Evaluating Air Pollution Regulation: Separating Firm Competitiveness and Ambient Effects*

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Abstract

Measuring environmental regulation's effect on firm competitiveness is central to designing optimal policies. Existing studies document significant negative effects of air pollution regulations on manufacturing competitiveness as measured by total factor productivity (TFP). A separate literature finds that air pollution lowers TFP through its ambient effect on workers' physical and mental health and cognition. Extant empirical measures of the competitiveness effect reflect both. We develop a boundary-discontinuity-difference-in-differences (BD-DD) approach to isolate the competitiveness effect based on the idea that only regulated firms suffer the competitiveness effect but both regulated and unregulated firms adjacent to each other enjoy the ambient effect via spillovers. We apply the approach to a major air pollution regulation in China. The traditional approach to estimating the regulation's effects yields a 3.8% TFP decline among surviving firms at a total cost of CNY 30.2 billion annually. The true competitiveness effect is 6.4% (51.6 billion). The implied ambient effect is 2.6% (21.4 billion) among regulated firms. While difficult to quantify, the ambient effect is also enjoyed by all proximate unregulated firms. Consistent with this, we find that the ambient effect on control firms declines with distance from a treatment region.

JEL Codes: Q52; Q51; Q53; L51
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1. Introduction

Theoretically, binding environmental regulations can raise or lower firms' costs. Regulations impose compliance costs on firms including capital costs, such as pollution abatement equipment, and labor costs, such as compliance personnel. On the other hand, regulations may increase productivity if it leads firms to rationalize their production processes or spurs innovations that lower costs or improve quality as argued by Porter (1991).[1] The direction and magnitude of the competitiveness effect is important for several reasons. Most directly, it is an important input in the cost-benefit analysis of environmental policies. Regulations involve implementation costs but also impose costs on firms if firm competitiveness is lowered. Second, if environmental regulations affect firms' costs then they affect a country's trade position and balance of payments vis-a-vis other countries. Third, from a political economy perspective, the answer to the question determines whether firms will resist or encourage the enactment of environmental regulations and how strongly.

Given the theoretical uncertainty about the direction of the competitiveness effect and the important ramifications, empirical estimates are critical. The most notable estimates for air pollution are by Greenstone *et al.* (2012) for the 1970 US Clean Air Act Amendments (CAAA) using a large plant-level data set from 1972 to 1993. The Act imposed regulations on plants not in compliance with pollution standards across multiple pollutants. Comparing non-attainment with attainment plants, the paper finds a 2.6% decline in total factor productivity (TFP) among surviving plants that were in non-attainment due to any pollutant. The other notable estimate of a competitiveness effect is He *et al.* (2020) for water pollution in China using an increase in regulatory stringency in 2003. Using data from 2000 to 2007, the paper finds a 24% reduction in TFP for firms subject to monitoring versus those not.

The typical approach to quantifying a competitiveness effect in the case of air pollution is a difference-in-differences (DD) estimate comparing treatment firms subject to the regulation to control firms that are not. A separate literature (Graff Zivin and Neidell, 2012; Chang *et al.*, 2019; He *et al.*, 2019; Fu *et al.*, 2021) estimates how air pollution reduces output due to effects on the physical and mental stamina of workers or work absences due to their or family members' health. This implies that regulations that reduce air pollution will result in productivity improvements. Because air pollution drifts spatially, these productivity improvements accrue not to a specific firm but rather to all firms in the proximate area regardless of whether they must comply with the regulations. We call this the "ambient effect." The standard DD approach will estimate the "combined effect" of the competitiveness

[1] The evidence for the "Porter Hypothesis" is primarily case-study based (Porter and van der Linde, 1995). Formal justifications rely on environmental regulations addressing X-inefficiency (Leibenstein, 1966) or very specific conditions in strategic trade models (Simpson and Bradford, 1996).

and ambient effects and understate the competitiveness effect (in absolute value) if interpreted as such.

Figure 1 illustrates these different effects. The competitiveness effect (the goal of our estimation) is displayed along the top path. This path reflects the net effect of the two forces – compliance costs and process improvements. The bottom path of the diagram shows the ambient effect – the extent to which pollution reductions increase output via lower morbidity, lower mortality, and improved cognition. The sum of these two effects equals the combined effect (shown on the right-hand side of Figure 1) and is what is measured in previous papers.

[Insert Figure 1 here]

Decomposing the combined effect into its two components is necessary in achieving socially-optimal air pollution reductions. Consider an environmental regulation aimed at reducing manufacturing emissions. The regulation creates a competitiveness effect, which is a cost, and an ambient effect, which is a benefit. Any associated air pollution reductions will convey the benefit of the ambient effect to all firms in the targeted areas. However, the cost of achieving the reduction (the competitiveness effect) is borne only by the firms that must comply with the regulation. To determine the optimal level of regulation, the competitiveness effect should be included as a cost (but applied only to the complying firms) and the ambient effect should be included as a benefit (applied to all the proximately-located firms). This also means that air pollution restrictions are less costly in regions with high firm densities.

For example, US EPA regulations often target counties in non-compliance with mandated pollution levels. In setting these levels optimally, the costs (the competitiveness effect) must be estimated accurately. If the competitiveness effect is quantified as the combined effect, then regulations will be too strict and the complying firms will bear socially-excessive costs. Interpreting the combined effect as a competitiveness effect also has relevance for the theoretical debate concerning the Porter Hypothesis. For example, Greenstone *et al.* (2012) estimate a small (1.7 to 2.2%) productivity increase for firms in non-attainment for CO in response to the CAAA. This could be consistent with the Porter Hypothesis, but if the ambient effect embedded in their estimate exceeds 2.2% this would be inconsistent.

To disentangle the competitiveness and ambient effects we develop a boundary-discontinuity-difference-in-differences (BD-DD) approach and apply it to a major air pollution regulation in China. We identify firms that are geographically close to each other (ten kilometers or less), some of which are subject to the regulation (the treatment group) and others of which are not (the control group). We then compare the response of the two groups to the advent of the regulation (the treatment). Since the control and treatment groups are in close proximity, they experience the same air pollution concentrations both before and after the policy implementation and differ only in the application of the regulation after its advent. This differs from the typical DD estimates which use treatment and control firms regardless of distance from each other. In this case, the two groups experience different ambient pollution levels with the advent of the regulation in addition to the difference in regulatory compliance.

We apply our approach to a regulation known as the "Plan of Key Cities Designation for Air Pollution Control" (KCAPC) which imposed air pollution controls on selected cities.[2] We apply the BD-DD approach to estimate the policy's competitiveness effect on TFP in China's manufacturing sector. We also apply the traditional DD approach to estimate the policy's combined effect. The difference between these two estimates equals the productivity improvements due to ambient pollution reductions from the policy. The standard DD approach estimates a combined effect of -3.8% among surviving firms for a total annual productivity cost to all firms of CNY 30.2 billion. The BD-DD approach estimates a competitiveness effect of -6.4% (CNY 51.6 billion annually) implying that the ambient effect is a 2.7% productivity increase for firms in treatment cities. Thus, the direct regulatory costs on firms would be understated by 2.6 percentage points (CNY 21.4 billion annually) or 42% using the pre-existing DD approach.

This paper is most closely related to Greenstone *et al.* (2012). It differs in that the focus is on developing a method to decompose the combined effect into the competitiveness and ambient effects. Also closely related to our work is He *et al.* (2020). The paper employs a regression discontinuity (RD) approach comparing the productivity of firms immediately upstream of a water quality monitoring station to those immediately downstream. Upstream firms are affected by the regulation while downstream firms are not because pollution upstream of a station is measurable while that downstream is not; and officials charged with implementing the policy are evaluated based on measurable pollution.

There are two key differences between this paper and ours. First, it is unclear whether there are significant productivity effects of cleaner water (the equivalent of the ambient effect in our setting). To the extent that polluted water needs to be purified before it can be used as a productive input, this "ambient" effect would be a byproduct of the regulation. This is likely to be much more localized than the

[2] In Chinese, the regulation is named"大气污染防治重点城市划定方案."

ambient effect for air pollution, which can extend hundreds of kilometers.[3] It is therefore less critical to quantify these for water pollution because they will apply to fewer firms. Second, but related, the purpose of He *et al.* (2020) is not to disentangle the competitiveness and ambient effects.

More broadly, our paper relates to three areas of literature. The first is the literature estimating the effects of air quality regulations on competitiveness, in particular Greenstone *et al.* (2012). As that paper notes, there is little other empirical evidence concerning the competitiveness effect of air pollution regulation on productivity except for specific industries (Gollop and Roberts, 1983; Ryan, 2012). We contribute to this area of literature by providing a method to isolate the competitiveness effect from the ambient effect in an air pollution context.

The second area is the literature quantifying the direct effects of air pollution on productivity – the ambient effect in our setting. This area of literature began by focusing on specific occupations or industries (Graff Zivin and Neidell, 2012; Chang *et al.*, 2016; Adhvaryu *et al.*, 2019; Chang *et al.*, 2019; He *et al.*, 2019) and then expanded to estimate nationwide or supra-national effects (Dechezleprêtre *et al.*, 2018; Fu *et al.*, 2021). These papers motivate the need to develop a framework for decomposing the combined effect into the competitiveness and ambient effects. In particular, Fu *et al.* (2021) shows that pollution has significant effects on TFP nationwide in China's manufacturing sector emphasizing the need to account for an ambient effect in evaluating China's environmental policies.

Third, there is a large literature that attempts to explain productivity dispersion among firms (Bartelsman and Doms (2000) and Syverson (2011) provide surveys). Environmental regulation is a contributing factor to this. However, quantifying this as the combined effect masks variation because there are actually two underlying contributions that are being averaged. The competitiveness effect applies to firms subject to a regulation while the ambient effect will be experienced by other firms depending on the density of firms and proximity to regulated regions.

The remainder of the paper proceeds as follows. The next section describes a conceptual framework for our analysis. Section 3 describes the institutional background and Section 4 our estimation approach. Section 5 describes the data to which we apply the estimation approach. Section 6 discusses identification and presents the results. We conclude in Section 7.

[3] Firms immediately upstream of a monitoring station might or might not experience an "ambient" effect. It depends on whether the purified water is re-used in their production processes versus floating downstream. This differs from our setting where pollution affects all firms in close proximity.

2. Conceptual framework

Our conceptual model closely follows that in Greenstone *et al.* (2012) which shows how environmental regulations might affect firm productivity. We augment their model to separate the combined effect into the competitiveness and ambient effects. We assume a manufacturing firm (also plant)[4] i produces a product according to a constant-returns-to-scale Cobb-Douglas production function employing $\tilde{L}$ units of labor and $\tilde{K}$ units of capital:

$$Q_i = A_i \tilde{L}_i^{\alpha} \tilde{K}_i^{1-\alpha}, \quad (1)$$

where Q is the firm's output and A is a Hicks-neutral technology shifter. $\tilde{L}$ and $\tilde{K}$ are production-effective labor and capital – the quantity actually used in production. Observed units of the two inputs (L and K) may differ because regulation may require firms to employ ineffective inputs in the production process such as compliance officers or pollution-reduction equipment. Observed units are related to effective units by:

$$\tilde{L}_i = \lambda_L(r, \Omega) L_i \quad (2a)$$
$$\tilde{K}_i = \lambda_K(r, \Omega) K_i, \quad (2b)$$

where λ_L and λ_K are proportionality factors that reflect the regulatory effect on input usage. r denotes regulatory stringency and Ω the ambient pollution faced by the firm. If more stringent regulations impose a greater competitiveness effect this decreases λ_L, λ_K, or both: that is, $\partial\lambda_L/\partial r \leq 0$ and $\partial\lambda_K/\partial r \leq 0$.[5] At the same time, more stringent regulations may reduce pollution $\partial\Omega/\partial r \leq 0$ and generate an ambient effect. This will indirectly increase input effectiveness: $\partial\lambda_L/\partial\Omega \leq 0$ and $\partial\lambda_K/\partial\Omega \leq 0$. To determine the effects of these on productivity, substitute them into the production function:

$$Q_i = A_i[\lambda_L(r, \Omega) L_i]^{\alpha}[\lambda_K(r, \Omega) K_i]^{1-\alpha} = A_i \lambda_L(r, \Omega)^{\alpha} \lambda_K(r, \Omega)^{1-\alpha} L_i^{\alpha} K_i^{1-\alpha}. \quad (3)$$

The firm's TFP is output divided by weighted inputs:

$$TFP_i = \frac{Q_i}{L_i^{\alpha} K_i^{1-\alpha}} = A_i \lambda_L(r, \Omega)^{\alpha} \lambda_K(r, \Omega)^{1-\alpha}. \quad (4)$$

Taking the derivative of logged TFP with respect to r gives the combined effect of regulation on TFP:

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[4] Only 5.2% of firms in our data set are multi-plant and we exclude them from estimation.

[5] If complying with the regulation forces firms to rationalize their processes resulting in greater output according to the Porter Hypothesis, this would increase either or both of these. We assume the derivative is negative given most previous evidence (and our results) favor a negative competitiveness effect.

$$\frac{\partial ln(TFP_i)}{\partial r} = \left[\alpha \frac{\partial ln(\lambda_L)}{\partial r} + (1-\alpha)\frac{\partial ln(\lambda_K)}{\partial r}\right] + \left[\alpha \frac{\partial ln(\lambda_L)}{\partial \Omega} + (1-\alpha)\frac{\partial ln(\lambda_K)}{\partial \Omega}\right]\frac{\partial \Omega}{\partial \mathrm{r}}. \quad (5)$$

The combined effect equals the effect on firm competitiveness (the first bracketed term) plus the regulation's effect on productivity via ambient pollution (the second bracketed term). To the extent that $\partial\Omega/\partial r < 0$, interpreting the overall estimate as the competitiveness effect will understate it (in absolute value). Our BD-DD approach eliminates the second bracketed term because it is differenced out by comparing firms that are exposed to the same pollution concentration levels (Ω).

3. Institutional background

On September 5, 1987, the State Environmental Protection Administration (SEPA) issued the "Air Pollution Prevention and Control Law of the People's Republic of China" (APPCL). The policy, implemented on January 1, 1988, specified air pollution reductions for 47 "key" cities. The law was regarded as being of limited effectiveness because it specified no formal pollution targets or monitoring mechanism.[6] As a consequence, it was revised in 1995 and again in 2000. We focus on this last revision issued on April 29, 2000.

On December 2, 2002 as a part of implementing this last revision, SEPA formally issued the KCAPC policy. The KCAPC identified 113 cities that were subject to regulations with the goal of meeting air quality targets by 2005.[7] The target was China's Class II air quality standard (formally designated GB3095-2000) with respect to six air pollutants: sulfur dioxide (SO_2), nitrogen dioxide (NO_2), total suspended particulate (TSP), ozone (O_3), carbon monoxide (CO), and particulate matter smaller than 10 micrometers in diameter (PM_{10}).[8] The standard specified maximum average annual, daily and hourly concentrations of these pollutants as shown in Appendix A.

The 113 cities subject to regulation under KCAPC were among the 338 cities with air pollution monitoring stations in 2000. They were chosen based on the city not meeting the GB3095-2000 standard in 2000 along with other criteria such as whether the city was a national key-tourism or culturally-protected city and its demographic and economic conditions. These are the treatment cities and all other cities (numbering 225) are control cities. The cities are defined by the four-digit level of the

[6] See http://www.gov.cn/gongbao/content/2000/content_60224.htm (in Chinese).
[7] A detailed description is at http://www.mee.gov.cn/gkml/zj/wj/200910/t20091022_172141.htm (in Chinese).
[8] The ambient air quality standard GB3095-2000 has three classes. Class II applies to residential, commercial, and traffic activities located in general industrial and rural areas. Class I is the strictest and applies to scenic areas and nature preserves. Class III is the least restrictive and applies to specialized industrial areas.

Administrative Division Codes of the PRC.[9] Appendix B shows the locations of the treatment and control cities.

The KCAPC policy did not go into effect until January 6, 2003 when SEPA issued its formal implementation.[10] We therefore take 2003 as the policy implementation threshold for our analysis. After the policy went into effect a city continued to be subject to regulation or not for the duration of our sample period.[11] The treatment cities were subject to oversight and restrictions while the control cities were not. The restrictions included promoting clean-energy use, barring high-polluting fuels, developing cogeneration and central heating, better controlling coal pollution, better restricting motor-vehicle emissions, better controlling construction and transportation dust, shutting down high-polluting plants, and requiring firms to establish environmental management systems.

SEPA supervised implementation at the national level. The policy targets were incorporated into the evaluation and promotion of government officials at the local level. Treatment cities were subject to frequent inspections. Both the national and local governments had enforcement powers to ensure compliance. Local city officials were required to regularly release information on the concentrations of each of the pollutants and their performance would influence promotions and demotions. The KCAPC policy achieved significant emissions reductions. By 2005, 48 of the treatment cities had met the Grade II standard.

4. Estimation approach

4.1 Overall approach

We first use the DD approach to estimate the combined effect for comparison to the previous literature. We then isolate the competitiveness effect using our BD-DD approach (see Figure 1 for the correspondence between policy effects and estimation). The difference between these estimates equals the ambient effect. To illustrate our approach, consider four firms in two cities A and B (Figure 2). City A is subject to the KCAPC policy while city B is not. A DD estimate comparing firms 2 and 4 quantifies the combined effect (competitiveness plus ambient effect). Firm 2

[9] The six-digit administrative code is published by the NBS' Administrative Division: http://www.stats.gov.cn/tjsj/tjbz/xzqhdm/201401/t20140116_501070.html (in Chinese). The first two digits identify one of the 31 provinces and the third and fourth digits the prefecture or major city.
[10] This is called the "Notice on the Work of Air Pollution Prevention and Control in Key Cities to Meet the Deadline." A detailed description is at http://www.mee.gov.cn/gkml/zj/bgt/200910/t20091022_173815.htm (in Chinese).
[11] The treatment cities' performance was formally evaluated in 2005. In 2005, the KCAPC's goals switched to a different standard (based on emissions rather than concentrations). The treatment cities, regardless of whether they had met the Class II air quality standard goal by 2005 or not, continued to be subject to controls though the end of the sample period while the control cities were not.

suffers from the competitiveness effect but also enjoys the ambient effect, while Firm 4 experiences neither given its far distance from the treatment city.[12]

[Insert Figure 2 here]

A BD-DD estimate comparing firms 1 and 3 isolates the competitiveness effect. Firm 3 enjoys the ambient effect because it is close to the boundary of the treatment city but does not bear the competitiveness effect because it need not comply with the regulation while Firm 1 also benefits from the ambient effect but must bear the competitiveness effect. The difference between the DD and BD-DD estimates equals the ambient effect.

We next describe the econometric model corresponding to the extant DD approach which estimates the combined effect. We then describe the econometric model for the BD-DD approach for isolating the competitiveness effect.

4.2 Combined effect (DD estimation)

Previous estimates of the effects of air pollution regulations on productivity (e.g., Greenstone *et. al.*, 2012) utilize a DD approach with firms in regulated locales as the treatment group and those in unregulated locales as the control group. We use this same approach to estimate the combined effect of KCAPC on productivity. For this estimation we include all firms in the sample that have data in at least one year before the policy and at least one year after:[13]

$$log(Productivity_{it}) = \beta^{CO} Post2003_t * KCAPC_{ct} + \eta_i^{CO} + \theta^{CO} X_{it} + \varepsilon_{it}^{CO}, (7)$$

where i indicates firm, t indicates year, and c indicates city and we index the parameters by CO to indicate combined effect. $Productivity_{it}$ is firm i's productivity in year t. The firm fixed effects (η_i^{CO}) capture time-persistent unobservables that affect firm productivity. Since firm fixed effects are included in all specifications the combined effect is identified from inter-temporal variation within firms.[14] X_{it} includes fixed effects which vary by specification (region-by-year or province-by-year and industry-by-year) and in some specifications weather controls. The region-

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[12] Previous DD estimates, and ours, include firms 1 and 3 in this estimation even though they are not separated far enough geographically to experience the difference in pollution levels brought about by regulation. They are usually included because studies typically involve large numbers of firms so that their influence is very small relative to the overall sample. In our case DD estimates excluding the BD-DD sample are very similar to those including it.

[13] We do so because firms that appear only before or after do not contribute to identifying the policy effects (firm fixed effects absorb the pre- or post-policy effects of any firm appearing only before or after the policy) and we want the summary statistics to reflect only data that aids in identification.

[14] Since firms rarely change cities (only 0.7%) and rarely change industries (only 1.1% using the 4-digit industry code) over the sample period, we do not include city or industry fixed effects since they would be nearly collinear with the firm fixed effects.

or province-by-year fixed effects control for geographic-specific unobservables within a year and the industry-by-year fixed effects control for industry-specific unobservables within a year that affect productivity.[15]

ε_{it}^{CO} captures firm-year specific shocks to productivity. In our baseline estimates we follow Greenstone *et al.* (2012) in clustering the standard errors by city-year to allow for spatial correlation across firms within a city-year but examine the robustness to clustering at the city level which allows for arbitrary correlations across firms and over time within a city.

The key variables for the DD estimation are the two indicators. $Post2003_t$ is set equal to zero prior to the imposition of the KCAPC and equal to one after. It captures the pre- versus post-policy periods. $KCAPC_{ct}$ is set to one if the city in which firm i is located is regulated under KCAPC and zero otherwise. β^{CO} captures the combined effect of the KCAPC policy on productivity – the differential effect of the policy on firms subject to its provisions and resulting ambient pollution reductions versus those not.

4.3 Competitiveness effect (BD-DD estimation)

To isolate the competitiveness effect, we embed this DD approach within a boundary discontinuity (BD) design that matches firms of opposite types (in regulated versus unregulated areas) that are geographically close to each other. In sufficiently close proximity, the two types of firms are exposed to the same ambient pollution concentrations but only those in regulated areas must incur costs to comply with the KCAPC. This estimation exploits the spatial discontinuity in regulations between treatment and control cities to estimate the causal effect of regulation on firm competitiveness. The BD-DD subsample includes all firms of opposite types that are sufficiently close that they experience the same $PM_{2.5}$ concentrations.

Specifically, we estimate Equation (7) but restrict the sample to treatment and control firms that are in close proximity ($i \in \{BD\}$):

$$log(Productivity_{it}) = \beta^C Post2003_t * KCAPC_{ct} + \eta_i^C + \theta^C X_{it} + \varepsilon_{it}^C, i \in \{BD\}. \quad (8)$$

β^C captures the competitiveness effect of the KCAPC policy on productivity: the differential effect of the policy on firms subject to its provisions versus those not but facing the same ambient pollution reduction due to the policy.

The BD aspect of our BD-DD estimation differs slightly from the typical BD approach. In the typical approach, we would compare outcomes for all firms within

[15] We divide China into seven geographic regions (North, Northeast, Northwest, East, Central, South, and Southwest based on the first digit of the Administrative Division Code as in Zhang *et al.* (2018).

a certain distance on either side of a physical boundary between treatment and control areas. Doing so would include many firms that do not have a corresponding firm of the opposite type (control versus treatment) in close enough proximity that they face similar ambient pollution levels. While including these firms would not bias our estimates it would add noise and reduce efficiency. The estimates' power depends on a high concentration of firms on both sides of a border. To ensure this, we include only firms that have another firm of the opposite type within a maximum distance. For example, suppose a treatment firm (A) has a control firm located eight kilometers away (B) and another control firm located fifteen kilometers away (C). If we impose a maximum distance cutoff of ten kilometers we would only include data for firms A and B in the estimation. If, instead, we impose a maximum distance cutoff of twenty kilometers we would include all three firms. An additional advantage of this approach is that it can be applied in settings in which air pollution regulations are applied to some but not all firms within the same geographic jurisdiction.

4.4 Illustrative example

To illustrate our estimation approach, consider a simple illustrative example. Suppose that a policy reduces pollution by 5.0% and imposes a competitiveness effect of -6.0%. Further, assume that the pollution gradient is 0.05% per kilometer (i.e., pollution drifts such that the pollution reduction declines by 0.05% per kilometer as you move away from a treatment area) and an elasticity of productivity with respect to pollution of -0.5. Figure 3a illustrates the policy's effect on pollution as a function of the distance from the boundary between a treatment and control region (with negative distances representing moving further into the treatment region and positive further into the control region) assuming a dense population of firms on both sides of the border. The dashed blue line shows the pollution reduction due to the policy. Firms in the treatment region reduce their emissions such that pollution concentrations decline uniformly by 5.0% in response to the policy while those in the control region do not reduce their emissions. In the control region, the further from the border (more positive distances) the lower the pollution reduction because the strength of the spillover declines with distance following the gradient of 0.05% per kilometer. The ambient pollution effect reaches zero at 100 kilometers into the control region.

[Insert Figure 3a here]

The green solid line in Figure 3a shows the change in productivity due to the pollution reduction (the ambient effect). Applying the elasticity, productivity improves uniformly by 2.5% in the treatment region. In the control region, the ambient productivity effect lessens as you move further from the border (at a rate of

0.025% per kilometer) as the strength of the pollution spillover declines, again hitting zero at 100 kilometers.

Figure 3b combines the ambient and competitiveness effects to show the combined effect as a function of the distance from the boundary. The solid green line replicates the ambient effect as a function of distance developed in Figure 3a (rescaled). The small-dashed red line shows the competitiveness effect of -6.0%. Only firms in the treatment region suffer from the competitiveness effect so it jumps discontinuously from -6.0% to 0% at the boundary between the regions.

[Insert Figure 3b here]

The long-dashed black line shows the combined effect (it coincides with the ambient effect in the control region) which is what is observed in the data. The discontinuous jump at the border equals the competitiveness effect (-6.0%). The combined effect hits zero at 100 kilometers since both the competitiveness and ambient effects are zero beyond this. Using this observed data, BD-DD estimates based on firms in close proximity to the border will yield an unbiased estimate of the competitive effect. DD estimates using the observed data, on the other hand, using a full sample that extends much deeper (well beyond 100 kilometers) into both the control and treatment regions than that illustrated will equal the average combined effect in the treatment region (-3.5%) minus the average combined effect in the control region (roughly zero since the non-zero effects between 0 and 100 kilometers will be a small part of the sample) or -3.5%. This estimate differs from the BD-DD estimates by 2.5% which is the average ambient effect.

5. Data

Our estimation combines data on firm productivity, pollution, and weather in China from 1998 to 2007. The policy change occurs in 2003.

5.1 Firm productivity data

Firm-level output and characteristics data is from the Annual Survey of Industrial Firms (ASIF) collected by China's National Bureau of Statistics (NBS). The survey includes all state-owned enterprises (SOEs) regardless of size and all non-SOEs whose annual sales exceed CNY 5 million (USD 0.75 million)[16] and contains detailed information on firm location, accounting measures, and firm characteristics. The survey includes only manufacturing firms so our results do not apply to the power generation sector or services firms. The survey captures 90.7% of China's total manufacturing output in the later years (Brandt *et al.*, 2012). We use the algorithm in Brandt *et al.* (2012) to match firms over time to form an unbalanced panel. This

[16] A 2022 exchange rate of 6.7 is used throughout the paper.

matching process is careful and avoids interpreting name changes as different firms. The panel is unbalanced because firms enter and exit during the sample period and non-SOEs may drop below or rise above the CNY 5 million threshold. We provide evidence that our estimates are unlikely to be greatly affected by this threshold. We also follow Brandt *et al.* (2012) in converting nominal into real values using industry-level price indices.

We drop observations with missing or unreliable data following the previous literature (Cai and Liu, 2009; Brandt *et al.*, 2012).[17] These represent 10.3% of observations and 7.9% of total manufacturing output. Also following the previous literature (Cai and Liu, 2009), we winsorize the top and bottom 0.5% of data based on each of the values of output, value added, employment, and capital because of the risk that these involve data entry or reporting errors; however, we check robustness to including these. Each firm is classified in an industry using the Chinese Industry Classification (CIC) code.[18]

We use the six-digit administrative code of the firm to assign it to a city and, in turn, to the treatment or control group. For the BD-DD analysis, we use the address provided in ASIF to determine the firm's latitude and longitude and use these to calculate the distance between firms when locating the nearest firm of the opposite type. For most firms, ASIF contains the street address. However, for 16.5% of firms, ASIF contains only the county or district level address. We drop these from the BD-DD sample since this is not specific enough to calculate a distance from the nearest firm of the opposite type. We drop multi-plant firms (5.2% of the data) because we are unable to allocate their productivity to a specific location.

We use three alternative measures for productivity. Our primary measures are TFP estimated using the OP and LP methods. We also check the robustness to labor productivity (output per worker) since this is commonly used in the environmental literature. We abstract from intermediate inputs and use value added as the measure of output. ASIF directly reports value added as the firm's 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.

Appendix C provides summary statistics for the final DD sample which includes 87,933 firms and 541,887 firm-year observations or 6.2 years of data per firm on average. The three productivity measures reveal significant variation and are highly

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[17] We drop observations with missing or negative values for output, value added, employment, or capital; firms with fewer than eight employees as they may have unreliable accounting systems; and firms violating accounting identities such as the components of net assets exceeding total assets or current depreciation exceeding cumulative depreciation.

[18] We use the National Economic Industry Classification (GB/T4754-2002) defined by the National Bureau of Statistics. This is similar to the US Standard Industrial Classification (SIC) code.

correlated with each other.[19] Appendix D provides summary statistics for the data used in our BD-DD estimation applying a maximum distance of ten kilometers between treatment and control firms (as we explain later, this is our preferred distance threshold). This ten-kilometer sample includes 35,398 unique firms and 224,334 firm-year observations or 6.3 years of data per firm on average.

5.2 Pollution data

We use data on $PM_{2.5}$ to confirm that the KCAPC policy affected pollution concentrations. Although $PM_{2.5}$ pollution was not directly regulated under KCAPC, it is the only pollutant for which data of nationwide coverage and sufficient geographic specificity is available. Different air pollutants are highly correlated so that our results provide indirect evidence that other pollutants were affected. We measure $PM_{2.5}$ as annual concentrations derived from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by the National Aeronautics and Space Administration (NASA).[20] The $PM_{2.5}$ concentrations are calculated following van Donkelaar *et al.* (2016) and van Donkelaar *et al.* (2018). This dataset has been used in other studies of China's air pollution (Freeman *et al.*, 2019; Greenstone *et al.*, 2021). The AOD pollution data are reported in 1- by 1-kilometer grids which we aggregate to the city level using the six-digit administrative code.

5.3 Weather data

In some specifications we include data for weather because it has been found to affect firm productivity (Zhang *et al.*, 2018) and also affects pollution levels. We include this only as a robustness check because it will only confound our estimates if weather conditions are correlated with the policy implementation. We obtain daily, station-level weather variables from the National Meteorological Information Centre of China.[21] We aggregate the data to the city level using the inverse-distance weighting method (Deschênes and Greenstone, 2011) to give less weight to stations more distant from the geographic centroid. We then compute an annual average of temperature, relative humidity, wind speed, sunshine duration and barometric pressure and a cumulative annual value for precipitation.

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[19] The Pearson correlation coefficients for TFP via the OP and LP methods is 0.79 and for labor productivity with respect to TFP via the LP and OP methods is 0.69 and 0.67 all significant at better than the 1% level.

[20] The AOD data are obtained from the Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, v1 (1998–2016) released by the Socioeconomic Data and Applications Center of NASA (https://beta.sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod).

[21] Available at http://data.cma.cn.

6. Results

We first confirm that the KCAPC policy had a significant effect on $PM_{2.5}$ concentrations before estimating the combined effect of the policy. We then estimate the competitiveness effect and back out the ambient effect. We discuss identification of each as we proceed.

6.1 Pollution effect

A necessary condition for the KCAPC to exert an ambient effect (i.e., separate from a competitiveness effect) is that it significantly reduced pollution concentrations. To see if this is the case, we estimate Equation (7) replacing productivity with the log ambient $PM_{2.5}$ concentration as the dependent variable. Returning to our earlier illustrative example in Figure 3a, this estimates the difference of the average pollution reduction (orange-dashed curve) to the left of the boundary relative to the right. The unit of observation is a city-year.[22] Appendix E tests the parallel trends assumption necessary for identifying this effect. The figure presents event-study estimates by substituting year dummies for $Post2003$ in Equation (7) (normalized to zero in 2002) and confirms that $PM_{2.5}$ concentrations follow a similar trend for control and treatment cities in the three years prior to the KCAPC implementation, but afterward pollution drops discontinuously for the treatment cities.

Table 1 shows the DD estimates. Both columns include city fixed effects which capture time-invariant factors that affect pollution in the city and year fixed effects that capture time-specific factors affecting pollution in all cities in a year. Standard errors are clustered at the city level to allow for arbitrary correlations among unobservables affecting pollution over time within a city. Column 2 includes the weather controls while Column 1 does not. The coefficient is significant for both specifications indicating that the KCAPC reduced pollution by 3.2 to 3.8% in treatment cities relative to the control cities before versus after the policy.

[Insert Table 1 here]

6.2 Combined effect

To estimate the combined effect we employ DD estimates using the three different measures of productivity as the dependent variable and including different combinations of fixed effects. It is useful to compare our specification to that in Greenstone *et al.* (2012) as it relates to the sources of variation in the two settings. The CAAA and the KCAPC both imposed regulatory measures only on selected regions.

[22] This analysis includes 113 treatment and 148 control cities with ten years of data each. $PM_{2.5}$ pollution data is not available for all cities because the geographic definition of cities changed over time and we are only able to access pollution data that defines cities as of the year 2000.

This provides the basis for control and treatment groups and allows firm-specific shocks to productivity to be separately identified from regulatory effects. The CAAA generated additional variation which we do not have available. Under the CAAA only plants that are major emitters of pollution are subject to regulation allowing controls for time-specific shocks to productivity within counties. Since we do not have intra-city variation, we must rely on province-by-year or region-by-year fixed effects. The CAAA also offers additional time-series variation as counties could move in and out of regulatory status while in our setting cities retained the same status throughout the post-policy period. Nonetheless, the identification conditions for our DD estimates are met and the combined effect is precisely estimated.

The identifying assumption for the DD estimates is that the pre-existing trends for the control and treatment groups are parallel prior to the policy intervention. Figure 4 shows coefficients and 95% confidence intervals for event studies (substituting year dummies for $Post2003$ in Equation (7)). The interaction terms (normalized to zero in 2002) show no significant differential trends prior to 2003 and display a downward trend beginning in 2003 that becomes significant in 2005 for all three measures. This time lag is similar to that found in Greenstone *et al.* (2012) which notes that it can take plants a couple years to implement abatement actions.

[Insert Figure 4 here]

Table 2 shows estimates of the combined effect (β^{CO} coefficient in Equation (7)). All specifications include firm fixed effects while Columns 1 through 3 use region-by-year fixed effects and Columns 4 through 6 province-by-year fixed effects. Industry-by-year fixed effects at the two-digit level are included in Columns 1 and 4, at the three-digit level in Columns 2 and 5, and at the four-digit level in Columns 3 and 6.[23] The results are very significant and fairly consistent across specifications. The fact that the estimates are fairly stable regardless of the region/province and industry fixed effects implies that while these factors may determine productivity, they are uncorrelated with treatment status. For the most saturated model (Column 6), the KCAPC policy reduces TFP as measured by the OP method by 3.4%, TFP as measured by the LP method by 4.1%, and labor productivity by 3.9%. We use the midpoint of the TFP OP and LP measures (3.8%) as our headline result. At this midpoint estimate, total annual value added for the treatment firms would be decreased by CNY 30.2 billion (USD 4.5 billion).[24]

[Insert Table 2 here]

[23] There are 30 two-digit, 162 three-digit, and 425 four-digit industry codes.
[24] The average value added per firm is 13.845 million annually and there are 58,245 treatment firms.

Robustness

We re-estimated clustering the standard errors at the city level to allow for arbitrary correlations across firms and over time within a city. The results are shown in Column 2 of Appendix F (Panel A) compared to the baseline results in Column 1. As in Greenstone *et al.* (2012), this more general level of clustering results in less significant results. The significance levels are 14% for TFP OP, 9% for TFP LP, and 12% for labor productivity. Column 3 re-estimates weighting observations by firm value added in each year. The results are fairly similar to the baseline results except that the OP measure of TFP loses some significance. Column 4 weights instead by firm employment in each year. The results are somewhat greater in absolute value consistent with larger firms experiencing a larger combined effect. Column 5 adds the weather control variables which produces very similar results to the baseline.

6.3 Competitiveness effect

Since measuring the competitiveness effect combines BD and DD estimation, there are two separate identification conditions. First, the BD aspect of the estimation requires that, in the limit, the firms are arbitrarily close to the boundary so that they experience the same ambient pollution before and after the policy change. In finite samples, there is a practical question of how short a distance is required. The relevant question for determining this is how far the regulated pollutants disperse so that firms in that proximity experience the same pollution levels. SO_2 pollution travels hundreds of kilometers (Fisher, 1975), as does O_3,[25] NO_X (EPA, 1999: 5), and PM_{10} (EPA, 1996: IV-6 and IV-7).[26] As another point of reference, Chen *et al.* (2013) and Ebenstein *et al.* (2017) both apply a BD analysis to the Huai River policy measuring TSP and PM_{10} pollution in one-degree buckets. This corresponds to about 100 kilometers distance.[27] Our preferred estimates use a ten-kilometer distance, which is well below these distances.

Second, the DD aspect of the estimation requires that the pre-existing trends in productivity for the control and treatment groups are parallel prior to the policy intervention. Figure 5 plots coefficients and 95% confidence intervals from regressing firm productivity on year dummies interacted with $APPCL_{ct}$ conditioning on firm fixed effects. The interaction terms (normalized to zero in 2002) show a slight, but insignificant, downward trend prior to 2003 but a more rapid downward trend

[25] "What is Ozone?" (EPA) at https://www.epa.gov/ozone-pollution-and-your-patients-health/what-ozone, accessed on August 4, 2022.
[26] TSP is an earlier measure of particulate matter and would exhibit similar properties to PM_{10}.
[27] The Huai River is located from 111°55' to 121°25' East longitude and from 30°55' to 36°36' North latitude. Calculating the distance in moving one degree from roughly the middle of these coordinates (115° East longitude and 33° North latitude) yields a distance of about 100 kilometers.

beginning in 2003 that becomes significant in 2005 for all three productivity measures.

[Insert Figure 5 here]

Table 3 shows estimates of the competitiveness effect from the KCAPC policy. For this estimation, we use the most demanding fixed-effects specification including firm, province-by-year, and year-by-4-digit industry code (corresponding to Column 6 in Table 2 for the DD estimates). The table shows different maximum distances between treatment and control firms. There is a tradeoff as the maximum distance increases. On the one hand, there is more data available to provide precision. On the other hand, as the distance increases the identification requirement that the treatment and control firms face the same ambient pollution is less likely to be met. The estimates are very significant except for the labor productivity measure at one kilometer.

[Insert Table 3 here]

We use the ten-kilometer estimates as our baseline since it is the shortest maximum distance that yields enough data to generate results significant at the 1% level for all three productivity measures. Again using the average of the OP and LP TFP estimates as our headline result, the competitiveness effect of the KCAPC is a 6.4% decline in TFP. At this midpoint estimate, total annual value added for the treatment firms would be decreased by CNY 51.6 billion (USD 7.7 billion) which exceeds the combined effect by CNY 21.4 billion (USD 3.2 billion).[28] The annual competitiveness effect is equivalent to stalling TFP growth by 3.0 years.[29]

Robustness

We re-estimated clustering the standard errors at the city level to allow for arbitrary correlations across firms and over time within cities. The results are shown in Column 2 of Appendix F (Panel B) compared to the baseline results in Column 1. This more general level of clustering reduces the significance of the coefficients although the TFP OP and TFP LP results remain significant at the 10% and 5% cutoffs. Column 3 weights observations by firm value added. The results are fairly similar and remain significant. Weighting by employment in the firm-year (Column 4) increases the coefficients somewhat in absolute value consistent with somewhat greater effects for large firms. Column 5 adds the weather controls. The results are fairly similar to the baseline results.

[28] The average value added per firm is 13.845 million annually and there are 58,245 treatment firms.
[29] Annual TFP growth over the sample period is 2.1% using the average of the annual growth rates for TFP calculated using the OP and LP methods.

Placebo tests

Table 4 extends the maximum distance in the BD-DD estimates between treatment and control firms and shows that the ambient effect confounds the competitiveness effect at far distances. The table shows estimates for maximum distances in 20-kilometer increments from 20 to 100 kilometers. As the maximum distance increases, the point estimates become monotonically less negative. Although the competitiveness effect remains the same as the distance increases (treatment and control firms are still being compared) the firms no longer face the same ambient pollution. As the maximum distance increases, firms in the control areas benefit less and less from the positive productivity spillovers created from reduced pollution in the treatment areas as in the illustrative example in Figure 3a (green-solid line).

[Insert Table 4 here]

6.4 Ambient effect

KCAPC's ambient effect on productivity in the treatment cities[30] is the difference between the combined and competitiveness effects. Our headline estimate of the competitiveness effect is -6.4% and of the combined effect is -3.8%. This implies an ambient pollution effect in the treatment cities of 2.6%. At this estimate, total annual value added would be increased by CNY 21.4 billion (USD 3.2 billion) for firms in the treatment cities. There are additional gains to firms in the control cities which are difficult to quantify because they depend on the rate of decay of the pollution spillover with distance and the geographic placement of the firms.

The reasonableness of this calculation depends on treatment firms in the BD-DD subsample being similar to treatment firms in the overall DD sample. Appendix G makes this comparison. Column 1 provides the mean characteristics for firms in treatment cities used in the DD estimation and Column 2 for firms in treatment cities used in the BD-DD estimation with a maximum distance of ten kilometers. Column 3 tests for the difference between the two means. Although many of the characteristics are statistically significantly different from each other in the two samples, the magnitude of the differences is not large (no more than 8.7%). This is an example of Simpson's Paradox in which a large amount of data results in statistical significance for even small differences.

We can combine the ambient effect estimate with our DD estimate of KCAPC's ambient effect on $PM_{2.5}$ to obtain an elasticity of productivity with respect to ambient pollution. KCAPC reduced $PM_{2.5}$ by 3.2% (using the estimates with weather controls) implying an elasticity of -0.81 for our headline estimates. This is higher than the -0.28

[30] In the control cities, the ambient effect will be lower (in absolute value) as the productivity improvements fade with distance from treatment cities.

estimate obtained in Fu *et al.* (2021). A possible reason is that the current estimate applies to 2003 while that in Fu *et al.* (2021) is an average across all years from 1998 to 2007.

6.5 Alternative specification based on distance

An alternative approach to identifying the competitiveness effect is to include data further from the boundary and include a measure of distance to the nearest firm of the opposite type (control versus treatment). The ambient effect declines with distance into a control city while the competitiveness effect is invariant to distance. Therefore, allowing the productivity to vary with distance forms a triple-differences estimator. For example, refer to the illustrative example in Figure 3b. If a control firm is located 20 kilometers from the boundary, the ambient effect it experiences would be 2.0% compared to 2.5% for the treatment firms (a difference of -0.5%). On the other hand, if the control firm is located 40 kilometers from the boundary the ambient effect it experiences would be 1.5% compared to 2.5% for the treatment firms (a difference of -1.0%).

Given the competitiveness effect is invariant to distance while the ambient effect is not, the two effects can be separated by including a policy-treatment interaction (to capture the competitiveness effect) along with a policy-treatment-distance interaction (to capture the ambient effect). The sample is the same as that used in the DD estimation. In order to assign a unique distance for each firm, if a firm is paired with more than one firm of the opposite type we use the distance to the nearest firm of the opposite type. Since this is an approximation of the true geospatial relationships we regard these estimates as supporting evidence only. We estimate the following equation:

$$log(Productivity_{it}) = \beta^{D1} * Post2003_t * APPCL_{ct} + \beta^{D2} * Post2003_t * APPCL_{ct} * Distance_{it} + \eta_i^D + \theta^D X_{it} + \varepsilon_{it}^D, \quad (9)$$

where $Distance_{it}$ is the distance between firm i and its nearest neighbor of the opposite type (control versus treatment). β^{D1} captures the competitiveness effect – the policy effect at a distance of zero. β^{D2} captures the decay of the ambient effect as the firms are further apart. We expect β^{D2} to be negative – the ambient effect for the control firms relative to the treatment firms declines as the firms are further apart.[31]

Table 5 shows the results of estimating Equation (9) for the different productivity measures. For ease of reporting we have rescaled all of the distances to hundreds of kilometers. The coefficient on the policy-treatment interaction term is very significant and estimates a somewhat smaller competitiveness effect than that

[31] A standalone distance term is not included as it would be collinear with the firm fixed effects.

estimated by the BD-DD approach for the OP measure (-5.2% versus -6.0%) as well as for the LP measure (-5.9% versus -6.8%). The coefficient on the policy-treatment-distance interaction term indicates that for the OP measure the ambient effect on productivity decreases at a rate of 0.083% per kilometer in the distance between the treatment and control firms and 0.085% per kilometer for the LP method. These correspond to twice the slope of the green, solid line in Figure 3b to the right of the threshold.[32]

[Insert Table 5 here]

7. Conclusion

Choosing optimal environmental regulations requires an accurate cost-benefit analysis of their impact. This paper isolates the net private costs to firms from complying with a regulation from the spillover benefits of improved productivity that accrue to all proximately-located firms regardless of whether they are subject to the regulation. Failing to separate these effects understates the private costs to regulated firms and ignores the benefits to other firms. While this paper has applied the approach to a geographically-targeted regulation, it would also be applicable to an industry-targeted regulation in which the private costs accrue to the industry but spillover benefits accrue to proximately-located firms in all industries.

Our paper examines only manufacturing firms. A similar decomposition may be necessary for services firms. For example, regulating emissions from transportation and distribution industries would impose compliance costs on these firms but also benefit other firms in improved productivity from reduced pollution concentrations. With slight modification, the approach developed in the paper could be applied to water pollution to determine whether productivity spillovers are significant and whether these productivity benefits also accrue to the regulated firms.

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[32] If the distance between treatment and control firms is d; on average a treatment firm is located at $-d/2$ and a control firm at $d/2$. So, on average, the distance of the control firm from the boundary is $d/2$.

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