employed (the κ parameter in (5)). To assess this, we estimate (6) with the log number of workers in each firm as the dependent variable using the annual number of days with a thermal inversion as the instrument. The survey data capture both permanent and contract employment, thereby making it likely we can capture annual adjustments in response to pollution. The survey measures end-of-year employment, so that employment changes due to pollution over the course of a year are captured.

The results are shown in column (2) of Table 6. A 1 $\mu g/m^3$ increase in $PM_{2.5}$ increases employment by 0.51%, implying an elasticity of 0.27. Although firms increase employment to compensate for some of the productivity loss, it is not enough to fully offset it. 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 1% increase in $PM_{2.5}$ increases employment by 0.27%, or 0.56 additional workers per firm. The average annual wage per worker in the sample is CNY 12,650 (USD 1,664), implying an additional cost per firm of CNY 7,147 (USD 940). Aggregated across all firms this equals CNY 1.14 billion (USD 0.15 billion) annually or 12.7% of the productivity loss from the 1% increase in $PM_{2.5}$.

In column (3) of Table 6, we show the results of estimating (6) with log capital as the dependent variable.[25] There is no significant effect. Column (4) estimates the effect of pollution on the log

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

Table 5. *2SLS Estimates—Effect of Air Pollution on Productivity by Firm Technology Level.*

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(value added per worker)						
		Four categories				Two categories	
	Full sample	High technology	Medium-high technology	Medium-low technology	Low technology	High technology	Low technology
$PM_{2.5}$	−0.0082***	−0.0119**	−0.0134***	−0.0061**	−0.0060***	−0.0128***	−0.0061***
	(0.0014)	(0.0056)	(0.0028)	(0.0028)	(0.0022)	(0.0025)	(0.0017)
KP *F*-statistic	8,249	365.6	1,796	2,495	3,902	2,178	6,348
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y
# firms	356,179	24,652	102,699	97,918	130,910	127,351	228,828
Sample size	1,593,247	112,792	467,768	435,842	576,845	580,560	1,012,687
Share of sample size (%)	100.0	7.1	29.4	27.4	36.2	36.4	63.6

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

Table 6. *2SLS Estimates—Effects of Air Pollution on Productivity, Employment, Capital and Value Added.*

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

Notes: All models use the 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. SEs 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).

value added. The effect is significant and the elasticity of the value added with respect to pollution is −0.17. This equals the summed effect of pollution on productivity ($\theta = -0.44$) and its effect on labour supply ($\kappa = 0.27$) and will also be used below in our general-equilibrium simulation.

4.7. *Mitigation of the Pollution-Productivity Effect*

As shown above, firms compensate for the reduced productivity that pollution causes by hiring more labour. It is useful to know whether high-polluting firms compensate more or less than low-polluting firms since this has ramifications for the resulting level of pollution and output. Columns (2) and (3) of Table 7 compare the effect of pollution on labour supply for ‘polluting’ versus ‘clean’ firms.[26] The effects do not differ significantly between the two. Columns (5) and (6) provide one possible explanation for this. ‘Clean’ firms experience a larger negative productivity shock than ‘dirty’ firms. While this would imply a greater incentive for ‘clean’ firms to hire more workers than ‘dirty’ firms, ‘clean’ firms may be more likely to utilise high-skilled labour that is also likely to be in less elastic supply than low-skilled labour.

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

Environmental regulations could result in differential effects on firms in different industries or locations, including due to different strategic responses to these regulations (Zou, 2021). However, we are unable to test for this. Prior to 2008, environmental regulation in China was minimal and the policies in place were often unenforced or under-enforced.[27] We suspect prior to this, GDP-based promotion criteria for local government officials led them to emphasise GDP

[26] We define ‘dirty’ and ‘clean’ based on the three-digit SIC codes in Mani and Wheeler (1998).

[27] Environmental protection measures were first added to government officials’ promotion criteria in December 2005. See http://www.gov.cn/zwgk/2005–12/13/content_125680.htm (in Chinese).

Table 7. *2SLS Estimates—Effects of Air Pollution on Employment and Productivity Split by 'Clean' Versus 'Polluting' Firms.*

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

Notes: All models use the annual number of days with thermal inversions as first-stage instruments. All models include firm fixed effects, year fixed effects and weather controls in both stages. The pollution intensity definition in columns (2), (3), (5) and (6) is from http://www.oecd.org/industry/inv/investmentstatisticsandanalysis/2076285.pdf. Sample period: 1998–2007. SEs 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 8. *Effect of Output on Pollution (OLS and 2SLS Estimates) Using the Effect of China Joining the WTO on Coastal Versus Inner Regions as an Instrument.*

	(1) OLS	(2) 2SLS
		First stage
Dependent variable:		ln(value added)
Coast × post-2001		0.0574***
		(0.0147)
KP F-statistic		15.3
		Second stage
Dependent variable:	$\ln(PM_{2.5})$	
ln(value added)	0.0048***	1.4317***
	(0.0012)	(0.3665)
County fixed effects	Y	Y
Year fixed effects	Y	Y
Sample size	25,357	25,357

Notes: Both models include county and year fixed effects (in both stages for 2SLS). Sample period: 1998–2007. SEs are clustered at the county-year 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).

growth to the exclusion of environmental quality. Nonetheless, differential effects will only be reflected in our results to the extent they are correlated with thermal inversions.

4.8. *Effect of Output on Pollution*

Estimating the effect of output on pollution depends on obtaining instrumented values of output that are uncorrelated with endogenous shocks to pollution. The key identifying assumption for our WTO instrument (9) is that the pre-treatment trends are parallel for coastal and inner regions prior to China joining the WTO. In Online Appendix K we plot coefficients and 95% confidence intervals from regressing county-level output on year dummies interacted with $\mathbb{I}_{c\in \text{Coast}}$ conditional on county fixed effects. The interaction terms (normalised to zero in 2001) show no obvious trend prior to 2002 and display an upward trend after 2002.

Table 8 reports the estimates of (8) and (9) using data for our sample period. The instrument is reasonably powerful and yields an elasticity of 1.43 for $PM_{2.5}$ with respect to output that is statistically very significant. The OLS estimate is about one-third of this, consistent with attenuation bias due to endogeneity.

5. General-Equilibrium Effects

5.1. *The Model*

To simulate the dynamic, general-equilibrium effects of pollution on output, we calibrate an IAM that integrates polluting activities into a standard growth model of a market economy (Xepapadeas, 2005 provides an overview of such models). There is a broad literature using IAMs to model climate change but a few focus on particulate matter (e.g., Carbone and Smith, 2008; Aldeco *et al.*, 2019). Like these papers, we do not model how $PM_{2.5}$ is emitted and accumulates in the atmosphere because it hovers in the air for a much shorter time than measured by our annual data (Aldeco *et al.*, 2019). The model treats pollution as a productivity-reducing input and undesirable output of firm production. The model dynamics capture the effects of capital-stock accumulation that is important given China's rapid growth during our sample period.

The model is an intertemporal, general-equilibrium model in which a representative agent chooses period-by-period consumption to maximise utility discounted by the rate of social time preference and subject to an economic constraint and a pollution-damage function. It assumes decentralised utility-maximising households and perfectly competitive profit-maximising firms (a Ramsey model). The production and pollution-damage functions are those in the illustrative models that inform our partial-equilibrium estimation. Population and technology grow exogenously while capital accumulates according to the optimal rate of investment.[28]

The model maximises the sum of lifetime discounted utility for a representative consumer in the population P_t using a logarithmic utility function of per-capita consumption ($c_t = C_t/P_t$), where C_t is the aggregate consumption. We assume that the fraction of the population in the work force remains the same over time ($P_t = ML_t$), i.e.,

$$\max_{c_t} \sum_{t=1}^{T} ML_t \ln(c_t)(1+\rho)^{-t},$$

where ρ is the annual rate of social time preference. Output is given by (5), which captures both pollution effects that we find in our partial-equilibrium analysis: changes in productivity and labour supply (effective units of labour). The pollution-damage function that relates contemporaneous pollution to output is given by (4).

Gross output is divided between investment (I_t) and aggregate consumption, i.e.,

$$Q_t = C_t + I_t,$$

and the law of motion for capital is

$$K_t = (1-\delta)K_{t-1} + I_t,$$

where δ is the rate of capital depreciation.

5.2. *Simulation*

We simulate the model to fit economy-wide data for China (Feenstra *et al.*, 2015; Zeileis, 2019) during our sample period using our partial-equilibrium estimates of θ, κ and μ. We simulate over a sufficient number of periods so that the outcome during our sample period is not significantly affected by endpoint conditions. We found that simulating 100 years (1996 to 2095) is sufficient. We assume that the effect of pollution on output ($\theta + \kappa$) is constant over the entire 100 years (i.e., firms cannot engage in avoidance behaviour), but we allow for exogenous improvements in abatement technology (μ decreases to 1.0 in 2095) that occur smoothly beginning after the sample period. Our chosen parameters result in simulated levels of output and pollution that are close to the actual during the sample period. Online Appendix L provides evidence of the fit and more details on data sources and how the model is calibrated and solved.

We set λ_t (the fraction of output produced by the manufacturing sector) equal to its actual values from 1996 to 2017 (National Bureau of Statistics of China, 2018) and we assume that

[28] Because we assume exogenous technological change, output will not grow in the long run without technological progress. However, our sample period is short and the capital stock does not accumulate rapidly enough that it is affected by the long-run growth rate in our simulations.

it remains constant at the 2017 value thereafter. While a more realistic model would allow for separate services and manufacturing sectors, manufacturing is a relatively constant fraction of GDP over the sample period (45.8% in 1998 versus 46.9% in 2007). The labour share $(1 - \gamma)$ is 0.425 based on the average labour share in China from 1996 to 2017 and the initial capital stock in 1995 is its actual value of USD 10.18 trillion. TFP is initialised to its actual value in 1996 and we assume that it grows at 7.96% per annum from 1996 to 2017 based on Brandt *et al.* (2012), after which it declines to 3.0% in 2033 and then remains constant. The actual capital, labour share and TFP data are from Feenstra *et al.* (2015) and Zeileis (2019). The depreciation rate is 0.09 based on Brandt *et al.* (2012) and the consumer's rate of time preference is 0.04 based on Chang *et al.* (2015). The pollution-damage function intercept (B) is set to fit average $PM_{2.5}$ concentrations over the sample period.[29] Population is based on actual and projected data from the United Nations.[30]

After calibrating the model, we run counterfactuals to assess the general-equilibrium effects of pollution. We vary μ_t slightly to generate a local derivative of output with respect to pollution. A 1% decrease in $PM_{2.5}$ over all years increases manufacturing output by 0.28% on average over the sample period compared to the partial-equilibrium increase of 0.17%. A 1% exogenous reduction in $PM_{2.5}$ increases the average firm's value added by CNY 35.9 (USD 4.7) thousand annually and increases the total value added across all firms by CNY 5.7 (USD 0.75) billion annually (0.039% of China's GDP). To assess the sensitivity of these results to the uncertainty in our partial-equilibrium estimates, we re-simulated the model using the 95% confidence intervals for the effect of pollution on output $(\theta + \kappa) \in [-0.329, \ -0.014]$ and the effect of output on pollution $\mu \in [0.713, 2.15]$. The elasticities ranged from -0.020 to -0.515.

Output is more responsive to pollution in the dynamic, general-equilibrium model because of the trade-off between current and future consumption. Because future consumption is discounted, an exogenous pollution increase results in a smaller decrease in current than future consumption. This lowers current investment and thereby the accumulation of capital stock, which lowers output more (in percentage terms) than is the case in a static model.[31]

These results can be used to directly evaluate the general-equilibrium effects of policies. For example, China's Air Pollution Prevention and Control Action Plan enacted in 2013 stipulated that, by 2017, $PM_{2.5}$ concentrations should fall by 25%, 20% and 15% in Beijing-Tianjin-Hebei, the Yangtze River Delta and the Pearl River Delta regions, respectively, which are China's main industrial centres.[32] Using the midpoint of these three goals (20%) and scaling our elasticity estimate linearly, the productivity boost from reaching this target would be 5.6% (0.77% of GDP) if derived from exogenous decreases in pollution.

It is useful to place these benefits in context by quantifying the costs of reducing $PM_{2.5}$. Unfortunately, we are unaware of direct estimates of the costs of $PM_{2.5}$ reductions. The best we can do is to rely on indirect measures for other pollutants estimated from policy interventions. The most useful estimate comes from the United States. Pollution-intensive industries in counties subject to regulation under the Clean Air Act lost on average USD 7.9 billion of output annually relative to counties that were not (Greenstone, 2002). At the same time, air pollution declined by roughly 12% more in non-attainment relative to attainment counties (Chay and Greenstone,

[29] Xepapadeas (2005) discussed the issue of modelling concentrations rather than emissions in IAMs.

[30] Data are found at https://population.un.org/wpp/.

[31] In a static analysis with the constant-elasticity relationship between output and pollution in (4) and (5), an exogenous increase in pollution will result in an output decrease equal to the partial-equilibrium estimate (-0.17). This will not be the case either with other functional forms in a static analysis or with dynamics.

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

2005).[33] Combining these two estimates, a back-of-the-envelope calculation indicates that a 1% reduction in pollution costs USD 0.66 billion. This is a lower bound on the costs because the estimate from Greenstone (2002) is a partial-equilibrium estimate that does not consider the effect of output on pollution. This is 83% of our estimate of the benefits of reducing $PM_{2.5}$ by 1% (USD 0.75 billion annually).

There are other studies that provide more indirect measures of the costs of reducing pollution. The pollution-reduction measures taken during the 2008 Beijing Olympic Games decreased PM_{10} concentrations from 24% to 33% in the city (Chen *et al.*, 2013b; He *et al.*, 2016). Restricting 1% of vehicles in Beijing one day per week reduces PM_{10} by 1% (Viard and Fu, 2015). A one SD increase in subway density in Beijing reduced particulate matter by 2% (Li *et al.*, 2019) and a subway opening decreases particulate concentrations by 4% around a city centre (Gendron-Carrier *et al.*, 2018). Derivation of these costs and explanations of the pollutants are given in Online Appendix M.

Our simulation has several important simplifications that could be relaxed with further modelling or data collection or that are better suited to other settings. First, we assume that China is a closed economy. Trade could be incorporated in the model at the expense of much greater complexity (Xepapadeas, 2005 provides examples) and loss of transparency. Our abstraction from this is an obvious simplification given that China is a large importer and exporter during our sample period. We implicitly assume that the consumer is representative of both domestic and export consumers and that input prices are determined domestically rather than worldwide.

Second, we do not treat pollution as a source of disutility. That is, air pollution is separable from consumption and leisure in utility. Awareness of air pollution was limited during our sample period and unlikely to directly affect consumer purchases.[34] It would be useful to analyse this using later data (Carbone and Smith, 2008 provided a model; Ito and Zhang, 2020 provided an estimate of the marginal willingness to pay for air quality). This would allow for two possible effects of pollution externalities absent from our model: pollution could affect consumption and labour supply, which would in turn affect output and thus pollution. Besides these, pollution may affect health and mortality negatively, which we ignore.

Third, we do not allow for endogenous changes in abatement technology over time. Abatement efforts are not significant during our sample period.[35] Allowing for endogenous abatement efforts would be important in analysing later time periods and could be incorporated by allowing the pollution-output elasticity to depend on a stock of knowledge that accumulates through research and development expenditures (Buonanno *et al.*, 2003; Gillingham *et al.*, 2008). As Gillingham *et al.* (2008) argued, it is useful to endogenise technological change to allow policies to affect the direction of technological change toward abatement efforts over time.

Fourth, we assume that manufacturing is an exogenous fraction of total output. In other contexts or time periods this may significantly depart from actual conditions, in which case multiple sectors could be accommodated as in Carbone and Smith (2008). Multiple sectors could

[33] This is for 'total suspended particulate', an older measure of particulate pollution but the closest measure available at that time to the pollutant we examine.

[34] Ito and Zhang (2020, Online Appendix A.4) marked increased awareness beginning in 2013: from 2006 to 2012, annual media mentions of air pollution in China averaged 158 headlines but jumped to 1,327 (1,549) in 2013 (2014).

[35] As discussed in footnote 27, government officials were not evaluated on environmental criteria until December 2005, so incentives to invest in abatement efforts was limited prior to this time.

also allow for endogenous choice of 'dirty' versus 'clean' intermediate inputs that would be important in contexts with significant abatement efforts.

6. Conclusion

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

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

Our findings shed new light on the debate about whether environmental regulations positively or negatively affect firm competitiveness (Jaffe *et al.*, 1995; Greenstone *et al.*, 2012). Historically, this debate has focused on the extent to which decreased competitiveness from environmental compliance costs is offset by process innovations that are both cleaner and of lower cost. Our results confirm another channel that influences this debate. Environmental regulations that decrease air pollution will in turn increase productivity and at least partially offset the decreased productivity due to complying.

Since our identification relies on yearly variation, we are unable to estimate long-run effects of pollution on productivity. In the long run firms may take steps to respond to pollution, such as protecting indoor workers or moving to lower-pollution areas to boost productivity. Workers may also 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.

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

Our general-equilibrium model of pollution effects could be expanded along several dimensions, including allowing for investments in abatement technologies, influence of trade, consumer disutility from pollution and multiple sectors. These extensions would allow an evaluation of other avenues that environmental policies may impact.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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