How Extensive are Air Pollution Spillovers?
An Application to China's Manufacturing Productivity*

Shihe Fu
Xiamen University
fushihe@xmu.edu.cn

V. Brian Viard
Cheung Kong Graduate School of Business
brianviard@ckgsb.edu.cn

Peng Zhang
The Hong Kong Polytechnic University
peng.af.zhang@polyu.edu.hk

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Abstract

The extent of trans-boundary pollution spillovers versus local effects is a necessary input in evaluating centralized versus decentralized environmental policies. We develop an estimation approach allowing for a flexible relationship between pollution and outcome as a function of distance. To estimate causal effects, it uses a mixed two-stage least squares method that combines high-frequency (daily) pollution with low-frequency (annual) outcome data. This avoids using annual pollution data which is vulnerable to inter-regional common shocks and insufficient variation. We apply the approach to spillovers of particulate matter smaller than 10 micrograms (PM_{10}) on manufacturing labor productivity in China. A one $\mu g/m^3$ annual increase in PM_{10} locally reduces output by CNY 4,613 and an increase at 50 kilometers by CNY 535. The spillovers decline quickly to CNY 83 at 600 kilometers and then slowly to zero at about 1,000 kilometers. Our approach is easily adapted to compare spillover and local effects for other outcomes.

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Key words: air pollution; spillovers; productivity; environmental costs and benefits, mixed two-stage least squares; regional coordination

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1. Introduction

Since the seminal work of Oates (1972) on fiscal federalism, there has been a debate on whether centralized or decentralized policies can achieve the most efficient outcome (Oates and Schwab, 1988; Ogawa and Wildasin, 2009; Banzhaf and Chupp, 2012; Eichner and Runkel, 2012; Fell and Kaffine, 2014). Local authorities have better information about costs and benefits and can better tailor local policies than central authorities whose policies tend to be overly uniform. However, local jurisdictions generally ignore the effects of their policies on other jurisdictions unless these are internalized administratively. Clear and enforceable assignment of property rights followed by Coasian bargaining can solve these externalities even under decentralized control (Coase, 1960) but require knowledge and quantification of the extra-territorial damages incurred.

Air pollution is a prototypical example of these issues with serious welfare implications. High levels of air pollution in developing countries have led to adverse effects on health, economic output, and physical and mental comfort. Ninety-two percent of all air pollution-related deaths are estimated to occur in low- and middle-income countries and ambient air pollution is estimated to have cost 4.4% of global GDP in 2016 (Ostro, *et al.*, 2018). Air pollution levels far exceed the social optimum because spillovers, including trans-boundary, are not internalized. Regardless of the method used to correct this, a necessary input is the magnitude and geographic extent of the spillovers involved. Centralized decision-making to internalize spillovers requires knowledge of how far spillovers extend at significant levels. Alternatively, assigning property rights and allowing for decentralized Coasian bargaining requires a method for the parties to estimate the origin of spillovers and their damage. And estimating air pollution spillovers requires estimating not just the quantity of pollution that drifts as a function of distance but also the harm that it causes upon arrival.

Despite this, we are not aware of any studies that quantify trans-boundary spillovers relative to local effects for any kind of pollution. Previous papers show that trans-boundary pollution spillovers exist and that they affect extra-territorial economic well-being[1] but they do not quantify how spillovers compare to local effects as a function of distance. Our paper begins to fill this gap by estimating an air pollution spillover gradient for labor productivity. While we demonstrate our estimation approach with productivity, it can be easily tailored to estimate the spillovers for other outcomes. We estimate the effect of trans-boundary drifts of particulate matter less than 10 micrograms in diameter (PM_{10}) on short-run manufacturing labor

[1] These include Sigman (2002), Sigman (2005), Zheng *et al.* (2014), Bošković (2015), Chen and Ye (2015), Kahn *et al.* (2015), Cai *et al.* (2016), Altindag *et al.* (2017), Jia and Ku (2017) , Lipscomb and Mobarak (2017), Sheldon and Sankaran (2017) and Goodkind *et al*. (2019). We comment more on these below.

productivity in China using a large firm-level data set from 2001 to 2007. A one $\mu g/m^3$ annual increase in PM_{10} in a city within 50 kilometers decreases the average firm's annual labor productivity by CNY 535 (0.035%).[2] This effect declines quickly to CNY 83 (0.005%) for nearby cities at 550-600 kilometers after which it declines slowly to zero at about 1,000 kilometers. This compares to a local effect of CNY 4,613 (0.302%). That is, the spillover is roughly 11.6% of the local effect at 50 kilometers, falling to 1.8% at 600 kilometers, and zero at 1,000 kilometers and beyond.

We focus on PM_{10} because it is the most prevalent air pollutant consistently monitored during the time period. We measure labor productivity as value-added per employee among manufacturing firms. There are two main determinants of the trans-boundary effect of pollution on productivity: how much air pollution is physically transported across cities (the pollution spillover) and the causal effect of this pollution on productivity upon its arrival in the destination city. Ideally, the pollution spillover can be estimated flexibly to allow for a highly nonlinear gradient. However, the causal effect requires instruments for pollution and is therefore constrained to linear estimating equations.

To accomplish this, we proceed in two steps. In the first step, we estimate the pollution spillover (which we call the spillover decay function) of nearby- on focal-city pollution flexibly as a function of distance using *daily* data conditional on wind blowing toward the focal city. In the second step, we estimate the causal effect of focal-city air pollution on labor productivity of the focal-city's firms. Multiplying the spillover decay effects from the first step by the causal effect from the second step is equivalent to a reduced-form approach[3] and allows us to estimate air pollution spillovers on labor productivity flexibly over a range of distances and compare it to the local effect.

When we estimate the causal effect of pollution on productivity in the second step, we instrument for the endogeneity of focal-city air pollution using the air quality of the nearest nearby city conditional on wind blowing toward the focal city. When wind blows toward the focal city, imported pollution from the nearby city degrades focal-city air quality. Although other instruments could be used in this step, using nearby-city pollution is convenient because the required data (daily pollution and wind measures) are commonly available and are already used to estimate the pollution decay function in the first step. The exogeneity of this instrument requires

[2] This estimate is for the average city given average weather.

[3] Although the spillover decay function is estimated at the daily level, the effects can be interpreted as the annual effects of a sustained and uniform increase in nearby-city pollution on all days of the year if wind blew toward focal cities on all days. Since the wind blows toward focal cities roughly half the time on average, annual spillovers are roughly half the daily effect as we describe when we present our results.

high-frequency data for two reasons. First, to capture wind direction shifts precisely enough and, second, to preclude confounding factors affecting both nearby-city pollution and focal-city productivity that might occur over longer time periods (in particular inter-regional productivity shocks).[4] We provide evidence that daily data are frequent enough but annual data are not. To combine the daily instrumenting data with the annual productivity data, we employ mixed two-stage least squares (M2SLS) (Lleras-Muney, 2005; Dhrymes and Lleras-Muney, 2006), a methodology for implementing 2SLS with different levels of aggregation in the two stages. This approach can be applied to other outcome variables such as GDP, morbidity, and mortality that are measured annually.

This paper contributes to three strands of literature. First, we quantify the magnitude of spillovers relative to local effects, a key input in choosing centralized versus decentralized environmental policies (Ogawa and Wildasin, 2009; Banzhaf and Chupp, 2012; Eichner and Runkel, 2012; Williams, 2012; Fell and Kaffine, 2014). Extant work on trans-boundary spillovers either shows that trans-boundary pollution spillovers exist (Sigman, 2002; Sigman, 2005; Chen and Ye, 2015; Kahn *et al.*, 2015; Cai *et al.*, 2016; Lipscomb and Mobarak, 2017) or that they affect extra-territorial economic well-being (Zheng *et al.*, 2014; Bošković, 2015; Altindag *et al.*, 2017; Jia and Ku 2017; Sheldon and Sankaran, 2017) but do not quantify their extensiveness or size relative to local effects.[5] Goodkind *et al.* (2019) estimate the pollution decay function for a different pollutant by a different method but use the exposure-response method to estimate health costs.

Second, we develop an approach based on M2SLS that allows high-frequency variation in wind direction to be used as an instrument for high-frequency air pollution in estimating its causal effect on low-frequency outcomes. There are a number of papers that use wind direction as the main source of exogenous variation in air pollution. These studies either use high-frequency wind direction to instrument for short-run air pollution (e.g., Rangel and Vogl, 2016; Schlenker and Walker, 2016; Deryugina *et al.*, 2016), or use low-frequency prevailing wind direction as the exogenous variation for long-run air pollution (Anderson, 2015; Freeman *et al.*, 2017). Although previous applications of M2SLS use it to increase efficiency of the estimates, we employ it because endogeneity is a concern with low- but not high-frequency data. The approach can be easily adapted to estimate the effect of air pollution on other economic outcomes measured at the quarterly or annual level. It

[4] Exogeneity also requires that wind direction is random with respect to nearby-city pollution conditional on control variables. We provide evidence that this is the case.

[5] The science literature has documented the long-range transport of pollutants across countries (e.g., Wilkening *et al.*, 2000) but these do not estimate pollution decay as a function of distance.

also offers the possibility of applying it to outcomes besides productivity that are longer than one year.

Third, our paper adds to the growing literature on estimating air pollution's effect on labor productivity (Graff Zivin and Neidell, 2012; Chang *et al*., 2016; Fu *et al*., 2018; Chang et *al*., forthcoming; He *et al*., forthcoming). These papers estimate the effect of an increase in local air pollution on local firms' productivity. In contrast to previous papers, we distinguish the effect of local and imported pollution sources on productivity and show that spillovers contribute significantly to productivity losses. There are multiple channels by which pollution can affect labor productivity. In the short run, pollution can decrease physical stamina and lead to lower output. In addition, employees may miss work days due to their own sickness or that of family members. Long-term exposure may lead to premature death with inexperienced workers replacing experienced. Pollution may also impair cognitive ability and cause psychological changes. While we cannot distinguish these channels we capture the aggregate effect of all of them.

We find that pollution exerts a substantial negative effect on productivity even at relatively far distances. Thirteen percent of PM_{10} produced from a city within 300 kilometers is imported into a focal city when the wind blows directly toward it. From a policy perspective, to internalize this would require centralized control of administrative areas that are 300 kilometers in radius or 283-thousand square kilometers of area. This is greater in size than many medium-sized provinces in China such as Hunan, Shaanxi, Hebei, Jilin, Hubei, and Guangdong (Ministry of Civil Affairs, 2017). Thus, our results indicate that environmental policies need to be coordinated at the supra-provincial level to internalize spillovers.

Our results have specific implications for the role of China's governance system in air pollution spillovers. China's reforms have succeeded in part because of its regionally decentralized system in which the central government provides incentives to local governments based primarily on local GDP to the exclusion of other criteria (Jin *et al*., 2005; Li and Zhou, 2005; Xu, 2011) such as environmental quality. Our results indicate that these incentives exacerbate the negative implications of air pollution spillovers on manufacturing productivity. This complements Jia (2017) which provides empirical evidence that these incentives result in more pollution.

The remainder of the paper proceeds as follows. The next section describes our estimation approach and Section 3 our data. Section 4 provides the results, and Section 5 concludes.

2. Estimation

2.1 Overview of estimation approach

To allow for a comparison of local and spillover effects on productivity, we rely on the fact that the reduced-form effect equals the intensity of treatment (how nearby-city pollution affects focal-city pollution) multiplied by the causal effect of focal-city pollution on focal-city productivity. Letting P^n represent nearby-city pollution, P^f focal-city pollution, and Y^f focal-city productivity:

$$spillover\ of\ P^n on\ Y^f = (effect\ of\ P^n\ on\ P^f) \times (causal\ effect\ of\ P^f\ on\ Y^f). \quad (1)$$

This follows because the causal effect estimated via 2SLS using nearby-city pollution as an instrument is (Angrist and Pischke, 2015: 107):

$$causal\ effect\ of\ P^f\ on\ Y^f = \frac{(effect\ of\ P^n\ on\ Y^f)}{(effect\ of\ P^n\ on\ P^f)}. \quad (2)$$

We therefore proceed in two steps. In the first step we estimate the effect of nearby- on focal-city pollution using daily data. We allow the effect to vary at different distances with controls for weather and seasonality. We call this the pollution decay function. In the second step we employ the M2SLS method to estimate the causal effect of focal-city pollution on focal-city productivity using annual data, instrumenting daily focal-city pollution with daily nearby-city pollution conditional on wind direction. This step estimates the local average treatment effect of pollution on productivity. We then multiply the estimates for the spillover decay function obtained in the first step by the instrumental variable coefficient from the second step to yield the spillover effect of nearby-city pollution on focal-city productivity according to Equation (1). We bootstrap to compute standard errors that account for estimation error across both steps. The spillover decay function is estimated at the city level because pollution is measured at that level while the causal effects of pollution on productivity are estimated at the firm level because productivity occurs and is measured at the firm level.

The next subsection describes the first step of our approach (estimating the pollution decay function) and the following subsection the second step (estimating the causal effect).

2.2 Step one: estimating the pollution decay function

The pollution decay function isolates the physical transport of PM_{10} between nearby and focal cities. If wind direction is orthogonal to omitted factors that jointly affect both nearby- and focal-city pollution, relating the two during periods when wind blows toward the focal city isolates these spillovers. We offer evidence that wind direction is orthogonal to these omitted factors when we present our results. In our sample, wind direction changes by more than 90 degrees (and therefore blows in the opposite direction) from day-to-day on more than 25% of days (Appendix A shows the full distribution of the change in wind direction across days). Thus, it is imperative to use daily data to isolate imported from local pollution for a focal city. Averaging over a long time period risks mingling periods in which the wind blows toward and away from the focal city.

We follow the concentric rings approach from the urban economics literature to estimate the pollution decay function.[6] This approach estimates the spillover between a location and each of several concentric rings radiating outward from that location. We use a piecewise linear regression to implement this, allowing the slope and intercept to differ for each of the concentric rings. We define rings at every 50 kilometers indexed by $b = 1,2,3, \dots, B$ and identify all the nearby cities within each ring (if at least one exists) for each focal city. That is, all nearby cities within 0 to 50, 50 to 100, . . . , $(B-1)$*50 to B*50 kilometers. We expand B far enough to ensure the decay function has plateaued or hit zero ($B = 36$ or 1,800 kilometers).

Having identified these focal-nearby city pairs, we then estimate the impact of nearby city n's PM_{10} on focal city f's PM_{10} level on day d of month m in year t by estimating the following equation conditional on the wind blowing from the nearby to the focal city:

$$P_{td}^{f} = \mathrm{I}_b\left[\lambda_{1b} + \lambda_{2b} abs\left[cos\left(\theta_{td}^{fn}\right)\right] P_{td}^{n}\right] + \lambda_3 W_{td}^{f} + \omega_f + \kappa_{rtm} + \varepsilon_{td}^{fn},$$

$$\forall f, n \in \mathcal{F}, n \neq f, \forall b = 1, \cdots B, \quad (3)$$

where $\mathcal{F}$ is the set of all cities in the data, P_{td}^{f} and P_{td}^{n} are the pollution levels of focal city f and nearby city n on day d of year t, and W_{td}^{f} are daily weather controls that affect pollution in the focal city. The indictor variable I_b is set to one for distance band b if nearby city n is within distance band b. λ_{1b} allows the intercept to vary for each distance band. λ_{2b} are the coefficients of interest and capture the average physical transport of nearby-city pollution to the focal city within each band. An observation in this regression is a focal-nearby city pair on a particular day. We form all possible combinations of focal and nearby cities within 1,800 kilometers. Since each focal city may have more than one nearby city across or even within bands this is a stacked regression with potentially multiple observations per focal city.

[6] The urban economics literature documents the spatial decay effects of agglomeration economies and knowledge spillovers (Rosenthal and Strange, 2003; Fu, 2007; Henderson, 2007; Arzhagi and Henderson, 2008; Rosenthal and Strange, 2008). Kernel-density smoothing across distances is another approach to estimate spillovers (Duranton and Overman, 2005) but requires more data than we have available.

We follow Schlenker and Walker (2016) in weighting nearby-city pollution by the absolute value of the cosine of the angle.[7] This angle $\left(\theta_{td}^{fn}\right)$ is the difference between the wind direction and the direction of the ray from the nearby to the focal city on day d of year t. For example, in Figure 1 where the focal city lies at an angle of 21° from the nearby city, if the wind is blowing at $-19°$ then $\theta_{td}^{fn} = -40°$ or if the wind is blowing at 43° then $\theta_{td}^{fn} = 22°$. We include a day in estimation as long as the wind blows within a 90° arc on either side of the ray connecting the nearby to the focal city. This is illustrated in the shaded area of Figure 1 for the example in which the focal city lies at an angle of 21° from the nearby city. In this example a day is included as long as $-69° < \theta_{td}^{fn} < 111°$. The pollution decay function is therefore identified from variation along two dimensions: distance between focal and nearby city and wind direction angle .

[Insert Figure 1]

W_{td}^{f} includes daily averages of relative humidity and wind speed, daily total precipitation, and temperature bins as described below. We include focal-city fixed effects (ω_f) to control for any time-persistent unobserved factors affecting the pollution drift to a focal city. Region-by-year-by-month fixed effects (κ_{rtm}) control for seasonal factors that affect pollution drift in a region such as wind patterns. We follow Zhang *et al.* (2018) in grouping the provinces into each of seven regions as described in Appendix B. The error term (ε_{td}^{fn}) captures any unobserved factors affecting drift between the focal-nearby city pair on day d of year t. We cluster standard errors at the focal-city level to allow for serial correlation across time within a focal city. This also allows for heteroscedasticity introduced by focal cities having different numbers of nearby cities.

2.3 Step two: estimating causal effect of pollution on productivity

In the second step we estimate the causal effect of focal-city pollution on focal-city productivity. Our productivity estimates capture all possible channels that affect per-hour productivity (intensive margin) and hours worked (one type of extensive margin). In the short run, high air pollution concentrations can lead to decreased lung function, irregular heartbeat, increased respiratory problems, nonfatal heart attacks, and angina.[8] Long-run cumulative exposure may lead to cardiopulmonary

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[7] We weight by the angle because more nearby-city pollution is imported the more directly wind blows toward the focal city. Using data for $-90° \leq \theta \leq 90°$ for the nearest nearby-city within 300 kilometers, the correlation between $cos(\theta)$ and residuals from regressing focal-city pollution on nearby-city pollution and focal-city weather is 0.046 significant at better than the 0.01% level. This means that if nearby-city pollution is increased by one μg/m³ while θ is moved from 90° (perpendicular to the focal city) to 0° (directly toward the focal city), imported pollution increases by 0.046 μg/m³ (36% of the total 0.129 μg/m³ spillover at 300 kilometers shown in Appendix E).

[8] See the EPA website: https://www.epa.gov/pm-pollution.

diseases, respiratory infections, lung cancer (EPA, 2004), and asthma (Neidell, 2004) that can surface in the short run. All of these health conditions may decrease physical stamina and lead to missed work days. Workers may also be absent from work to care for the young and elderly affected by pollution (Chay and Greenstone, 2003; Hanna and Oliva, 2015; Deryugina *et al*., 2016; Aragón *et al*., 2017). Increased mortality (Chen *et al*., 2013; Ebenstein *et al*., 2017) can lead to experienced workers being replaced by less experienced ones. Air pollution can also have psychological effects including lowering cognitive ability, altering emotions, and increasing anxiety (Levinson, 2012; Lavy *et al*., 2014; Pun *et al*., 2016; Chen *et al*., 2018) which would affect both physical and mental performance. While our estimates are unable to distinguish between these various channels they capture the effect of all of them.

2.3.1 Step two: identification

OLS estimates of pollution's effect on labor productivity are subject to simultaneity and omitted variable biases. Even without any effect of pollution on productivity, cities with more output will produce more pollution, leading OLS estimates to be biased upward toward or above zero. If pollution lowers labor productivity, the lower productivity will result in less pollution biasing OLS estimates downward. Firms may also respond to the lowered labor productivity by substituting from labor to alternative inputs biasing OLS estimates upward if cleaner inputs are used or downward if dirtier ones are used.

Omitted-variable biases due to local, time-varying conditions are also possible (firm fixed effects absorb any time-invariant effects). For example, high-productivity firms may implement advanced, lower-polluting technologies over time while low-productivity firms do not. Spatial sorting could also introduce spurious correlations. Firms may choose to locate in cities with less severe pollution because it will raise their productivity, biasing OLS estimates upward, or choose to locate in cities with more severe pollution because they have lax environmental regulations and impose fewer costs (Becker and Henderson, 2000; Greenstone, 2002; Brunnermeier and Levinson, 2004), biasing OLS estimates downward. Workers may also systematically sort across cities. In particular, high-skilled workers generally have a higher willingness-to-pay for clean air which would lead to low-skilled workers being located disproportionately in dirtier cities (Chen *et al*., 2017; Lin, 2017) and biasing OLS estimates downward. The inclusion of firm fixed effects means that only migrations of firms or workers during the sample period will bias the results.

We address these issues using nearby-city pollution that drifts to the focal city as an instrumental variable. A firm's productivity is affected by both locally-produced pollution and nearby cities' pollution that is transported in by wind. To ensure exogeneity, we condition on the wind blowing from the nearby to the focal city.[9] Exogeneity also requires that wind direction timing is random with respect to air pollution, conditional on controls, which we confirm below. Identification requires that the instrument be sufficiently correlated with the endogenous regressor (inclusion restriction) and uncorrelated with any unobserved determinant of the dependent variable (exogeneity condition).

The inclusion restriction requires that the nearby city is close enough that significant amounts of pollution can drift from it to the focal city. To ensure this, we include only focal cities that have a nearby city sufficiently close. Fine particulates such as PM_{10} can travel hundreds of kilometers (according to EPA, 1996, page IV-7 and confirmed by our pollution decay function estimates below). We consider maximum distance cutoffs ranging from 150 to 300 kilometers and find robust results. There is a tradeoff in increasing the distance: it increases the available data but weakens the instrument's power. To also increase the instrument's power we include only the nearest nearby city for each focal city. As a result, even with a maximum distance of 300 kilometers the average distance between focal and nearby cities is only 106.6 kilometers.

The exogeneity condition requires that unobserved determinants of focal-city productivity are uncorrelated with the nearby city's pollution. This requires high-frequency data for two reasons. First, periods in which the wind imports pollution from outside must be isolated from those when it does not. To ensure this, in the instrumenting equation we condition on the wind blowing from the nearby to the focal city on a particular day. We offer evidence when we present our results that daily data succeeds in isolating periods when wind blows toward the focal city.

Second, high-frequency data is required to ensure common shocks do not affect both focal- and nearby-city output. For example, regional shocks to productivity could raise both cities' output thereby increasing nearby-city pollution as well. Alternatively, if focal- and nearby-city production are substitutes in output markets then output growth in a focal city will reduce output and pollution in the nearby city. While common regional shocks are likely to induce correlated actions across cities over a long time period, they are unlikely to do so over a short time frame due to lags in shock propagation and delays in responses to those shocks. With the use of daily data, violating the exogeneity condition would require that shocks affect focal- and nearby-city productivity on a *daily* basis. Conveniently, this high-frequency instrument is already available as it is required to estimate the pollution decay function. We show that aggregating the data to lower and lower frequencies leads to

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[9] When the wind blows toward the nearby city its pollution is not exogenous because greater focal-city output increases the nearby city's air pollution.

increasingly unintuitive results in the first stage and insignificant results in the second stage. This is consistent with bias introduced by regional correlations over longer periods.

Our instrument addresses each of the potential endogeneity biases. Nearby-city pollution is uncorrelated with focal-city output in the absence of common regional shocks that are propagated and responded to on a daily basis. Any time-varying local trends in pollution and productivity would need to be correlated across the focal and nearby city on a daily basis to bias the estimates. Substitution away from labor and toward other inputs by focal-city firms would also need to be reflected in nearby-city pollution on a daily basis. Entry and exit may be correlated with pollution levels over long periods such as a year. However, such correlations are unlikely to manifest themselves on a daily basis. Similarly, worker migration would need to be correlated across the focal and nearby cities on a daily basis to induce bias.

2.3.2 Step two: procedure

The remaining problem is that the outcome that we wish to estimate (productivity) is measured annually. To accommodate daily data for the pollution instrument, we employ M2SLS to estimate the causal effect of local pollution on local productivity. M2SLS estimates are consistent and asymptotically normal (Lleras-Muney, 2005; Dhrymes and Lleras-Muney, 2006) provided that the groupings are independent of the structural error as they are when the grouping is a primitive (in our case grouping daily observations into years).[10]

The first-stage equation predicts air pollution for firm i located in focal city f of region r on day d in month m of year t conditional on the wind blowing from the nearby to the focal city. While the spillover equation in step one uses city data, this equation uses firm data to be consistent with the firm data used in the second stage:

$$P_{itd}^{f} = \gamma_1 abs\left[cos\left(\theta_{itd}^{fN^*}\right)\right] P_{itd}^{N^*} + \gamma_2 W_{itd}^{f} + \alpha_i + \kappa_{rtm} + \epsilon_{itd}^{f}, \quad (4)$$

where P_{itd}^{f} is the pollution in firm i's focal city f on day d of year t, $\theta_{itd}^{fN^*}$ is the wind direction relative to the ray from the nearest nearby city to firm i's focal city on day d of year t, and $P_{itd}^{N^*}$ is the pollution level on that same day in focal city f's nearest nearby city $N^* \in \mathcal{F}$ within a maximum radius distance. If no nearby city is available for a focal city it is dropped from the estimation. Every nearby city is also a focal city although it might be paired with a different nearby city that is closer to it. We test the sensitivity of our results to maximum distance cutoffs ranging from 150 to 300

[10] Lleras-Muney (2005) applies M2SLS to estimate the causal impact of education on health, Massa and Žaldokas (2014) to estimate international demand for US bonds, and Jordan (2016) to estimate local environmental preferences on mine closures.

kilometers.[11] W_{itd} is a vector of daily weather variables faced by firm i on day d of year t. We include linear and quadratic functions of daily relative humidity, wind speed, and cumulative precipitation. We allow for a flexible, nonlinear function of temperature following Deschênes and Greenstone (2011) and Zhang *et al.* (2018) since it has been found to affect productivity (Zhang *et al.*, 2018). We construct indicator variables for the daily average temperature below 0°, 5° intervals from 0 to 30°, and above 30° Celsius.

In defining whether the wind blows toward the focal city, we impose more stringent criteria than in the pollution decay function estimation to ensure a sufficient quantity of pollution is imported from the nearby city. This is necessary for the instrument to be powerful.[12] For our baseline estimates, we include a day if the wind passes within a 45° arc on either side of the ray connecting the two cities. We refer to this as the "middle" funnel. Figure 2 illustrates this for the example in which the focal city lies at an angle of 21° from the nearby city. In this case a day is included as long as $-24° < \theta_{td}^{fn} < 66°$ (the shaded region of the figure). We check the robustness of our results to arcs of $\pm 40°$ ("narrow" funnel) and $\pm 50°$ ("broad" funnel). As in the pollution decay estimation, the nearby-city's pollution is weighted by the absolute value of the cosine of the angle.

[Insert Figure 2 here]

Firm fixed effects (α_i) capture time-persistent unobservables that affect firm i's pollution exposure. Since no firms switch focal cities or industries over the sample period, these also absorb city-specific and industry-specific time-invariant factors that affect local pollution. Region-by-year-by-month fixed effects (κ_{rtm}) control for any year-month specific unobservables affecting the pollution in a region. We cluster standard errors at the focal-city level to allow for spatial correlation for all firms within each focal city and serial correlation across days within a focal city over time.

This equation differs from the pollution decay function (Equation (3)) in two ways. First, in order to ensure the power of the instrument, Equation (4) restricts estimation to shorter distances (a maximum of 300 kilometers), it utilizes only the nearest nearby city, and includes only days when the wind direction is within a funnel rather than within a half-circle. This maximizes the potential for the nearby city's pollution to drift to and affect the focal city. The objective of Equation (3) is to estimate spatial decay and it therefore utilizes all of the nearby cities to a focal city,

[11] Distances below 150 kilometers yielded insufficient data and distances above 300 kilometers yielded a weak instrument as we demonstrate below.

[12] Footnote 7 provides evidence that nearby-city pollution is a stronger instrument when the wind blows more directly in the direction of the focal city. Broader funnels (up to $\pm 90°$) yield similar but less precisely estimated results.

utilizes all days with wind direction within a half-circle, and extends the measurement of these spillovers to a much greater distance. Second, Equation (3) also allows for a much more flexible functional form for estimating the spillover decay function than the linear restriction that 2SLS imposes on Equation (4).

Using the results from estimating Equation (4), we compute predicted values $\hat{P}_{itd}^{f}$ for each day included in the estimation (wind blowing toward the focal city) and average them over days within each firm-year to obtain instrumented pollution for the second-stage: $\bar{\hat{P}}_{it}^{f}$. The second-stage equation is:

$$\ln\left(Y_{it}^{f}/L_{it}^{f}\right) = \beta_1 \bar{\hat{P}}_{it}^{f} + \gamma_2 \bar{W}_{it}^{f} + \alpha_i + \delta_{rt} + \eta_{it}^{f}, \quad (5)$$

where Y_{it}^{f}/L_{it}^{f} is value added per employee for firm i in the focal city f in year t and $\bar{W}_{it}^{f}$ contains the weather controls from the first stage averaged over all days within each firm-year (i.e., averages of the linear and quadratic functions of non-temperature variables and temperature bins containing the fraction of days in which the average temperature is below 0°, in 5° intervals from 0 to 30°, and above 30° Celsius).[13]

Firm fixed effects α_i capture time-persistent firm attributes that affect labor productivity. Region-by-year fixed effects (δ_{rt}) capture time-varying, regional shocks to firm output. The error term (η_{it}) includes time-varying, firm-level shocks to productivity. We cluster standard errors at the focal-city level to allow for serial correlation within each firm over time and spatial correlation within each city. We adjust for the error introduced in the first-stage estimation using a block bootstrap as in Schlenker and Walker (2016) with 100 iterations.

3. Data

We estimate pollution spillovers on labor productivity for manufacturing firms in China from 2001 to 2007 in two steps. The first step (estimating the pollution decay function) requires daily pollution and weather data. The second step of our procedure (estimating the causal effect of air pollution on productivity) requires daily data for the instrument to address the endogeneity of pollution and accommodates annual data on productivity.

[13] To ensure the exclusion restriction is met, the first-stage equation must include the non-averaged values of all the exogenous variables from the second stage. The weather controls in the second stage ($\bar{W}_{it}^{f}$) are yearly averages of the linear and quadratic terms of all non-temperature variables in the first stage. For the temperature variable, the bins in the second stage are annual averages of the daily indicator variables included in the first stage. The firm fixed effects remain the same as in the first stage. Finally, the region-by-year fixed effects included in the second stage are averages of the region-by-year-by-month fixed effects in the first stage.

3.1 Pollution data

The highest-frequency pollution data available with significant geographic coverage during our time period is the daily Air Pollution Index (API) published by the Ministry of Ecology and Environment and Beijing Environmental Protection Bureau.[14] This is available at the city level and only for larger cities. The number of cities reporting API data increases over time in the sample. Our sample includes 60 unique cities (Appendix C shows the location of the cities).

The API ranges from 0 to 500 with higher values indicating higher pollution concentrations and more harmful health effects (Andrews, 2008). During our sample period, a city's daily API reports the worst of three pollutants: particulate matter (PM_{10}), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) whose concentrations are measured at multiple monitoring stations within the city. Each is rescaled as an API measure to make them comparable and the pollutant with the maximum API is reported.[15] The identity of the maximal pollutant is reported if the API exceeds 50.

The API is potentially subject to manipulation by those who collect and report the data. Using 2001 to 2010 data, Ghanem and Zhang (2014) find a discontinuity in the API distribution around 100 which suggests that self-reported data is manipulated by local officials who are evaluated on the annual number of "Blue Sky" days (those below 100). Also consistent with this, Andrews (2008) finds that a significant number of days in 2006 and 2007 with reported API values between 96 and 100 would fall in the range 101 to 105 if calculated using the underlying monitoring station data. To avoid any possible bias in our estimates we exclude days when the API is between 95 and 105 in either the focal or nearby city.

We use PM_{10}, the density of particulates ten micrometers or smaller in diameter, in our analysis rather than the API index because we wish to use physical pollution levels in quantifying spillovers and PM_{10} is overwhelmingly the worst of the three pollutants (about 90% of days). We drop days in which PM_{10} is not the maximal pollutant and for the remaining days infer its value from the API based on the piecewise-linear relationship between PM_{10} and the API (Appendix D). Although we do not observe the worst pollutant when the API is below 50 we assume it is PM_{10} because at these low levels air quality is assumed to be safe regardless of pollutant.

[14] The satellite-based pollution data used in Fu *et al*. (2018) are more comprehensive and available at the county level; however, they are only available at the monthly level. We cannot use more recent API data because productivity data is not available then.

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

3.2 Wind and weather data

We require daily wind data for estimating the spillover decay function and to instrument pollution when estimating its effect on productivity. We use station-level wind direction data from the World Weather Records Clearinghouse collected by the U.S. National Oceanic and Atmospheric Administration (NOAA).[16] The data provide a direction from which the wind is blowing stated in degrees clockwise from true North in each three-hour period of each day in each city. We use a "unit-vector" average method defined by the NOAA to arrive at an average daily wind direction for each city.[17] For wind direction we use data for the focal not the nearby city. Regardless of the wind direction in the nearby city, pollution cannot be imported if the wind in the focal city is not blowing from the nearby city's direction. Differences in wind direction between the nearby and focal cities will not bias the estimates but will weaken the power of the instrument.

To control for weather conditions that affect the transport of pollution and productivity we use daily weather data downloaded from the Weather Underground.[18]

3.3 Firm productivity 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 state-owned enterprises (SOEs) regardless of size and all non-SOEs whose annual sales exceed CNY 5 million (USD 0.8 million).[19] The survey also contains detailed information on firm location, accounting measures, and firm characteristics. Before matching with the pollution data this captures 90.7% of China's total manufacturing output during our sample period (Brandt *et al.*, 2012). We follow Fu *et al.* (2018) in matching firms over time to create an unbalanced panel, converting nominal into real values, eliminating observations with unreliable data, and winsorizing the data.

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

[17] Some cities have more than one monitoring station for wind direction and the number varies slightly over time for some cities. In 2017, cities averaged 1.5 stations each with a maximum of four stations. In each three-hour period, we convert the direction for each station to a unit vector with coordinates $\langle u, v \rangle$. The u-component is the North-South wind direction and v the East-West. We average the two coordinates separately across the periods of each day and all stations to yield $\bar{u}$ and $\bar{v}$. We then translate the direction into a 0 to 360 degree scale based on the signs of $\bar{u}$ and $\bar{v}$: $180 - \theta$ if $\bar{u} < 0$ and $\bar{v} > 0$, $\theta - 180$ if $\bar{u} < 0$ and $\bar{v} < 0$, $360 - \theta$ if $\bar{u} > 0$ and $\bar{v} < 0$, and θ if $\bar{u} < 0$ and $\bar{v} > 0$ where $\theta = (180/\pi) * arctan(\bar{u}/\bar{v})$. This is method 1 described at: http://www.ndbc.noaa.gov/wndav.shtml.

[18] Available at www.wunderground.com.

[19] A 2007 exchange rate of 7.6 is used throughout the paper.

We measure output as value added per worker which is common in the productivity (Syverson, 2011; Brandt *et al.*, 2012) and temperature-productivity literature (Hsiang, 2010; Dell *et al.*, 2012). Firms report value added directly in the data and it equals total production (including both sales and inventory) of all goods produced in the year valued at their market prices less the cost of all intermediate inputs employed in producing them. Using aggregate measures of productivity requires that prices do not reflect market power in either the primary or upstream input markets. We cannot guarantee this; however, nearby-city pollution is independent of firm-level market power in the focal city allowing us to consistently estimate pollution's effect on productivity via instrumented pollution. The mix of products is also not discernible from firm-level value added and may be correlated with local pollution levels. However, our instrumenting strategy also addresses this issue: nearby city pollution is uncorrelated with the product-mix decisions of a firm in the focal city thereby removing any bias in the instrumented results. Fu *et al*. (2018) contains more details on how we measure value added and deal with issues in using aggregate productivity measures.

As explained below, we impose a maximum distance of 1,800 kilometers in estimating the spillover decay function and 300 kilometers in our causal estimates of productivity effects. After merging the productivity, API, and weather data for the spillover estimates, our data include 60 focal cities with 132,105 firms that represent 26% of China's population. The total annual output of these cities is CNY 2.02 trillion (11.7% of China's annual GDP and 29% of China's manufacturing sector).[20] For our casual estimates, our data includes 88,716 firms in 47 focal cities with total annual output of CNY 1.35 trillion (7.8% of China's annual GDP and 20% of China's manufacturing sector). Although our sample of cities is not comprehensive these are major cities representing a significant fraction of manufacturing output and population.

4. Results

We report the first-step estimates (pollution decay function) followed by the second-step estimates (causal effects of focal-city air pollution on focal-city productivity) and then combine the results from these two steps to calculate the spillover effects of nearby-city pollution on focal-city productivity. After this, we demonstrate the value of our M2SLS procedure. In particular, we show that estimating causal effects using 2SLS with annual data produces insignificant second-stage results and unintuitive first-stage results. We offer supporting evidence that this is because aggregating the

[20] China's average annual real GDP over the seven-year sample period is CNY 17.27 trillion. The manufacturing sector accounts for roughly 40% of China's GDP.

data to a lower frequency eliminates variation and introduces the possibility of confounding factors.

4.1 Pollution decay function

To estimate the pollution decay function we include all focal cities with at least one nearby city within 1,800 kilometers. This distance was chosen because it was far enough that the spillover effects were indistinguishable from zero. We use all cities that have daily API and weather data available from 2001 to 2007. This yields 60 unique cities in an unbalanced panel because API data was not reported for some cities in the earlier years. There are some days with missing API or wind data but these are limited (all cities have at least 335 days of data in each year) and we believe are due to random non-reporting.

Table 1 shows the summary statistics for the pollution spillover data. There are 2,586 focal-nearby-city pairs (about 43 nearby cities for each focal city). If city B is a focal city for A then A is also a focal city for B. The focal cities' PM_{10} levels average 96.9 and exhibit significant variation. Wind blows toward the focal city on 52.1% of the days and PM_{10} is the dominant pollutant on 92% of the days for the focal cities. The mean distance between cities (1,009 kilometers) is about one-half the maximum allowed distance.

[Insert Table 1 here]

The solid, black line in Appendix E shows the λ_{2b} coefficients from estimating Equation (3) along with the 95% confidence interval in red, dashed lines. These are the effects of a one $\mu g/m^3$ increase in PM_{10} in nearby cities conditional on wind blowing directly toward the focal city $\left(\theta_{td}^{fn} = 0\right)$. The effect in each distance band is conditional on holding PM_{10} in other bands constant. Roughly 25% of pollution drifts from nearby cities that are within 50 kilometers and more than 16% out to 250 kilometers.

The solid, black line in Figure 3 plots the effect of a one $\mu g/m^3$ *annual* increase in nearby-city PM_{10} along with the 95% confidence interval in red, dashed lines. This adjusts the coefficients using the empirical distribution of θ_{td}^{fn}. That is, for the fact that the wind blows toward the average focal city on only 52.1% of days in a year and does not always blow directly towards the focal city. Again, this is the effect of increasing PM_{10} in the distance band conditional on holding pollution constant in all other bands.[21] The spillover effect within 50 kilometers is 0.116. That is, a one $\mu g/m^3$

[21] It would be useful to compare the local effect to spillovers from raising pollution in all nearby cities simultaneously. However, to do so using our estimates requires making arbitrary assumptions about the degree to which pollution from a nearby city affects other nearby cities that are between it and the focal city. Alternatively, one could estimate spillovers including interaction effects between each

annual increase in PM_{10} in all nearby cities within 50 kilometers, but not in any other distance band, increases annual focal city pollution by 0.116 $\mu g/m^3$. Similarly, a one $\mu g/m^3$ annual increase in PM_{10} in all nearby cities within 50 to 100 kilometers, but not in any other band, increases annual focal city pollution by 0.068 $\mu g/m^3$. A similar analysis applies to all the further distance bands. These effects are for the average focal city in the sample given average weather. Spillovers drop somewhat quickly and smoothly from 0.116 at 50 kilometers to 0.018 at 600 kilometers after which they fall more slowly to zero at about 1,000 kilometers.

[Insert Figure 3 here]

4.2 Randomness of daily wind data

Before estimating the causal effect of pollution on productivity, we check the randomness of wind direction with respect to pollution. To ensure that the instrument is exogenous we must exclude days in which the wind does not blow from the nearby to the focal city. If wind direction is not randomly distributed with respect to the distribution of nearby-city air quality, conditional on control variables, this may bias the coefficients.[22] Appendix F compares cumulative distribution functions (cdfs) of nearby-city air pollution conditional on the control variables used in the first stage of our M2SLS procedure for all days versus excluded days using the 150-, 200-, 250-, and 300-kilometer distance cutoffs in choosing nearby cities. The cdfs are very similar for all cutoffs.[23]

4.3 Effect of local air pollution on local labor productivity

In this subsection we estimate the causal effect of focal-city pollution on focal-city labor productivity using nearby-city pollution as an instrument. In choosing which nearby cities to include, we check robustness to maximum distances from the focal city of 150, 200, 250, and 300 kilometers. There is a tradeoff as this distance increases. There are more data available to identify the effects thereby increasing their precision; however, the instrument is weaker because nearby-city pollution has less effect on focal-city pollution. Below 150 kilometers there were insufficient data to

distance band and all closer distance bands to estimate these "pass-through" effects. However, the number of independent variables required makes this infeasible with more than a few distance bands.

[22] This highlights the importance of the control variables. For example, in northern regions of China air quality is worse in the winter than in other seasons. If wind directions are systematically different in winter than other times of the year this will introduce bias in the absence of control variables. In this example, the region-by-year-by-month fixed effects should capture this region-specific seasonality.

[23] A two-sample Kolmogorov-Smirnov test rejects the null hypothesis of the equality of distributions at the 1% level for all four radiuses. However, the magnitude of the differences is very small: 0.031 for 150-, 0.029 for 200-, 0.024 for 250-, and 0.027 for 300-kilometer radiuses. This is an example of Simpson's Paradox in which a large amount of data results in statistical significance for even small differences.

identify effects and we show that beyond a distance of 300 kilometers the instrument is no longer powerful. Unlike the spillover estimates, we choose the nearest nearby city to the focal city, if one exists, within the maximum distance to maximize the instrument's power.

Table 2 shows summary statistics for the main variables for the 150- and 300-kilometer radiuses. The top panel summarizes the first-stage data which are at the firm-day level. The summary statistics are fairly similar across the two distance cutoffs. The PM_{10} levels are high enough to potentially affect productivity. The annual mean is over 110 $\mu g/m^3$ compared to a World Health Organization (WHO) recommended guideline of 20 $\mu g/m^3$ annual average and many days exceed the WHO guideline of 25 $\mu g/m^3$ for a 24-hour average (World Health Organization, 2006). As the cutoff increases from 150 to 300 kilometers, the number of focal cities increases from 30 to 47. The average distance between nearby and focal cities does not increase much because we use the nearest nearby city for each focal city. The bottom panel summarizes the second-stage data which are at the firm-year level. The data exhibit significant variation in value-added per employee. Appendix G shows summary statistics for the 200- and 250-kilometer radiuses which are similar.

[Insert Table 2 here]

Panel A of Table 3 shows OLS results that do not address the endogeneity of air pollution. The firm-year data included here correspond to those included in the second stage of M2SLS estimation described below. For all four distance cutoffs, the coefficients on PM_{10} are insignificantly different from zero and for all but the 150-kilometer the point estimates themselves are close to zero. This is consistent with either pollution having no effect on productivity or with an upward bias due to endogeneity.

We now turn to M2SLS estimates. Panel B shows the results of estimating the first-stage equation (Equation (4)) using PM_{10} of the focal city's nearest nearby city as an instrument conditional on wind blowing toward the focal city within the middle funnel. This estimation is at the firm-day level and the wind is within the middle funnel on about one-fourth of the days. The results reveal a strong instrument. A one $\mu g/m^3$ increase in a nearby city's PM_{10} increases the focal city's PM_{10} by between 0.70 and 0.72 with a high level of significance.[24] The Kleibergen-Paap Wald rk (KP)

[24] These coefficients exceed even the estimates at distances below 300 kilometers in the spillover decay function because here we estimate using only the nearest nearby city and a narrower funnel.

F-statistic (Kleibergen and Paap, 2006) for weak identification significantly exceeds the Stock-Yogo critical value of 16.38 for all four cutoffs.[25]

Panel C shows the second-stage estimates of Equation (5) at the firm-year level using the average values of the predicted pollution from the first stage as an instrument and controlling for weather and region-by-year fixed effects. The estimated coefficients of PM_{10} are negative and significant for all but the 150-kilomoter cutoff which is significant at the 12% level. The estimates become more significant as the cutoff increases consistent with more data used in estimation. The coefficients are fairly consistent across the four cutoffs and imply that a one $\mu g/m^3$ annual increase in PM_{10} decreases productivity by 0.25 to 0.31%. Evaluated at the mean focal-city PM_{10} in each subsample, these estimates imply elasticities of labor productivity with respect to air pollution of -0.26 to -0.32.

These results are consistent with the instrument attenuating an upward endogeneity bias. The results also imply that improving air quality generates substantial productivity benefits. Using the 300-kilometer cutoff data and estimates, a 1% reduction in PM_{10} increases per-firm productivity for the average firm by CNY 4,613 (USD 607) annually. Throughout the remainder of the paper we use the 300-kilometer estimate as our preferred since it is the most significant and is close to the midpoint of the estimates from the four cutoffs.

[Insert Table 3 here]

Appendix H contains robustness checks of our estimates using the 300-kilometer cutoff. Column 1 reproduces our baseline estimates using the middle funnel. Column 2 uses a narrow funnel (an 80° arc). The point estimate is slightly smaller and is significant only at the 12% level due to the loss of data in the first stage. Employing a broad funnel (a 100° arc) in Column 3 produces a more significant result and somewhat larger effect than the baseline estimate. Dropping days with API below 50, for which the major pollutant is unknown, lowers the coefficient somewhat (Column 4). This is presumably due to years with a relatively high number of low-pollution days corresponding to years with a relatively high proportion of high-productivity days. Columns 5 and 6 evaluate the influence of fixed effects. Including year-by-month rather than region-by-year-by-month fixed effects in the first stage (Column 5) yields almost identical results to the baseline while including region-by-year fixed effects in the first stage results in somewhat

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

different estimates (Column 6).[26] Therefore, the estimates are more sensitive to controlling for overall seasonality than region-specific seasonality.

Appendix I provides supporting evidence for our choice of 300 kilometers as the maximum distance for the nearest nearby city to include as an instrument. Column 1 estimates M2SLS using as an instrument pollution in the nearest nearby city for each focal city that is further than 300 but less than 350 kilometers away and using the middle funnel in defining whether wind blows toward the focal city. The first-stage results in Panel A reflect the reduced power of the instrument. The coefficient is about half that in the baseline estimates and the KP *F*-statistic is much lower. The second-stage coefficient (Panel B) is negative but about half the magnitude of the baseline estimates and insignificant. Columns 2 through 4 expand the data by increasing the range of distances for the nearest nearby cities. The first-stage estimates remain similar and the second-stage coefficients remain insignificant consistent with a weak instrument.

4.4 Spillover effect of nearby-city pollution on focal-city labor productivity

As shown in Section 2.1, multiplying the first-step spillover decay function by the second-step causal effects yields the spillover effects of nearby-city pollution on focal-city productivity. To obtain appropriate standard errors clustered at the city level for these spillover effects we employ a block bootstrap with 100 iterations.[27] We estimate this using a 300-kilometer cutoff and middle funnel for the instrument in the M2SLS estimation.

Figure 4 summarizes the results converting them to the monetary impact for the average firm's annual productivity on an average weather day. The solid, black line shows the effect of a one $\mu g/m^3$ annual increase in nearby-city PM_{10} in that distance band (holding pollution in all other bands constant) on focal-city productivity with 95% confidence intervals shown in dashed, red lines. Since these are annual productivity effects this assumes a one $\mu g/m^3$ increase in nearby-city PM_{10} for the entire year and for the empirical distribution of wind direction across the year. The costs are CNY 535 (USD 70) for nearby cities within 50 kilometers and decline fairly quickly and smoothly to CNY 83 (USD 11) for nearby cities at 550 to 600 kilometers. Beyond this, the spillovers decline slowly to approach zero at about 1,000 kilometers. In comparison the effect of local sources of PM_{10} on productivity is CNY 4,613 (USD 607).

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[26] We experimented with using province-by-year-by-month fixed effects but the model was too saturated. There is an average of only 1.5 cities per province in the data.

[27] Specifically, for each iteration we draw (with replacement) a block bootstrap by city. In the first step (spillover decay function) we use all days in all years for these cities. In the second step (causal effects) we use all firms and all days in all years for the sampled cities.

[Insert Figure 4 here]

While the spillover decay function estimates alone tells us the relative tradeoff between local and extra-territorial effects, they do not tell us the absolute amounts at stake. This requires both steps of our procedure. For example, if PM_{10} increases by one $\mu g/m^3$ annually in both a focal city and a nearby city located at 125 kilometers, productivity falls by CNY 4,613 annually for the average firm due to local sources of pollution and another CNY 318 due to imported pollution. The latter is smaller because pollution dissipates as it drifts and the wind blows directly toward the focal city only part of the time.

These results can also be used to calculate Coasian prices. Consider Tianjin which is located 107 kilometers from Beijing and let θ_{td}^{BT} be the angle of the wind relative to the ray from Tianjin to Beijing. If each city were assigned rights to keep its city free of other cities' air pollution, Tianjin would have to compensate Beijing CNY 2.41*$abs[cos(\theta_{td}^{BT})]$ times the number of firms in Beijing on each day when $-90^{\circ} \leq \theta_{td}^{BT} \leq 90^{\circ}$. This is the λ_{2b} coefficient from Equation (3) multiplied by the annual causal effect converted to a daily cost.[28] Similarly, on days when the wind blows toward Tianjin, Beijing would have to compensate Tianjin 2.41*$abs[cos(\theta_{td}^{TB})]$ times the number of firms in Tianjin for each $\mu g/m^3$ of PM_{10} that Beijing produces on a day when the wind blows between $-90^{\circ} \leq \theta_{td}^{TB} \leq 90^{\circ}$ where θ_{td}^{TB} is the angle of the wind relative to the ray from Beijing to Tianjin.

4.5 Wald (2SLS) estimates

An alternative to our M2SLS procedure is to combine our first-step estimates of the pollution decay function using daily data with causal estimates based on Wald (2SLS). Estimating 2SLS requires aggregating the first-stage data to match the annual data used in the second stage. We aggregate the first-stage data by taking firm-year averages conditional on wind blowing toward the focal city (i.e., computing mean values of focal-city pollution, cosine-weighted nearby-city pollution, and weather control variables using only days when the wind blows toward the focal city). We also include firm and region-by-year fixed effects and cluster standard errors by focal city to be consistent with our M2SLS estimates. Table 4 shows the results at the different distance cutoffs using the middle funnel. The coefficients for the first-stage results (Panel A) are all significant but are opposite of the expected sign. The results also suggest weak instruments with all of the KP *F*-statistics below the critical value of 16.38. The second-stage coefficients in Panel B are insignificant. This is consistent

[28] The λ_{2b} coefficient is 0.191 for nearby cities between 100 and 150 kilometers away. The annual causal effect is CNY 4,613 or CNY 12.6 on a daily basis. Multiplying these two numbers yields CNY 2.41.

with lack of sufficient variation to precisely identify the coefficients[29] or endogeneity bias introduced by confounding factors at the annual level or both. We now investigate this further.

[Insert Table 4 here]

Table 5 shows how the level of aggregation in the first-stage affects the estimates of the causal effects of pollution on productivity (second-stage estimates are all at the firm-year level). These estimates use the 300-kilometer cutoff in choosing the nearest-nearby city, apply the middle funnel in choosing which days to include in the first-stage, and include the same controls as our baseline estimates except that region-year fixed effects are used rather than region-by-year-by-month.[30] Column 1 of the table uses firm-day data in the first stage conditional on wind blowing toward the focal city. This specification is the same as the baseline except that region-year fixed effects are used.[31] Column 2 aggregates the first-stage data to the weekly level conditional on wind direction (i.e., averages all days when wind is blowing toward the focal city across each week). Columns 3, 4, 5, and 6 aggregate in a similar way to the monthly, quarterly, semiannual, and annual levels (the last is the Wald estimates discussed above).

Fairly clear patterns emerge as the level of aggregation is increased. The first-stage coefficient declines in magnitude (and turns negative with annual aggregation) consistent with less variation or confounding factors in aggregated pollution levels.[32] The second-stage coefficients become less significant and are insignificant with aggregation at frequencies lower than weekly (weekly aggregation appears to be sufficient to achieve identification). These results suggest that aggregating data to a lower-frequency in the reduced-form and 2SLS estimations faces one or both of two issues. First, it provides insufficient variation to identify the relationship between focal- and nearby-city pollution. Second, it introduces the possibility of confounding factors, in particular seasonal shocks to productivity. This is also consistent with the

[29] Assuming that 2SLS estimates are unbiased, Dhrymes and Lleras-Muney (2006) show that M2SLS estimates could be more or less efficient than 2SLS. M2SLS is more efficient because it uses disaggregated data in the first stage thereby utilizing more information; however, the grouping of the first-stage predicted values changes the nature of the first stage errors and their relationship to the second-stage errors which could decrease efficiency.

[30] Region-by-year-by-month fixed effects are not used since they cannot be included once data is aggregated for periods longer than one month.

[31] As we showed in our robustness checks (Appendix H), the causal effects are somewhat lower using region-by-year fixed effects than in our baseline estimates using region-by-year-by-month fixed effects.

[32] The negative coefficient at the annual level could occur because production cost shocks in a city led to production being diverted to a nearby city on an annual basis or, alternatively, binding environmental regulations in a city led to production being shifted to a nearby city on an annual basis.

results in Column 5 of Appendix H that show the importance of including year-by-month fixed effects to control for seasonality.

[Insert Table 5 here]

In summary, the daily data utilized in our M2SLS approach appear necessary to generate sufficient variation for identification and to avoid endogeneity bias.

5. Conclusion

We provide a methodology for estimating the causal effect of air pollution spillovers on outcomes that are measured with lower frequency than pollution and weather data. Measuring air pollution spillovers requires high-frequency (such as daily) data to ensure that shifts in wind direction are properly captured, but outcome variables are often available on only an annual basis.

We proceed by estimating the pollution decay function at high frequency separately from the causal effects and estimating the causal effects using a mixed two-stage least squares (M2SLS) procedure using high-frequency changes in imported pollution from nearby cities as an instrument. The M2SLS procedure allows high-frequency data for the instrumenting (necessary for isolating high-frequency shifts in wind direction) in the first stage but low-frequency outcome data in the second stage. This estimation is a natural by-product of estimating the spillover decay function since this also requires high-frequency wind and pollution data. We show that typical 2SLS fails in estimating causal effects due to the aggregation of pollution data over a long period and the resulting loss of variation and endogeneity issues introduced with low-frequency data.

Use of high-frequency data also allows spillovers to be examined at relatively short distances while minimizing the chance of spurious correlation from regional and seasonal shocks to the outcome variable. This allows an examination of spillovers between cities that are geographically close but administratively distinct and therefore potentially suffer from a free-rider problem in pollution production.

While we illustrate quantification of spillover effects on productivity, our procedure can easily be adapted to estimate the spillover effects on any outcome for which data is of a lower frequency than pollution and weather data. For example, if only annual health measures are available our instrumenting technique works as long as daily pollution and weather data are available. It is also potentially applicable to estimating outcomes over longer periods than one year.

While previous papers document the presence of spillovers, our paper specifically quantifies how their intensity varies with distance— a necessary input for determining the scope of administrative control necessary to internalize externalities. PM_{10} spillovers are large and extend quite far suggesting the need to coordinate environmental policies at the supra-provincial level.

References

Altindag, D. T., D. Baek, and N. Mocan (2017). "Chinese Yellow Dust and Korean Infant Health," *Social Science & Medicine*, 186, 78 – 86.

Anderson, M. L. (2015). "As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality," *NBER Working Paper 21578*.

Andrews, S. Q. (2008). "Inconsistencies in Air Quality Metrics: 'Blue Sky' Days and PM10 Concentrations in Beijing," *Environmental Research Letters*, 3, 1 – 14.

Angrist, J. D. and J. S. Pischke (2015). *Mastering 'Metrics: The Path from Cause to Effect*. Princeton: Princeton University Press.

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

Arzaghi, M. and J. V. Henderson (2008). "Networking off Madison Avenue," *Review of Economic Studies*, 75, 1011 – 1038.

Banzhaf, H. S. and B. A. Chupp (2012). "Fiscal Federalism and Interjurisdictional Externalities: New Results and an Application to US Air Pollution," *Journal of Public Economics*, 96, 449 – 464.

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

Bošković, B. (2015). Air Pollution, Externalities, and Decentralized Environmental Regulation," working paper.

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

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

Cai, H., Y. Chen, and Q. Gong (2016). "Polluting thy Neighbor: Unintended Consequences of China' s Pollution Reduction Mandates," *Journal of Environmental Economics and Management*, 76, 86-104.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016). "Particulate Pollution and the Productivity of Pear Packers," *American Economic Journal: Economic Policy, 8,* 141 – 69.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (forthcoming). "The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China," *American Economic Journal: Applied Economics.*

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

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

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

Chen, X. and J. Ye (2015). "When the Wind Blows: Spatial Spillover Effects of Urban Air Pollution," Environment for Development Discussion Paper Series 15-15.

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

Coase, R. H. (1960). "The Problem of Social Costs," *Journal of Law and Economics*, 3, 1 – 44.

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

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

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

Dhrymes, P. J. and A. Lleras-Muney (2006). "Estimation of Models with Grouped and Ungrouped Data by Means of '2SLS'," *Journal of Econometrics*, 133, 1 – 29.

Duranton, G. and H. G. Overman (2005). "Testing for Localisation using Micro-Geographic Data," *Review of Economic Studies*, 72, 1077 – 1106.

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

Eichner, T. and M. Runkel (2012). "Interjurisdictional Spillovers, Decentralized Policymaking, and the Elasticity of Capital Supply," *The American Economic Review*, 102, 2349 – 2357.

EPA (U.S. Environmental Protection Agency) (1996). "Review of the National Ambient Air Quality Standards for Particulate Matter: Policy Assessment of Scientific and Technical Information," OAQPS Staff Paper.

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

Fell, H. and D. T. Kaffine (2014). "Can Decentralized Planning Really Achieve First-Best in the Presence of Environmental Spillovers?" *Journal of Environmental Economics and Management*, 68, 46 – 53.

Freeman, R., W. Liang, R. Song, and C. Timmins (2017). "Willingness to Pay for Clean Air in China," NBER Working Paper 24157.

Fu, S. (2007). "Smart Café Cities: Testing Human Capital Externalities in the Boston Metropolitan Area," *Journal of Urban Economics,* 61, 86 – 111.

Fu, S., V. B. Viard, and P. Zhang (2018). "Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China," SSRN Working Paper.

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

Goodkind, A. L. *et al*. (2019). "Fine-Scale Damage Estimates of Particulate Matter Air Pollution Reveal Opportunities for Location-Specific Mitigation of Emissions," *PNAS*, 116, 8775 – 8780.

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

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

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

He, J., H. Liu, and A. Salvo (forthcoming). "Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China," *American Economic Journal: Applied Economics*.

Henderson, J. V. (2007). "Understanding Knowledge Spillovers," *Regional Science and Urban Economics*, 37, 497 – 508.

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

Jia, R. (2017). "Pollution for Promotion," working paper.

Jia, R. and H. Ku (2017). "Is China's Pollution the Culprit for the Choking of South Korea? Evidence from the Asian Dust," working paper.

Jin, H., Y. Qian, B. R. Weingast. (2005). "Regional Decentralization and Fiscal Incentives: Federalism, Chinese Style," *Journal of Public Economics*, 89, 1719 – 1742.

Jordan, B.W. (2016). "Can we Dig It? An Empirical Study of Environmental Attitudes and Social License to Operate in Mineral Extraction," working paper.

Kahn, M. E., P. Li, and D. Zhao (2015). "Water Pollution Progress at Borders: The Role of Changes in China's Political Promotion Incentives," *American Economic Journal: Economic Policy*, 7, 223 – 242.

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

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

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

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

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

Lipscomb, M., and A. M. Mobarak (2017). "Decentralization and Pollution Spillovers: Evidence from the Re-drawing of County Borders in Brazil," *The Review of Economic Studies*, 84, 464 – 502.

Lleras-Muney, A. (2005). "The Relationship between Education and Adult Mortality in the U.S.," *Review of Economic Studies*, 72, 189 – 221.

Massa, M. and A. Zaldokas (2014). "Investor Base and Corporate Borrowing: Evidence from International Bonds," *Journal of International Economics*, 92, 95 – 110.

Ministry of Civil Affairs (2017). "The Brochure of Administrative Divisions of Townships in China."

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

Oates, W. E. (1972). *Fiscal Federalism*. New York: Harcourt, Brace Jovanovich.

Oates, W. E. and R. M. Schwab (1988). "Economic Competition among Jurisdictions: Efficiency Enhancing or Distortion Inducing?" *Journal of Public Economics*, 35, 333 – 354.

Ogawa, H. and D. E. Wildasin (2009). "Think Locally, Act Locally: Spillovers, Spillbacks, and Efficient Decentralized Policymaking," *American Economic Review*, 99, 1206 – 1217.

Ostro, B. *et al*. (2018). "Assessing the Recent Estimates of the Global Burden of Disease for Ambient Air Pollution: Methodological Changes and Implications for Low- and Middle-Income Countries," *Environmental Research*, 166, 713 – 725.

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

Rangel, M. A., and T. Vogl (2016). "Agricultural Fires and Infant Health," NBER Working Paper 22955.

Rosenthal, S. S. and W. C. Strange (2003). "Geography, Industrial Organization, and Agglomeration," *The Review of Economics and Statistics*, 85, 377 – 393.

Rosenthal, S. S. and W. C. Strange (2008). "The Attenuation of Human Capital Spillovers," *Journal of Urban Economics*, 64, 373 – 389.

Schlenker, W. and W. R. Walker (2016). "Airports, Air Pollution, and Contemporaneous Health," *Review of Economic Studies*, 83, 768 – 809.

Sheldon, T. L. and C. Sankaran (2017). "The Impact of Indonesian Forest Fires on Singaporean Pollution and Health," *American Economic Review: Papers & Proceedings*, 107, 526 – 529.

Sigman, H. (2002). "International Spillovers and Water Quality in Rivers: Do Countries Free Ride?" *American Economic Review*, 92, 1152 – 1159.

Sigman, H. (2005). "Transboundary Spillovers and Decentralization of Environmental Policies," *Journal of Environmental Economics and Management*, 50, 82 – 101.

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

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

Viard, V. B. and S. Fu (2015). "The Effect of Beijing's Driving Restrictions on Pollution and Economic Activity," *Journal of Public Economics*, 125, 98-115.

Wilkening, K. L., L. Barrie, and M. Engle (2000). “Trans-Pacific Air Pollution,” *Science*, 290, 65-67.

Williams, R. C. (2012). “Growing State–Federal Conflicts in Environmental Policy: The Role of Market-Based Regulation,” *Journal of Public Economics*, 96, 1092 – 1099.

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

Xu, C. (2011). “The Fundamental Institutions of China’s Reform and Development," *Journal of Economic Literature*, 49, 1076 – 1151.

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

Zheng, S., J. Cao, M. Kahn, and C. Sun (2014). “Real Estate Valuation and Cross-Boundary Air Pollution Externalities: Evidence from Chinese Cities,” *Journal of Real Estate Finance Economics*, 48, 398 – 414.