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Abstract

Although the environmental impact of trade has been a long-standing concern, there is still only scant evidence on the *channels* through which international market access affects pollution. In this paper, we exploit the unique episode of China's world market integration in the early 2000s to provide direct empirical evidence on three such mechanisms. We combine granular satellite data on air pollution with detailed information on manufacturing firms and coal power plants, and leverage exogenous foreign demand shocks for identification. Three main findings emerge: exporting firms *reduce* local pollution (scope-1); pollution levels around coal power plants *rise* due to regional export shocks (scope-2); and upstream suppliers *reduce* pollution in the face of export demand shocks to downstream firms (scope-3). Our findings point to China's reliance on coal power plants to fuel its export-driven growth as one of the main drivers of the rise in pollution.

Keywords

Trade, pollution, satellite, supply chain, coal power plants, electricity

JEL Classification

D22, F18, F64, H23, Q53

1 Introduction

A longstanding question in economics concerns whether trade helps or hurts the environment.[1] This is particularly relevant for developing countries that hope for export-led growth, but fear the environmental and ensuing public health costs. The right policies to accompany a push for openness depend on the precise underlying mechanisms of how international market access affects pollution: Do firms change their direct net emissions when serving the world market? Do they cause additional pollution due to their rising demand for energy generation? How do suppliers and customers of exporters in the domestic production network respond? Direct evidence on these channels—in jargon scope-1, 2, and 3 pollution—remains incomplete, limiting the ability to guide policymaking.

To make progress, in this paper we examine one of the most important episodes of trade expansion in recent times, China's world market integration between 2000 and 2007. China's world market integration implied export growth in the order of 15% per year and a multifold expansion of absolute Chinese exports and their share of world exports. There is no question that accessing international markets led the Chinese economy to expand considerably (Jarreau and Poncet 2012; Brandt and Lim 2024).

At the same time, pollution became one of the most prominent issues for the country's residents (Tang 2005; Yao et al. 2022). We combine granular satellite data with detailed firm and power plant information to (re-)examine the relationship between exporting and air pollution. Employing a shift-share identification approach inspired by Mayer et al. (2021), we start at the regional level and confirm that the export demand shock led to higher concentrations of several pollutants, including fine particulate matter ($PM_{2.5}$). Next, we zoom in on individual plants of firms and find that export activity *reduces* the $PM_{2.5}$ load, so that scope-1 emissions appear to react in a desirable way. To investigate how this local effect can be reconciled with the regional estimates, we turn to scope-2 pollution and document that air pollution around coal power plants *increases* significantly when manufacturers in the region scale up their exports. Finally, we use information from input-output tables to identify a firm's potential suppliers in the same region, which allows us to study the effect on pollution through scope-3 emissions. We find that downstream export demand shocks also *reduce* local $PM_{2.5}$ concentrations upstream. Hence, our analyses attribute the large increase in pollution following trade expansion as measured at the regional level to the way this expansion was powered. By relying heavily on coal power plants for electricity generation (more than 80%, Yang 2006), China's export-driven growth was in fact coal-powered growth.

In addressing our research question, we face two main challenges. First, we require universal, highly granular and objective information on air pollution. We therefore rely on satellite data, and primarily on $PM_{2.5}$ concentration measurements within 1km $\times$ 1km grid cells. This approach has several advantages compared to the firm survey data often used in the previous literature. First, we

[1] E.g., Grossman and Krueger (1991), Copeland and Taylor (1994), Antweiler et al. (2001), Levinson (2009), Taylor (2011), Shapiro and Walker (2018), and Shapiro (2021).

can measure air pollution anywhere in China, allowing us to observe changes in pollution for a large sample of firms potentially affected by export shocks, direct and indirect, and to track down pollution around coal power plants. Second, satellite data on $PM_{2.5}$ is available at a very high spatial resolution, which reduces measurement error when we match with firm addresses and power plant coordinates. Third, we do not depend on pollution records from monitoring stations or firm surveys in China, which have been widely questioned, especially in the early 2000s (Ghanem and Zhang 2014; Stoerk 2016).[2]

Our second main challenge stems from tracing the causal effect of exporting and avoiding bias from other correlated events and activities. Our identification strategy relies on a shift-share instrumental variables approach. In the spirit of Mayer et al. (2021), we first construct proxies for foreign demand shocks at the country $\times$ product $\times$ year level as imports by those countries from all origins *except China*. These 'shifts' are numerous and assumed to be exogenous and quasi-randomly assigned. Throughout the paper, we provide supportive empirical evidence in line with the best practices outlined for shift-share instruments in Borusyak et al. (2025). Next, we assign these shocks to units of observation, such as prefectures or firms, by means of their initial destination-product-level value shares.[3] Supported by the fixed effects we introduce throughout our regression analyses, we rely on changes in the demand for Chinese products after its accession to the World Trade Organization (WTO) for identification.

We implement our empirical strategy leveraging the rich data that we could access to address our research question. In addition to information on air pollution, our analysis use data from several additional sources. The main data on firms come from the Chinese Annual Survey of Manufacturing Firms (ASIF), which is exhaustive for manufacturing companies above a low size threshold in terms of revenue. This survey provides information on exports and a host of firm characteristics, such as addresses, balance sheets, income and loss statements etc. Moreover, we employ Chinese customs data, which provide us with the population of international trade transactions at the firm-product-country-year level, in addition to aggregate trade data. To investigate electricity generation, we use Global Energy Monitor data, which contain the exact location and fuel types of all power plants, and to study scope-3 pollution along the supply chain, we use official input-output tables.

The first step in our analysis is to confirm that exporting increased pollution in China at the regional level, as documented by Bombardini and Li (2020), who rely on tariff variation for identification purposes. Despite the different identification strategy, we find that larger exports at the prefecture level over time led to significantly higher concentration of $PM_{2.5}$. Our estimates imply sizable magnitudes, with an inter-quartile effect of around 3 percent. Our findings at the regional level are also consistent with the concurrent study by Gong et al. (2023), which provides evidence on the nexus between

[2]Even if pollution monitors were reliable, as the comparison with the recordings from the few monitoring stations run by the U.S. Embassy may suggest (Bombardini and Li 2020), sparseness and strategic siting may still be an issue (Meng and Kc 2025), which has also been shown to affect other countries such as the United States (Grainger and Schreiber 2019).

[3]The main Chinese administrative units in descending order or size are *provinces*, *prefectures*, and *counties*. During our sample period, mainland China was divided into 22 provinces (average population of 40 million) with about 330 prefectures (4 million) and 2,860 counties (450,000).

pollution and mortality using satellite data and sustained trade-induced changes in economic activity.

Next, we zoom in on individual plants and document that the $PM_{2.5}$ concentration in their immediate vicinities *falls* when the firm becomes an exporter or increases its international shipments. The decline is statistically significant, and the magnitude of the effect is highly skewed due to the skewed distribution of firm-level exports: While the inter-quartile effect implies a modest reduction of 0.3 percent, a firm at the 99$^{\text{th}}$ percentile experiences 3.4 percent lower ambient air pollution than a firm at the median. This finding regarding scope-1 pollution is highly robust to a battery of alternative specifications. First, we present evidence that the exclusion restriction for our instrumental variables approach is not violated due to offshoring, other firm characteristics like state-ownership, local weather conditions or population movements from rural to urban areas. Second, we show that the finding holds in a sample of single-plant firms and that the imbalance of the manufacturing firm panel over time—China experienced significant growth in the number of firms over our time period—does not affect it either. Third, the finding extends to pollution with NO_2, albeit in a smaller sample due to data availability. Finally, we run several other checks, such as focusing on exported quantities as opposed to values, using alternative instruments to explore the identifying variation, and exploring exports to countries at different levels of income per capita. Overall, our estimates are in line with Rodrigue et al. (2024), for the particular case of China, as well as for instance Cherniwchan (2017), suggesting that the technique effect dominates the scale effect at the exporter level.

Following this evidence on scope-1 air pollution, and noting that it is in stark contrast with the regional findings, we extend our analysis to scope-2 pollution from electricity generation and scope-3 pollution from input-output linkages. We first relate $PM_{2.5}$ concentrations around coal power plants over time to total export volumes in the regional power grid where the power plant is located, once again instrumenting with foreign demand shocks. Chinese electricity grids in the early 2000s were still heavily fragmented, a feature that allows us to establish a tight connection between additional electricity demand due to export demand and largely coal-based power supply. We find a significant and economically large effect: Comparing the power grid with the largest increase in export demand to the one with the lowest, the former is predicted to incur a 22 percent higher $PM_{2.5}$ concentration because of such differential in trade activity. We furthermore show that this effect is not driven by nearby coal mines and more than triples for areas downwind of a coal power plant. Scope-2 pollution therefore appears to play a central role in the polluting effect of international market access.

Finally, we study how scope-3 air pollution reacts to exporting. On the one hand, exporters may have a detrimental regional effect if their additional demand for intermediate inputs causes a scale effect at their supplier plants. On the other hand, their technique effects may spill over through their supply relationships, thus reducing pollution. We make use of disaggregate input-output tables from China in the beginning of our sample period and identify all *potential* suppliers of our target firms as those that operate in one of the 10 most important upstream industries (measured by the direct requirement) and in the same prefecture. Analogously, we can also identify sets of potential customers. No matter whether we regress average upstream $PM_{2.5}$ concentrations on a downstream firm's individual export shock or a firm's local $PM_{2.5}$ concentration on its customer's average export shock, we find that exporting downstream *reduces* air pollution upstream. This pattern is fully robust to expanding the potential sourcing area of firms, as infrastructure projects in China improved market access over time. In sum, scope-3 emissions are likely to dampen the negative effects of market access on overall pollution.

To our knowledge, this is the first study to shed light on the three focal mechanisms through which market access affects air pollution. In doing so, it contributes to several (overlapping) strands of research. First, it advances an established strand of research examining empirically the relationship between trade and the environment (e.g. Grossman and Krueger 1991; Copeland and Taylor 1994; Antweiler et al. 2001; Levinson 2009; Taylor 2011; Levinson 2015; Cherniwchan 2017; Forslid et al. 2018; Shapiro and Walker 2018; Gutiérrez and Teshima 2018; Banerjee et al. 2021; Barrows and Ollivier 2021; Shapiro 2021, as well as the reviews of Copeland and Taylor 2004; Tamiotti 2009; Cherniwchan et al. 2017). Second, we speak to a growing stream of work analyzing the implications of the large shock that was represented by China's accession to the WTO, domestically (e.g. Jarreau and Poncet 2012; Bombardini and Li 2020; Rodrigue et al. 2022; Kwon et al. 2023; Gong et al. 2023; Rodrigue et al. 2024) and globally (e.g. Autor et al. 2013; Acemoglu et al. 2016; Jia and Ku 2019; Autor et al. 2020).

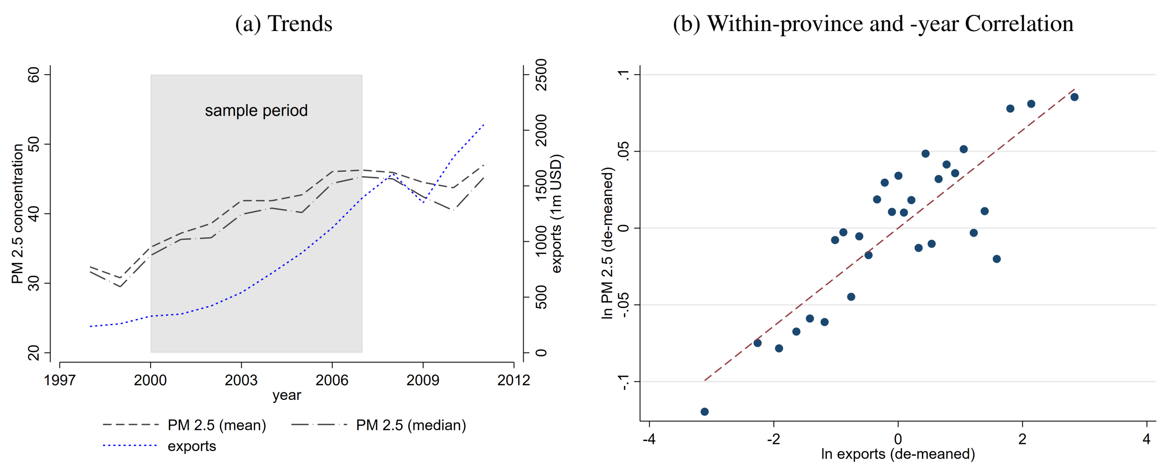
Third, we add to a set of studies assessing firms' abatement decisions in a variety of contexts (e.g. Barbera and McConnell 1990; Berman and Bui 2001; Morgenstern et al. 2001; Martin et al. 2014; Cullen and Mansur 2017). In this paper, we provide a novel angle on the domestic impact of China's trade expansion, through changes in pollutants for firms exposed to trade shocks, but also across their supply chains, including the provision of electricity. Fourth, with our detailed analysis by pollution scopes, and in particular our findings concerning scope-2 pollution, we also contribute to literature concerned with capturing indirect pollution when designing policy, in the trade realm or otherwise (Elliott et al. 2010; Fischer and Fox 2012; Larch and Wanner 2017; Brander et al. 2018; Lyubich et al. 2018; Rocchi et al. 2018; Carattini et al. 2022; Fontagné and Schubert 2023; Köveker et al. 2025).

The remainder of the paper is organized as follows. Section 3 describes our empirical approach. Section 4 presents our data. Section 5 introduces our empirical results. Section 5 shortly concludes.

2 Background

China's accession to the WTO in 2001 marked a watershed moment in its integration with the global economy. Falling trade costs, lower trade policy uncertainty, rising productivity, access to better foreign inputs, and booming foreign demand, catalyzed an unprecedented surge in exports in China (Handley and Limão 2017; Brandt and Lim 2024; Huang et al. 2024). Between 2000 and 2007, average exports increased fivefold at the prefecture level, as shown by Figure 1a. This rapid export expansion coincided with a significant rise in air pollution, as industrial activity intensified to meet global demand. Average $PM_{2.5}$ concentration in Chinese prefectures went up by more than 30% from below $40\mu g/m^3$ in 2000 to above $50\mu g/m^3$ in 2007. To put these numbers into context, in 2005 the World Health Organization recommended an annual average exposure of less than $10\mu g/m^3$ to moderate the impact of particulate matter on health (World Health Organization 2021). China would go on to become the world's largest consumer of energy and coal by 2010 as well as the largest emitter of CO_2 and SO_2 (Greenstone et al. 2021). The co-movement of export growth and pollution remains strong even when we compare prefectures in the same province and controlling for trends in these variables: as Figure 1b indicates, exports de-meaned by province and year are strongly and positively correlated with de-meaned $PM_{2.5}$ concentration.

Figure 1: Export and Pollution at the Prefecture Level



Notes: Figure (a) displays $PM_{2.5}$ concentration and total exports in million USD for the average and median prefectures over time. Figure (b) shows a bin-scatter plot of average $PM_{2.5}$ concentration within 30 quantile-bins along the (ln) export distribution (variables were de-meaned by province and year).

China's integration into global markets provides an ideal laboratory to examine the environmental impact of international trade. At the same time, its unique situation creates significant obstacles for obtaining precise pollution data. While China's foundational environmental protection law passed in 1989 established a regulatory framework, its vague language granted local governments substantial discretion when it came to enforcement (Ma and Ortolano 2000). Local officials, whose career advancement depended on economic performance, prioritized growth over environmental protection, often adopting lax regulatory standards (Jia 2024). This incentive structure also encouraged strategic data manipulation: pollution measurements were routinely under-reported to central authorities and to the public due to high verification costs and weak accountability mechanisms (Ghanem and Zhang 2014; Greenstone et al. 2022). Only after 2014—well outside our time frame of interest—China started the "war on pollution" and implemented significant regulatory changes to tackle pollution, including improved and centralized measurement (Greenstone et al. 2021, 2022).

China's environmental damages during the 2000s were closely tied to its coal-dominated energy system. Coal-fired power plants accounted for 74% of generating capacity and 82.9% of electricity output in 2003 (Yang 2006), and their share was largely unchanged at 80.3% in 2010 (Jia 2024). Cleaner hydropower only accounted for 14.8% of electricity output in 2003 and increased modestly to 18.4% in 2010. Coal power plants, especially older, inefficient ones without state-of-the-art filtering technology, are well known for their polluting potential (Weng et al. 2023).

A defining characteristic of China's power infrastructure during this period was its highly fragmented grid system. The main reason for the lack of development in the grid system was local protectionist policies that constrained inter-provincial electricity trading (Pittman and Zhang 2008; Lin and Purra 2010; Jia 2024). Although the Chinese central government unveiled an ambitious plan in January 2022 to establish a unified national electricity market by 2030, progress remains limited: as of 2022, 97% of mid-to-long-term electricity contracts were still negotiated within provincial borders (International Energy Agency 2023). This fragmentation of the energy infrastructure also implies that manufacturing companies source electricity locally and generation capacity can be viewed as province-specific to a large extent, for our time frame of interest as well as well beyond including present-day China.

3 Empirical Approach

3.1 Scope-1 Pollution and Baseline Estimation Strategy

In our firm-level exercises, we estimate linear models of the form

$$air\ pollution_{f,t} = \beta_1 exports_{f,t} + \boldsymbol{\beta_2 X_{f,t}} + \gamma_t + \boldsymbol{\delta} + \varepsilon_{f,t}, \tag{1}$$

where t and f indicate years and firms, respectively. Our main outcome measure of air pollution is the local (ln) concentration of $PM_{2.5}$ in the vicinity of the firm (details presented in Section 4).[4] As an alternative measure, we also explore NO_2. In both cases, the advantage of using air pollution rather than emissions is that the former is the relevant dimension for health and mortality implications. Exposure to international trade, $exports_{f,t}$, is proxied by the inverse hyperbolic sine-transformed total value of exports, which takes both the skewness of export values and the prevalence of non-exporters into account. In our robustness checks, we furthermore swap total export values for exported quantities and exports to high income countries, which allows us to capture real production and product mix or technological heterogeneity (albeit at the cost of reduced sample sizes).

Importantly, we use various sets of fixed effects in our regressions. Year effects γ_t absorb aggregate shocks that affect export values and pollution around firms in China in the same way. $\boldsymbol{\delta}$ is a placeholder for various other sets of fixed effects that absorb confounding variation. In a less demanding approach,

[4] Our outcome variable is continuous and strictly positive, implying the use of natural logarithms without incurring in the issues highlighted in Chen and Roth (2024), which arise in the presence of outcome variables for which the extensive margin may be affected by the treatment.

we include indicators for a firm's province and 4-digit industry, which address location- and technology-specific patterns of trade and pollution that are unrelated to a manufacturer's production and emissions. In a more demanding approach, we focus on variation in exporting and local pollution that occurs *within firm over time*. These firm fixed effects not only absorb spatial and industry variation, but also control for time-invariant characteristics of companies such as their relative size.

Finally, we include additional regressors to shore up the identification strategy outlined below. We assume that error terms are predominantly correlated spatially, so that we cluster standard errors by prefecture-year throughout.[5]

Serving foreign markets via exporting is a choice and likely depends on several underlying factors that are correlated with emissions and local air pollution. For instance, managerial staff play a key role for both trade participation and corporate environmental policy (e.g., Bloom et al. 2021, Gaganis et al. 2023). Fixed effects control for a range of potential concerns about such omitted variables, but to the extent that some of the above-mentioned underlying factors may change over time, some endogeneity may persist. Consequently, we adopt a shift-share instrumental variables strategy, where we use foreign demand shocks to shift Chinese firms' exports exogenously. Changes in foreign demand are ideal for our purpose: for the most part, they occur far away from China, are not driven by individual Chinese firms, and were the quantitatively biggest driver of Chinese export growth since 2000 as shown by Brandt and Lim (2024). Thus, identification is based on "shifts", rather than "shares."

We follow the by-now standard approach of Mayer et al. (2021) to distill exogenous variation for Chinese firms: We compute a destination country d's total import value of product p from all origins *except China* and take logs to obtain $\ln M_{dpt}$. Excluding imports from China addresses the concern that we pick up Chinese supply shocks, which may affect pollution through channels that are not trade-related. Following the best practices for shift-share instruments outlined in Borusyak et al. (2025), we provide evidence that the number of shifts is large as required for identification below and for all empirical exercises in this paper.

Next, we assign these shocks to firms. Starting with current exporters for which we have customs data, we weight the Mayer et al. (2021) shocks using the firm's export value share $s_{fpd,t_0(fpd)} X_{fpd,t_0(fpd)} / \sum_{pd} X_{fpdt_0(fpd)}$ by destination-product. As Chinese firms rapidly expanded their product-destination pairs following China's ascendancy, we use the shares in the first period a firm-product-destination is observed, $t_0(fpdt)$. While our identification relies on exogeneity of the shifts, and not of the shares, we nevertheless keep the latter constant and largely pre-determined. As a final note on the shares, their construction implies that they do not sum up to unity and we apply the standard adjustment of controlling for this sum interacted with year indicators in all regressions throughout this paper (Borusyak et al. 2025).

Our first instrumental variable, which we call the *intensive margin IV*, is computed as

[5]Especially in the presence of firm fixed effects, error terms may be highly correlated within firm over time, so that we alternatively cluster by firm. Since this approach generally yields smaller standard errors, we opt for the more conservative approach of clustering at prefecture-year level.

$$IV_{ft}^{int} = \sum_{dp} \underbrace{\frac{X_{fdp,t_0(fpd)}}{\sum_p X_{fdp,t_0(fpd)}}}_{\text{initial export shares}} \underbrace{\ln M_{dpt}}_{\text{foreign demand shocks}} .$$

This instrument is not defined for years in which a firm does not export or for firm-years that we cannot match to customs information (the details are discussed in Section 4 below). Yet, these firms do experience a latent export demand shock and excluding this firm extensive margin of exporting may be particularly problematic: Standard trade theory, where firms select into exporting based on their core productivity (e.g., Melitz 2003), predicts that the firm extensive margin consists predominantly of comparatively unproductive companies that use relatively less advanced machinery, processes, and filters, as Qi et al. (2021) show for the case of China. Relying only on the intensive margin IV, we therefore ignore a potentially important mechanism; even if emissions are reduced by extant exporters as documented by, for example, Cherniwchan (2017), new entrants to the world market may cause an opposing effect. Irrespective of potential heterogeneity, however, analyzing the largest possible sample of firm-level observations is in any case useful to broaden the scope of our insights.

We therefore construct a second instrument by extrapolating IV_{ft}^{int}. In particular, we assume that non-exporters in a given 4-digit industry $\times$ prefecture cell experience similar (latent) demand shocks from abroad as the average current exporter in that same cell. The extrapolated instrument, IV_{ft}^{full} is therefore equal to IV_{ft}^{int} for current exporters and equal to $\overline{IV^{int}}_{jrpt}$, where we use the industry and prefecture indices j and r to make the level of variation explicit.[6]

There are two channels through which the instruments manipulate Chinese exports, so that the first stages could *a priori* be positive or negative. On the one hand, Chinese exports and the number of exporters are expected to decline if goods imported from countries other than China act as substitutes—in this case, $\ln M_{dpt}$ is an inverse measure of the demand shock. On the other hand, if variation in $\ln M_{dpt}$ is due to income effects abroad or if Chinese goods are complements to the ones from other countries, exports rise and more exporters enter the market. Since the vast majority of Chinese trade exports go to developed countries where they either replace domestic production ("offshoring") or broaden the portfolio of varieties available to firms and customers, we strongly expect the demand shocks to have a positive effect on exports, as in Mayer et al. (2021).

As a final note, we also subject our instrumental variables approach to a set of additional tests as recommended in Borusyak et al. (2025), the results of which we report together with the main findings in Section 5.

[6] To be precise, we use $\rho \times \overline{IV^{int}}_{jrpt}$ for non-exporters, where ρ is a factor close to, but below one. The reason is that the instrument for non-exporters switches from $\overline{IV^{int}}_{jrpt}$ to IV_{ft}^{int} when they start exporting, which implies a negative "shock" in that period for some firms if $\rho = 1$. To alleviate this issue, we set $\rho = 0.85$ and provide evidence based on balance tests—following again Borusyak et al. (2025)—that this mechanical assignment is innocuous in the design of the shift-share instrument. Moreover, we show that all our main results hold with either instrument.

3.2 Scope-2: Power Generation

Serving additional demand from abroad requires energy and China's electricity consumption was predominately satisfied by coal during the early 2000s, as discussed in Section 2. Since coal power plants are particularly polluting, we examine the effect of regional demand surges due to exporting. To do so, we estimate the following power plant-level regression models (c denotes a coal power plant):

$$air\ pollution_{ct} = \beta_1 exports_{grid(c),t} + \gamma_t + \boldsymbol{\delta} + \varepsilon_{ct}. \tag{2}$$

We measure the pollution outcome in the immediate vicinity of each of China's coal power plants—leveraging the granularity of satellite data for $PM_{2.5}$—and regress it on the (inverse hyperbolic sine-transformed) total export volume in the *regional power grid* where the power plant is located. As described in Section 2, in the late 1990s and early 2000s, China's power grid was divided into seven regional sub-grids with little or no interconnection. Even though the central government prioritized connectivity since the 2000s, we can exploit the regionalization of electricity provision to assign demand to individual plants. Inevitable measurement error is expected to work against finding any effects.

To identify the effect of exporting, we rely on year (γ_t) and spatial or power plant-level fixed effects (δ) as well as on our shift-share instrumental variables strategy. In particular, we calculate exposure measures as initial export shares at the grid level, once again in the first period that a grid - 6-digit product - destination is observed in the data. As the extensive product-destination margin plays no significant role at the high aggregation level of power grid regions, we do not extrapolate the instrument as for scope-1 regressions.

3.3 Scope-3: Input-Output Analysis

To study the role of changes in scope-3 pollution, we investigate whether, and to what extent, an export demand shock downstream affects pollution at supplier plants upstream.

To this end, we conduct two different exercises. In the first, we estimate regressions of the form

$$air\ pollution_{f,t}^{potential\ suppliers} = \beta_1 exports_{f,t} + \boldsymbol{\beta_2 X_{f,t}} + \gamma_t + \boldsymbol{\delta} + \varepsilon_{f,t}. \tag{3}$$

Here, we measure pollution in the locations of firm f's potential manufacturing *suppliers* and relate the simple average of $PM_{2.5}$ concentrations across those to firm f's (inverse hyperbolic sine-transformed) total value of exports as a proxy for downstream shock due to exporting.

There are two challenges we have to overcome in order to achieve clean identification of this relationship. First, the regressor may be endogenous due to omitted variable bias. In particular, upstream suppliers could experience their own changes in export demand, which may be correlated with the downstream firm f's shock and influence air pollution. We address this concern in two ways. For one, we include the (ln) average export value of the upstream suppliers, the (ln) number of exporters among suppliers, and their (ln) average sales as control variables. Moreover, we employ the firm-level instrumental variables approach described above.

The second challenge concerns the domestic production network. On the face of it, running regression 3 using *actual* suppliers appears preferable to using *potential* ones, but we do not have access to information about local firm-to-firm trade networks in China. Even if such data were available, however, downstream export demand shocks may induce changes in firms' production networks, which raises its own concerns and challenges. We therefore focus on suppliers that are potentially relevant candidates for sourcing intermediate goods as inputs.

We define potential suppliers as follows. For each downstream customer firm f, we obtain the main activity according to the 4-digit industry classification of China (CIC). By means of a Chinese 3-digit input-output table—to be precise, a USE table—for the year 2002 (122 industries), we identify the 10 most important upstream supply industries according to the direct requirements. To avoid conflating an export demand shock to suppliers with effects on competitors, we conservatively drop the diagonal of the input-output table. The 10 biggest local suppliers in these industries in terms of sales are selected as potential suppliers, where "local" refers to the same prefecture as firm f.[7] This approach is consistent with the idea of relatively strong "gravity" in production networks, i.e., firms tend to source more inputs from suppliers that are closer (see, e.g., Bernard et al., 2019; Arkolakis et al., 2023). Overall, we expect that including a large number of upstream firms would bias our results towards finding no effect, because production networks tend to be sparse (Bernard et al. 2022; Bernard and Zi 2022; Huang et al. 2024).

In the second, complementary approach, we view firm f as a supplier company in the value-chain and study how pollution in its vicinity changes when it experiences a *domestic* demand shock induced by downstream export activity at their *customers'* sites. In the absence of production network information, we again identify potential customers using input-output tables, just as in the case of potential suppliers above. The only difference lies in how we find the 10 most important downstream industries: Instead of a USE table, we employ a MAKE table, i.e., a matrix where each element captures the share of purchases of a downstream industry in an upstream industry's sales.

The regression model is now

$$air\ pollution_{f,t} = \beta_1 exports_{f,t}^{potential\ customers} + \boldsymbol{\beta_2 X_{f,t}} + \gamma_t + \boldsymbol{\delta} + \varepsilon_{f,t}, \tag{4}$$

where the outcome is $PM_{2.5}$ concentration in the grid cell of firm f, as in the baseline firm-level exercises. The regressor of interest to measure the downstream demand shock is now the average value of the (inverse hyperbolic sine-transformed) exports across potential customers. Since we expect

[7] The number of candidates we include is subject to a trade-off. It should not be too low, so that we catch all actual and the most relevant potential suppliers. At the same time, in the light of great sparsity in production networks, it is unlikely that a firm sources from a large number, let alone all of the upstream firms. We have confirmed that our results are not sensitive to using 5 or 25 candidates. In both cases, and consistent with the trade-off described, the t-statistics are slightly lower, but the coefficients retain their level of significance.

larger demand shocks from customers in more important downstream industries, we weight potential customers's exports with their industries' input-output coefficients in the MAKE table.

To achieve identification, we rely on our shift-share approach once again. We instrument $exports_{f,t}^{potential\ customers}$ with the full instrument $IV_{s(f)t}^{full}$ described above, taking the direct requirement-weighted average across firm f's potential suppliers $s(f)$ to aggregate. Moreover, we include $exports_{f,t}$ in all regressions to address the concern that localized export demand shocks shift firm f's local air pollution through its own exports. To afford comparability with our scope-1 results, we instrument this regressor with IV_{ft}^{full} as well.

As a final methodological remark, note that this analysis focuses on the role of supply chain linkages, the key component in the standard definition of scope-3 pollution. Scope-3 pollution may in principle also include more minor indirect pollution not included under scope-1 and scope-2 pollution, such as waste disposal, business travel, and commuting by workers. Acknowledging this limitation, we focus on air pollution due to intermediate goods supply, given its absolute and relative importance.[8]

4 Data

In this section, we describe the data sources used for our analyses in detail. We use four main sources of data. First, firm-level data on economic activity, including information on exporting activity and employment. Second, we use satellite data on local air pollution, which provide our outcome variables. Third, we include data on coal power plants. Fourth, we use customs data and data on input-output linkages. We generally focus on the period from 2000 to 2007 due to data availability (and quality).

4.1 Local Air Pollution

We retrieve satellite reanalysis data from Shen et al. (2024) and Anenberg et al. (2022) to construct our measures of $PM_{2.5}$ and NO_2 concentrations, respectively. The particulate matter data combine Aerosol Optical Depth from multiple satellite data with a chemical transport model to construct surface-level estimates of $PM_{2.5}$ concentrations after calibration with the ground-based pollution monitors. The nitrogen dioxide data are produced by extrapolating an existing concentration dataset for 2010-12 from a land use regression model based on monitors and land use variables to other years, using NO_2 column densities from several satellite and reanalysis datasets. The spatial resolution of these data is $0.01° \times 0.01°$, which roughly corresponds to a spatial grid of 1km × 1km. The temporal resolution of the $PM_{2.5}$ data is the month and we aggregate to the annual level by means of simple averages (NO_2 is directly provided at annual level). While particulate matter concentrations are available for every year in our sample period, nitrogen dioxide information is limited to the years 2000 and 2005-2007.

To assign concentrations to prefectures, manufacturing firms, and coal power plants, we use precise geo-location information. For prefectures, we take the average pollution concentration across

[8] Some local scope-3 emissions such as those caused by commuting may be captured in our scope-1 exercises.

grid cells within each spatial unit. Whenever a grid cell spreads across a border, the concentration value enters with a weight based on the share of the cell that lies within the the prefecture. For manufacturing companies in China (further details below), we use headquarters addresses and Gaode Map API's geo-coding services to assign pollution concentrations based on the grid cell in which each firm is located.Since some firms operate multiple establishments in different locations for which we do not have addresses, we confirm that our findings hold in the subsample of single-plant firms. Finally, we follow the same procedure for coal power plants, for which we have exact geographic coordinates.

Table 1: Descriptive Statistics

	2000				2007			
	Mean	25th Perc	50th Perc	75th Perc	Mean	25th Perc	50th Perc	75th Perc
Panel A: Prefecture level								
$\text{PM}_{2.5}$ $\mu g/m^3$	38.13	29.42	36.30	46.34	50.52	39.67	47.00	59.76
Exports (100k USD)	53.66	2.26	8.15	23.43	271.54	9.10	34.63	109.77
Panel B: Firm level								
$\text{PM}_{2.5}$ $\mu g/m^3$	41.76	34.70	39.40	47.20	55.79	46.80	53.10	61.90
Exports (10k USD)	2.20	0.00	0.00	1.34	3.83	0.00	0.00	1.14
Exporter indicator	0.47				0.38			
Exports (10k USD, conditional)	4.64	0.64	1.46	3.54	10.23	0.81	2.09	5.52
# of plants	1.09	1.00	1.00	1.00	1.07	1.00	1.00	1.00
Firm age	12.17	5.00	8.00	14.00	10.15	5.00	7.00	13.00
$\mathbb{1}$(State Owned Enterprise)	0.12				0.02			
$\mathbb{1}$(Multinational Enterprise)	0.36				0.29			
$\mathbb{1}$(Located in Special Economic Zone)	0.05				0.05			
$\mathbb{1}$(Located on coast)	0.29				0.31			
Panel C: Coal power plant level								
$\text{PM}_{2.5}$ $\mu g/m^3$	45.13	35.40	46.80	54.00	60.81	46.00	59.60	75.80
Exports (10m USD)	21.80	6.80	21.78	21.78	114.75	36.62	107.95	107.95

Notes: Summary statistics based on estimation sample in preferred specifications. Numbers of observations across the two years are 259 and 265 (Panel A), 53,894 and 174,162 (Panel B), and 547 (Panel C).

The descriptive statistics for our estimation sample in Table 1 illustrate that pollution intensified significantly over our sample period and for all units of observation: Local $\text{PM}_{2.5}$ concentrations rose by around one third at the prefecture, firm, and coal power plant level—on average and for all percentiles in the distribution. Since air pollution is particularly intensive around coal burning thermal power plants, the greatest absolute increase occurs around such facilities, which suggests a substantial expansion of pollution. Moreover, as manufacturing plants are typically clustered in industrial districts, air pollution at the firm level generally exhibits a higher $\text{PM}_{2.5}$ concentration.

4.2 Firm-level Data on Economic Activity and Exports

We access data from the Chinese Annual Survey of Industrial Firms (ASIF) from 2000 to 2007. The National Bureau of Statistics of China collects ASIF data from reports submitted by sampled enterprises. The sample includes all State-Owned Enterprises (SOEs) and non-SOEs with annual sales of over 5 million RMB, or roughly 600,000 USD in 2000. The sample covers firms in the manufacturing, mining, and utilities sectors, and we focus on the 30 manufacturing industries, which range from agricultural and sideline food processing to handicraft and other manufacturing industries.[9]

The dataset provides a diverse and broad set of information, including details on balance sheets, income statements, cash flow statements, and basic information on firms, including name, location, ownership, industry, date of establishment, employment, etc. We exclude data from years after 2007 due to the unavailability of key variables and changes in sampling scheme (Brandt et al. 2014). To ensure the quality of our analysis, we follow the data cleaning procedures described by Brandt et al. (2012), which include dropping firms with missing, zero, or negative values for capital stock, exports, or value-added, and only retain firms with more than eight employees.[10]

Panel B of Table 1 shows key firm-level variables that characterize these companies and allow us to document several salient patterns. First, and prefacing more substantive points, the estimation sample expanded substantially over time: Due to policy- and growth-induced firm entry and increased coverage of ASIF, the number of firm observations more than doubled from 54,000 to 174,000 between 2000 and 2007. We will explore the implications of entry and exit explicitly in our robustness checks below.

Second, and in line with a substantial body of international trade research, export activity is highly skewed (Bernard et al. 2007; Mayer and Ottaviano 2008). In our estimation sample, only around 40% of firms are exporters, and conditional on exporting, the value shipped at the 75$^{\text{th}}$ is roughly 35,000 USD. Moreover, the mean export value among exporters greatly exceeds the median, which suggests that a small number of "superstar exporters" account for the lion's share of trade. Third, export activity expanded significantly over time. Between 2000 and 2007, the average value of exports overall rose by 74%, reflecting a larger number of exporters (the extensive margin) and rising export values conditional on exporting (the intensive margin). These patterns imply that transforming the export variable with the inverse hyperbolic sign is appropriate and that we can expect a substantial effect of trade participation on local air pollution.

Finally, the firms in our sample displays several features that are well known in the context of China. The vast majority of companies operates only a single factory, state and multinational ownership falls over time, and economic growth takes place everywhere in China, both inside and outside special economic zones. Notably, firm age falls from 12 to 10 years over time, which is consistent with the widespread emergence of new manufacturers during China's economic miracle

[9] We use the industry mapping from Brandt et al. (2012) to concord industries before and after the implementation of industry classification code of GB/T4754-2002.

[10] Export values at the prefecture- and regional electricity grid-level are the sum of firm-level exports in our sample.

in the beginning of the century. In one of the robustness checks below, we control directly for these and several other firm characteristics to address concerns about the exclusion restriction and the relationship between exports and air pollution at the firm level in general.

4.3 Coal Power Plant, Customs, Input-Output and other Data

We use coal power plant unit data from Global Energy Monitor, Global Coal Plant Tracker, July 2023 release (Global Energy Monitor 2023). These data provide information on the geo-location, capacity, operational years (from the date the power plant started operations to the date when it was decommissioned), coal type, and combustion technology of each coal power plant.

In addition to the key datasets discussed so far, we make use of the Chinese customs data and the BACI database (Gaulier and Zignago 2010) to construct our instrument. The customs data come from the General Administration of Customs of China. This dataset provides transaction data at the 8-digit Harmonized System (HS) code level, covering the universe of import and export records between China and other countries or regions. The variables include basic information such as HS product code, HS product name, value, quantity, unit, customs region involved, transportation method, trade regimes (processing versus others etc.), and the identity of the Chinese firms. Unfortunately, the customs dataset does not share the same firm identifier as ASIF. Therefore, we follow the literature (Manova and Yu 2016; Chor et al. 2021) and match the two datasets based on firms' names, addresses, telephone numbers, and zip codes.

Information on connections between upstream and downstream sectors—which we employ to study production network effects—is based on the official Chinese Input-Output tables (National Bureau of Statistics of China 2006). The NBS publishes input-output tables every five years and we use the 2002 edition. The tables contain the value transacted by each selling and buying sector for 122 individual manufacturing industries. On this basis, we can calculate the USE and MAKE tables mentioned in Section 3.3 above. That is, we divide each flow by the total expenditures of a downstream sector on all upstream sectors to arrive at the standard direct requirement in a USE table. Analogously, for the MAKE table, we calculate sales shares of downstream sectors in each upstream sector as the ratio between a flow and the total sales of the upstream sector to all downstream ones.

To conclude the exposition, we introduce various other data sources. First, we use information on precipitation, temperature, and wind direction from Muñoz Sabater (2019) in several robustness exercises. In each case, we aggregate data at a higher frequency up to the annual level by taking simple averages. Second, we obtain information on population density at the county level from the Statistical Yearbooks (National Bureau of Statistics of China 2023).

5 Results

In this section, we describe how China's export activities between 2000 and 2007 affected air pollution. We start by confirming that exports raise air pollution at the regional level and subsequently zoom in on localities of individual firms. In a second step, we provide evidence on how individual firm-level exporting translates into aggregate air pollution: We study pollution outcomes around coal power plants in the vicinity of exporters (to scrutinize scope-2 pollution) and how export shocks generate pollution through local production networks (scope-3 pollution).

5.1 Scope-1: Exports and Pollution at the Regional and Firm Level

In Table 2, we summarize estimation results based on equation (1) at the prefecture and the firm level. The first main finding is that export-intensive *prefectures* experienced significantly *higher* air pollution. Based on the preferred estimate in column (2), prefectures with total exports at the 75^{th} percentile of the distribution suffered from a 3 percent higher concentration of $PM_{2.5}$ than a prefecture at the 25^{th} percentile.[11] Over time, the local average treatment effects imply that the average increase in exporting within province between 2000 and 2007 can explain 10 percent of the increase in particulate matter concentration. In sum, our results confirm the findings in Bombardini and Li (2020) with a different approach and relying on satellite data for measurement.

Table 2: Scope-1 – Results

	ln $PM_{2.5}$					
	prefecture level		firm level			
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(total value of exports)	0.021*	0.018*	-0.014***	-0.002***	-0.005***	-0.009**
	(0.012)	(0.010)	(0.002)	(0.001)	(0.002)	(0.004)
N	2,104	2,104	995,784	995,781	995,784	279,547
OLS Coefficient	0.036	0.032	-0.008	-0.002	0.000	-0.001
OLS P-value	0.000	0.000	0.000	0.000	0.050	0.000
KP-Statistic	226.0	197.8	2423.6	5915.5	867.2	101.5
Mean outcome	3.753	3.753	3.896	3.896	3.896	3.842
Year FE	YES	YES	YES	YES	YES	YES
Province FE		YES		YES		
4-digit Industry FE				YES		
Firm FE					YES	YES

Notes: The table shows 2SLS regression results at the prefecture and the firm level (first stage results are reported in online Appendix Table A.1). Outcome variables are the local (ln) concentrations of $PM_{2.5}$. The regressor of interest is the inverse hyperbolic sine-transformed total export value of the prefecture or firm. The shift-share instrument is described in Section 3.1 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by province × year in columns (1) and (2), and by prefecture × 4-digit industry in columns (3) to (6). * p<.10 ** p<.05 *** p<.01

The second main finding concerns pollution at the local level, i.e., in the direct vicinity of individual firms that start to export for the first time or increase shipments abroad. In columns (3) to (5), where

[11] These figures are calculated on the de-meaned distributions to give an accurate impression. In the case of $PM_{2.5}$, the inter-quartile effect is $\exp(0.018 * (0.916 - (-0.875))) - 1 \approx 3\%$.

we use the full shift-share instrument, the effect is *negative*: Exporters reduce the local burden of pollution. This finding is consistent, for instance, with Cherniwchan (2017), and with a technique effect dominating a scale effect due to expanding production. The decline is statistically significant, and the magnitude of the effect is highly skewed due to the skewed distribution of firm-level exports: While the inter-quartile effect implies a modest reduction of 0.3 percent, a firm at the 99$^{\text{th}}$ percentile experiences 3.4 percent lower ambient air pollution than a firm at the median. Moreover, while average local air pollution worsened over the sample period as shown in the descriptive statistics, this increase in $PM_{2.5}$ concentration would be even more pronounced in the absence of the effect of exporting; the reduction due to exports amounts to around 0.8 percent of the total increase in pollution over time. Both figures are substantial, given that not even half of the manufacturers in our sample export in the first place. To round out the picture, this finding also holds when we rely on the intensive margin instrument in column (6).

This main finding is highly robust as we demonstrate by means of various exercises in Table 3.[12] First, to the extent that the demand shocks used for identification reflect general globalization, one may be worried that the effects we find are confounded by offshoring, i.e., by Chinese firms sourcing intermediate inputs from abroad. In this case, our instrument would no longer be excluded. For the relatively small subsample of firms for which we have customs information and which are both exporters and importers, however, we can directly control for the total value of imports (doing so also means that we ignore the entire extensive margin of new exporters). While the estimate of interest in column (1) is smaller than the preferred one and only marginally significant, it is still negative.

Second, we control for the firm-level characteristics described in Table 1, for precipitation, for temperature, and for local population density. Column (2) illustrates that the estimate remains virtually unchanged, suggesting that the instrument is balanced for firm-level and locational characteristics.

Third, we explore several sub-samples. We begin by restricting to single-plant firms to address the concern that we measure pollution at service-intensive headquarters, while production and export activity happen somewhere else. The estimate in column (3) suggests that this is not a first-order problem. In columns (4) to (6) we alternatively focus on firms that do not exit the sample at any point during the period, firms that do not enter later during the period, and firms that are present in every year (balanced panel). Interestingly, the main effect appears to be relatively homogeneous across incumbents, entrants, and exiters. In a fourth empirical exercise, we study NO_2 as a different pollutant, although the sample is reduced due to the lower availability of granular satellite information as described in Section 4. Column (7) illustrates that the export-induced reduction in air pollution is not confined to particulate matter, but instead a broad and robust pattern.[13]

[12] The same exercises based on the intensive margin shift-share instrument are shown in online Appendix Table A.4.

[13] We also explored several changes in the estimation strategy, the results of which are reported in online Appendix Table A.3. First, we restrict the origins for other countries' imports to a set of competitor developing countries for China, namely Bangladesh, India, Indonesia, Malaysia, Mexico, Thailand, Turkey, and Vietnam. Demand shocks based on countries that may produce substitutes for Chinese goods could be mis-measured and hence monotonicity of our instrument may be violated. However, we do find a positive and significant first stage estimate and the same effect of exports on air pollution (see column 1). Second, one may be worried that price variation contained in export *values* biases our findings upwards

Table 3: Scope-1 – Robustness

	ln $PM_{2.5}$						ln NO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
asinh(total value of exports)	-0.002*	-0.004**	-0.005***	-0.005***	-0.005***	-0.005***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
N	224,525	728,276	871,719	872,812	375,961	252,989	545,254
OLS Coefficient	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000
OLS P-value	0.021	0.037	0.074	0.024	0.111	0.049	0.062
KP-Statistic	285.8	593.5	754.1	769.3	587.1	461.3	315.7
Mean outcome	3.837	3.904	3.890	3.904	3.859	3.870	2.510
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Import control	YES						
Firm, weather, pop. density controls		YES					

Notes: The table shows 2SLS regression results at the firm level. Outcome variables are the local (ln) concentrations of $PM_{2.5}$ and NO_2. The regressor of interest is the inverse hyperbolic sine-transformed total export value of the firm. The shift-share instrument is described in Section 3.1 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Column (1) features (ln) import values as a control. Column (2) features indicators for MNE, SOE and coastline locations as well as (ln) firm age, the (ln) number of plants, local wind speed, local precipitation, local maximum and minimum temperatures, and (ln) population density in the county as controls. The samples in columns (3) to (6) contain only single-plant firms, firms that never exit the sample, firms that do not enter the sample later, and firms that are always in the sample, respectively. Standard errors are clustered by prefecture $\times$ 4-digit industry. * $p<.10$ ** $p<.05$ *** $p<.01$

Before we conclude this section with the third main finding, we first turn to a discussion regarding the validity of our shift-share approach and the discrepancy between the OLS and 2SLS results in Table 2. The export demand shocks used for identification typically have a strong effect on both prefecture- and firm-level export activities and the KP-statistics usually exceed conventional thresholds. Moreover, the first stage coefficients are positive as shown in online Appendix Table A.1, consistent with the idea that Chinese goods complement imports from other countries on the world market or add additional varieties during our sample period. Finally, OLS estimates typically have the same sign as the relevant 2SLS estimates in both the prefecture- and firm-level exercises, but the magnitude is smaller in the former. It is likely that this implied bias arises due to measurement error: Exports reported in the ASIF data may have been reported with considerable noise and values contain price variation that may be unrelated to pollution.

Apart from always controlling for the sum of non-unitary shares and clustering standard errors appropriately (Adão et al. 2019), we have conducted further diagnostic checks for our instrumental variables approach at the firm level, following the best practices in Borusyak et al. (2025) in the case of exogenous shifts. First, we compute the number of "effective" shocks employed in our design. In principle, if all firms exported the same amount of all destination-products—i.e., if all firms

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or downwards (Rodrigue et al. 2022). For the subsample of firms where we have detailed customs information, we can compute total *quantities* (in kg) exported and use this variable as an alternative regressor. Column (2) shows that our main finding fully extends to actual physical units of production. From an exploratory point of view, it is interesting to investigate if the income level of a destination country affects the impact of exporting on local air pollution. In column (3), we focus on shipments to high income countries in the sample of firms for which we have customs information. We find that the coefficient is in fact smaller in absolute magnitude. Finally, in column (4) we provide suggestive evidence that exporting induces a technique effect that reduces air pollution by using the export share in sales, rather than export values, as the regressor.

had the same exposure to all import demand shocks abroad—, we could leverage a total of around $185 * 4860 \approx 900k$ shocks per period. Since exports and exposure are highly concentrated, however, it is more insightful to compute the "effective" number as recommended by Borusyak et al. (2025), which amounts to around 33k shocks per period in the estimation sample. This number appears to be sufficiently large for identification.[14] Second, we conduct the recommended balance-tests for all preferred specifications in this paper, where we regress *lagged* levels of $PM_{2.5}$ on the instrument, the sum-of-shares control interacted with year fixed effects, and further relevant fixed effects as appropriate. A significant correlation between the instrument and pollution in the previous period would suggest that the instrument is not quasi-randomly assigned. The results for the prefecture- and firm-level regressions are reported in columns (1) to (3) in online Appendix Table A.2, and, reassuringly, none of the three instruments used in this subsection shows a significant correlation.

The third main finding is the observation that the impact of exporting at the local level does not match the impact at the regional level. While scope-1 air pollution fell, exporting likely worsened regional air quality, suggesting that international market access affects air pollution via multiple channels. In the next two sections, we explore two such candidates to explain the apparent discrepancy.

5.2 Scope-2: Power Generation

We start with evidence on pollution due to power generation. Table 4 reports estimates of equation (2), where each column features different sets of fixed effects.[15] According to the results in column (3), the effect of exporting in a coal power plant's regional electricity grid on the local $PM_{2.5}$ concentration is positive and highly significant, despite the demanding specification where we only rely on variation within power plant over time. This finding is consistent with the idea that coal power plants were pushed towards capacity following the export shock to local customers. The concentration of $PM_{2.5}$ in the direct locality of the power plant increases by $\exp(0.464*0.468)-1 \approx 22$ percent when the export volume rises from the regional grid with the lowest, to the regional grid with the highest (de-meaned) export shock.

To substantiate this key finding, we conduct two robustness exercises. First, given transportation costs, the location of coal power plants is at least partially determined by proximity to coal mines, which also produce substantial amounts of particulate matter. To address this potential ambiguity regarding the source of pollution, we compute the number of coal mines within a 2.5km radius of a coal power plant and control for it in our regression. Column (4) of Table 4 shows that the point estimate is virtually unchanged, so that mining-related concerns do not appear to be first order.

[14]For comparison, Aghion et al. (2023) study access to automation technology in France, using imports of 167 HS 6-digit product categories of robots from 98 origin countries that yield 341 effective shocks. Our share of effective shocks in the total possible number is similar and slightly higher: Robot imports are expected to be somewhat more concentrated than Chinese exports.

[15]The balance-test for the coal power plant-level shift-share exercise is shown in column (4) of online Appendix Table A.2. The conditional correlation between the grid-level instrument and lagged (ln) $PM_{2.5}$ concentration is insignificant, suggesting quasi-random assignment.

Table 4: Scope-2 – Pollution around Coal Power Plants

	ln $PM_{2.5}$				
	power plant location				downwind
	(1)	(2)	(3)	(4)	(5)
asinh(total value of exports)	-0.105***	0.469	0.468***	0.428*	1.443***
	(0.019)	(0.481)	(0.133)	(0.228)	(0.330)
N	4,375	4,375	4,375	4,375	4,375
OLS Coefficient	0.022	0.127	0.128	0.128	0.360
OLS P-value	0.002	0.244	0.000	0.000	0.000
KP-Statistic	200.0	35.8	31.4	13.3	31.4
Mean outcome	3.930	3.930	3.930	3.930	3.615
Year FE	YES	YES	YES	YES	YES
Grid FE		YES			
Power Plant FE			YES	YES	YES

Notes: The table shows 2SLS regression results at the coal power plant level (first stage results are reported in online Appendix Table A.6). The outcome variable is the (ln) concentration of $PM_{2.5}$ in the immediate vicinity of a plant in columns (1)-(4) and the (ln) concentration of $PM_{2.5}$ in a 90° circle segment with 2.5km radius downwind from the coal power plant. The regressor is the inverse hyperbolic sine-transformed total export value of manufacturing firms in the same electricity grid as the coal power plant. The shift-share instrument is described in Section 3.2 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Unified sample across columns. Standard errors are clustered by prefecture × year. * p<.10 ** p<.05 *** p<.01

Second, we try to eliminate any local pollution that is unlikely to come from burning coal. If coal power plants are typically located in industrial districts to be close to their most important customers, air pollution measurements could reflect both scope-1 and scope-2 pollution. We therefore compute $PM_{2.5}$ not in the plant's satellite grid cell, but in a quarter circle segment with radius 2.5km *downwind* from the plant's geo-coordinates. The estimate in column (5) of Table 4 is more than four times larger and highly statistically significant. Unless manufacturing factories are systematically built downwind of coal power plants, this evidence suggests that, if anything, our main results may underestimate the role of burning coal for the polluting effects of exporting.

5.3 Scope-3: Input-Output Linkages

We now turn to the second indirect effect of international market access and investigate whether one firm's exporting activity influences the emissions of other firms in the same local production network. Spillovers could be positive or negative. If suppliers are affected by the scale effect, but not the technique effect, we could see pollution increase around the location of suppliers. The same logic applies to the case in which there is a technique effect that does not dominate the scale effect. Conversely, we could observe a decrease in pollution if the technique effect sufficiently affects suppliers, too.

In Table 5, we report estimates from regression model (3) in columns (1) to (3), and from model (4) in columns (4) to (6).[16] In the first triplet of regressions, the outcome is the local (ln) $PM_{2.5}$ concentration averaged across all of a firm's supplier candidates, while the regressor of interest is that firm's own export shock, which we instrument with the full shift-share instrument. Importantly, we control for the upstream supplier candidates' exports and sales throughout.

Table 5: Scope-3 – Pollution in Production Networks

	ln $PM_{2.5}$					
	supplier locations			firm locations		
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(exports of firm)	-0.008***	-0.001**	-0.005***	-0.012***	-0.000	-0.005***
	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)
cus_aexport_sp				-0.029***	-0.005***	-0.015***
				(0.005)	(0.002)	(0.003)
N	824,325	824,320	824,325	841,323	841,321	841,323
KP-Statistic	1230.2	3343.5	729.5	380.0	112.7	324.9
Mean outcome	3.892	3.892	3.892	3.890	3.890	3.890
Upstream export controls FE	YES	YES	YES			
Year FE	YES		YES	YES		YES
Prefecture FE		YES			YES	
4-digit Industry FE		YES			YES	
Firm FE			YES			YES

Notes: The table shows 2SLS regression results in input-output relationships (first stage results are reported in online Appendix Table A.7). Outcome variables are the (ln) concentration of $PM_{2.5}$ averaged across locations of all potential suppliers within a firm's prefecture and the (ln) concentration of $PM_{2.5}$ in a firm's own location. The regressors of interest are the inverse hyperbolic sine-transformed total export value of the firm and the average inverse hyperbolic sine-transformed total export value of all potential customers within a firm's prefecture. In columns (1) to (3), the control variables are the (ln) average export value of the upstream suppliers, the (ln) number of exporters among suppliers, and the (ln) average sales across suppliers. All displayed regressors are instrumented with the shift-share instruments described in Section 3.3 and all regressions include the sum(s) of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by 4-digit industry × prefecture. * p<.10 ** p<.05 *** p<.01

Regardless of the fixed effects used, we find that a positive shock to exports downstream propagates upstream and leads to a *reduction* in pollution *around the suppliers' sites*. The size of these production network effects is of the same order of magnitude as the direct impact of exporting in Table 2, which suggests that changes in scope-3 emissions are a relevant component to understand the overall effect of exporting.

A similar conclusion can be drawn when we study positive export demand shocks to a firm's *customers downstream*. In columns (4) to (6) of Table 5, the outcome is the $PM_{2.5}$ concentration at a firm's site and the regressor of interest is the average export value of all customer candidates downstream. Once again, we control for the firm's own exports to address the concern that the

[16] The balance-tests for the supplier- and buyer-level shift-share exercises are reported in columns (5) and (6) of online Appendix Table A.2. The conditional correlation between the instrument and lagged (ln) $PM_{2.5}$ concentration is marginally significant in the supplier-level regressions, while neither instrument is significantly correlated in the buyer-level regressions.

downstream demand shock is correlated with the upstream one, and instrument both regressors as described in Section 3.3. Irrespective of the specific variation we exploit, we find that when a firm's customers start exporting or expand their sales abroad, this leads to a reduction of pollution at the supplier's site *ceteris paribus*.

These results may be affected by measurement error, however, if the supplier and customer candidates are not correctly identified. During our sample period, China substantially improved and expanded its highway road network, which allowed manufacturers to access business partners located farther away. Restricting potential suppliers and customers to those in the same prefecture may therefore appear somewhat more problematic over time. To explore this issue, we re-compute the sets of candidates taking not only the same, but also all directly adjacent prefectures into account. When we run the regressions using the resulting variables, the estimates are not significantly different, as shown in online Appendix Table A.8.

Overall, we find that domestic production networks act as an amplification mechanism: Exporting not only reduces emissions and therefore air pollution directly through scope-1 emissions, but also through the indirect effect that domestic demand shocks due to exports downstream lead to lower emissions upstream (scope-3 emissions). This finding is related to a recent strand of research that documents the benefits in terms of productivity and working conditions of supplying to internationally active companies in developing countries (e.g. Alfaro-Urena et al. 2022, 2023). Our results suggest that such positive local spill-overs also include beneficial environmental effects.[17]

6 Conclusions

We exploit one of the most interesting and important trade experiments in recent times, China's world market integration between 2000 and 2007, to provide evidence on the mechanisms through which international market access affects air pollution in the economy benefiting from such access. To do so, we combine granular satellite data with detailed information on manufacturing firms and coal power plants, and employ a shift-share identification approach inspired by Mayer et al. (2021). Starting at the regional level, we confirm that the export demand shock China experienced after its accession to the World Trade Organization led to higher concentrations of several pollutants, including fine particulate matter ($PM_{2.5}$). Next, we study the effect on scope-1 pollution by zooming in on individual plants of firms, and find that export activity *reduces* the $PM_{2.5}$ load.

To investigate how this local effect can be reconciled with the regional estimates, we focus on scope-2 pollution and document that air pollution around coal power plants *increases* significantly when manufacturers in the region up their exports. Finally, we use information from input-output tables to identify a firm's potential suppliers in the same region, which allows us to study the effect of scope-3 pollution. We find that downstream export demand shocks also *reduce* local $PM_{2.5}$ concentrations.

[17]Similar to our findings, Mo et al. (2024) finds Chinese firms report lower pollution once they become suppliers or customers of foreign invested firms in China.

The increase in pollution from export-driven growth is thus largely driven by China's almost complete reliance, at the time, on coal power plants.

Our paper combines granular satellite data and firm-level data to obtain these findings, shedding new light on how trade shocks reverberate across the economy and ultimately affect air quality, thus informing policymakers about the potential downsides from trade expansion. It can also help inform future research aimed at decomposing the contribution of each channel in a structural way, to further our understanding of trade shocks' pervasive economic effects.

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Online Appendix

A Additional tables

Table A.1: Regional and Firm-level Results – First Stages

	asinh(total value of exports)					
	(1)	(2)	(3)	(4)	(5)	(6)
prefecture-level IV	0.666***	0.385***				
	(0.044)	(0.027)				
firm-level IV (full)			0.860***	0.966***	0.193***	
			(0.017)	(0.013)	(0.007)	
firm-level IV (intensive)						0.059***
						(0.006)
N	2,104	2,104	995,784	995,781	995,784	279,547
Year FE	YES	YES	YES	YES	YES	YES
Province FE		YES		YES		
4-digit Industry FE				YES		
Firm FE					YES	YES

Notes: The table shows first stage results for the 2SLS regressions at the regional and firm level in Table 2. All regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by 4-digit industry × prefecture. * p<.10 ** p<.05 *** p<.01

Table A.2: Balance Regressions

	lagged ln $PM_{2.5}$					
	(1)	(2)	(3)	(4)	(5)	(6)
prefecture-level IV	0.007					
	(0.004)					
firm-level IV (full)		-0.001			-0.001*	-0.001
		(0.000)			(0.000)	(0.000)
firm-level IV (intensive)			-0.000			
			(0.000)			
electricity grid-level IV				0.167		
				(0.102)		
customer-level IV						-0.002
						(0.002)
N	1,834	720,657	244,706	2,612	583,115	601,537
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES					
Firm FE		YES	YES		YES	YES
Power Plant FE				YES		

Notes: The table shows balance regressions for instruments at the prefecture, firm and power plant level. Outcome variables are the lagged local (ln) concentrations of $PM_{2.5}$ except for column (4), where it is measured at the upstream supplier-level. The regressors are the instrumental variables used in prefecture-level regressions in column (1), in firm-level regressions in columns (2) and (3), in coal power plant-level regressions in column (4), in supplier-level regressions in column (5), and in buyer-level regressions in column (6). The instruments are described in Section 3.1 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by province × year in column (1), and by prefecture × year in columns (2)-(6). * p<.10 ** p<.05 *** p<.01

Table A.3: Scope-1 – Further Robustness

	ln $PM_{2.5}$			
	(1)	(2)	(3)	(4)
asinh(total value of exports)	-0.005***			
	(0.002)			
asinh(total quantity of exports)		-0.007*		
		(0.004)		
asinh(total value of exports to high income dest.)			-0.001**	
			(0.001)	
export intensity (exports/sales)				-0.124***
				(0.048)
N	995,784	281,846	281,846	934,911
OLS Coefficient	0.000	-0.000	-0.000	-0.002
OLS P-value	0.050	0.001	0.002	0.009
KP-Statistic	812.3	35.5	456.4	337.5
Mean outcome	3.896	3.843	3.843	3.905
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Notes: The table shows 2SLS regression results at the firm level. Outcome variables are the local (ln) concentrations of $PM_{2.5}$ and SO_2. The regressors of interest are the inverse hyperbolic sine-transformed total export value (1 and 5), total quantity (2), total exports to high income destinations (3), and export intensity of the firm. The shift-share instrument in (1) is described in Section 3.1, but based on competitor countries of China; the instrument in columns (2) to (5) is constructed in the same way but using all countries. All regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by prefecture × 4-digit industry. * p<.10 ** p<.05 *** p<.01

Table A.4: Scope-1 – Robustness – Intensive Margin Instrument

	ln $PM_{2.5}$						ln NO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
asinh(total value of exports)	-0.004	-0.002	-0.011**	-0.008*	-0.013***	-0.013**	-0.035**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.015)
N	192,083	193,279	246,671	244,878	138,862	104,193	137,262
OLS Coefficient	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
OLS P-value	0.001	0.000	0.000	0.000	0.000	0.001	0.000
KP-Statistic	86.6	74.4	81.4	89.3	76.1	63.5	34.1
Mean outcome	3.829	3.866	3.834	3.851	3.814	3.826	2.590
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Import control	YES						
Firm, weather, pop. density controls		YES					

Notes: The table shows 2SLS regression results at the firm level. Outcome variables are the local (ln) concentrations of $PM_{2.5}$ and NO_2. The regressor of interest is the inverse hyperbolic sine-transformed total export value of the firm. The shift-share instrument is described in Section 3.1 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. The samples in columns (3) to (6) contain only single-plant firms, firms that never exit the sample, firms that do not enter the sample later, and firms that are always in the sample, respectively. Standard errors are clustered by prefecture × 4-digit industry. * p<.10 ** p<.05 *** p<.01

Table A.5: Scope-1 – Further Robustness – Intensive Margin Instrument

	ln $PM_{2.5}$			
	(1)	(2)	(3)	(4)
asinh(total value of exports)	-0.009**			
	(0.004)			
asinh(total quantity of exports)		-0.007**		
		(0.004)		
asinh(total value of exports to high income dest.)			-0.001**	
			(0.001)	
export intensity (exports/sales)				-0.128
				(0.086)
N	279,547	279,547	279,547	276,698
OLS Coefficient	-0.001	-0.000	-0.000	-0.004
OLS P-value	0.000	0.001	0.001	0.000
KP-Statistic	100.9	39.2	535.0	17.5
Mean outcome	3.842	3.842	3.842	3.868
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Notes: The table shows 2SLS regression results at the firm level. Outcome variables are the local (ln) concentrations of $PM_{2.5}$ and SO_2. The regressors of interest are the inverse hyperbolic sine-transformed total export value (1 and 5), total quantity (2), total exports to high income destinations (3), and export intensity of the firm. The shift-share instrument in (1) is described in Section 3.1, but based on competitor countries of China; the instrument in columns (2) to (5) is constructed in the same way but using all countries. All regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by prefecture × 4-digit industry. * p<.10 ** p<.05 *** p<.01

Table A.6: Scope-2 – Pollution around Coal Power Plants – First Stages

	asinh(total value of exports)				
	(1)	(2)	(3)	(4)	(5)
electricity grid-level IV	0.987***	0.230***	0.230***	0.135***	0.230***
	(0.070)	(0.038)	(0.041)	(0.037)	(0.041)
N	4,375	4,375	4,375	4,375	4,375
Year FE	YES	YES	YES	YES	YES
Grid FE		YES			
Power Plant FE			YES	YES	YES

Notes: The table shows first stage results for the 2SLS regressions at the coal power plant level in Table 4. The outcome variable is the inverse hyperbolic sine-transformed total export value of manufacturing firms in the area of the regional electrictiy grid where the plant is located. The instrument is described in Section 3.2 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Unified sample across columns. Standard errors are clustered by prefecture × year. * p<.10 ** p<.05 *** p<.01

Table A.7: Scope-3 – Pollution in Production Networks – First Stages

	asinh(exports of firm)			asinh(total value of customers' exports)			asinh(exports of firm)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
firm-level IV (full)	0.321***	0.325***	0.081***	0.804***	0.916***	0.188***	-0.017	0.010**	0.001
	(0.009)	(0.006)	(0.003)	(0.019)	(0.013)	(0.007)	(0.015)	(0.005)	(0.006)
cus_iv_firm_ini_f_v_4_6d_sp				0.659***	0.039	0.018	1.018***	0.620***	0.435***
				(0.071)	(0.034)	(0.015)	(0.050)	(0.042)	(0.055)
N	824,325	824,320	824,325	841,323	841,321	841,323	841,323	841,321	841,323
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture FE		YES			YES			YES	
4-digit Industry FE		YES			YES			YES	
Firm FE			YES			YES			YES

Notes: The table shows first stage results for the 2SLS regressions investigating input-output relationships in Table 5. Outcome variables are the inverse hyperbolic sine-transformed total export value of the firm and the inverse hyperbolic sine-transformed total export value of all potential customers within a firm's prefecture. In columns 1 to 3, the control variables are the (ln) average export value of the upstream suppliers, the (ln) number of exporters among suppliers, and the (ln) average sales across suppliers. The instruments are described in Section 3.3 and all regressions include the sum of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by 4-digit industry × prefecture. * p<.10 ** p<.05 *** p<.01

Table A.8: Scope-3 – Pollution in Production Networks – adjacent prefectures included

	ln $PM_{2.5}$					
	supplier locations			firm locations		
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(exports of firm)	-0.008***	-0.001***	-0.005***	-0.013***	-0.000	-0.006***
	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
asinh(average value of customers' exports)				-0.028***	-0.009***	-0.012***
				(0.004)	(0.002)	(0.002)
N	846,310	846,308	846,310	839,956	839,954	839,956
KP-Statistic	1338.4	3367.0	779.4	543.9	78.3	323.4
Mean outcome	3.895	3.895	3.895	3.888	3.888	3.888
Upstream export controls FE	YES	YES	YES			
Year FE	YES		YES	YES		YES
Prefecture FE		YES			YES	
4-digit Industry FE		YES			YES	
Firm FE			YES			YES

Notes: The table shows 2SLS regression results in input-output relationships. Outcome variables are the (ln) concentration of $PM_{2.5}$ averaged across locations of all potential suppliers within a firm's prefecture and the (ln) concentration of $PM_{2.5}$ in a firm's own location. The regressors of interest are the inverse hyperbolic sine-transformed total export value of the firm and the average inverse hyperbolic sine-transformed total export value of all potential customers within a firm's prefecture. In columns (1) to (3), the control variables are the (ln) average export value of the upstream suppliers, the (ln) number of exporters among suppliers, and the (ln) average sales across suppliers. All displayed regressors are instrumented with the shift-share instruments described in Section 3.3 and all regressions include the sum(s) of initial shares interacted with year fixed effects as unreported controls. Standard errors are clustered by 4-digit industry × prefecture. * p<.10 ** p<.05 *** p<.01