Air Pollution as Comparative Disadvantage †

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Abstract

This paper is the first to examine the impact of air pollution on exporters' comparative advantage in the global market and their ensuing strategic responses. Using comprehensive firm-product export data from China spanning 2000 to 2007 and exploiting exogenous variation in air pollution induced by thermal inversion for identification, we unveil a detrimental effect of increased air pollution on exports through its adverse impact on labor productivity. The effects are particularly pronounced for labor-intensive products, prompting firms to restructure their product scope away from labor-intensive varieties. Moreover, larger firms exhibit greater resilience to these adverse effects.

Keywords: Air pollution, exports, multi-product firms, comparative advantage
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1 Introduction

Firms in developing countries are vulnerable to adverse productivity shocks, particularly when underdevelopment exacerbates the risks and costs associated with these fluctuations (Jayachandran, 2006). Therefore, understanding how firms are affected by and respond to such shocks is of significant interest. Among these shocks, air pollution emerges as a serious global concern, posing threats to public health, environmental sustainability, and economic development. Given its significance, an emerging literature has documented air pollution's detrimental impact on firms' productivity, from particular occupations such as fruit picking (Graff Zivin and Neidell, 2012), garment assembly (Adhvaryu et al., 2022), pear packing (Chang et al., 2016), call centre services (Chang et al., 2019) or textile assembly (He et al., 2019), to a country's (China) manufacturing sector (Fu et al., 2021).

Building on these works, in particular Fu et al. (2021), we investigate the causal impact of air pollution on trade through its effect on labor productivity. Firm-level productivity is crucial in determining trade performance (Melitz, 2003; Bernard et al., 2012; Melitz and Redding, 2014, etc.), making it important to understand the interplay between air pollution, productivity, and trade outcomes. Furthermore, international trade can amplify local pollution impacts into broader macro-level effects, potentially shaping a country's comparative advantage in the global market. By delving into these aspects, we aim to shed light on the intricate interplay between air pollution and the dynamics of international trade.

To guide our empirical analysis, we develop a variant of the multi-product heterogeneous firm model by Bernard et al. (2007, 2010) and Ma et al. (2014). In this model, firms are heterogeneous in their level of productivity, and their product varieties vary in attractiveness to consumers relative to other producers of the same products. Firms utilize capital and labor to produce multiple products, with labor productivity being negatively affected by air pollution. The model provides several key insights. First, increased local air pollution lowers labor productivity and thus the firm-product level exports, particularly for labor-intensive products. Second, the adverse impact of air pollution prompts exporters to discontinue labor-intensive varieties that are more susceptible to the effects of air pollution. Lastly, we extend the model to incorporate fixed costs to adopt endogenous anti-air pollution technology, revealing that the adverse effects of air pollution on exports are mitigated for more productive or larger firms.

We combine transaction-level export data from China Customs that cover all transactions of Chinese exporters from 2000 to 2007 with satellite-based nationwide air pollution data. Our study period coincides with a unique episode of China's fastest-growing air pollution as well as trade. Figure 1 plots the average concentrations of $\mathrm{PM}_{2.5}$ across all counties and the total value of exports spanning from 1995 to 2010. Generally, $\mathrm{PM}_{2.5}$ concentrations exhibited substantial growth during this period. By 2007, the average $\mathrm{PM}_{2.5}$ concentrations exceeded 64.51 $\mu g/m^3$, which is more than six times higher than the World Health Organization's (WHO) recommended annual mean standard of 10 $\mu g/m^3$ (WHO, 2005). At the same time, exports increased significantly over this period. In 2000, China's total export value was 249 billion US dollars. By 2007, it had risen nearly fivefold to reach 1,220 billion US dollars.

In the empirical analysis, the key challenge in estimating the causal effect of air pollution on firms' export performance arises from the simultaneous impact of air pollution and exports on each other. To deal with endogeneity concerns arising from the simultaneous impact of air pollution and exports on each other, we use thermal inversion, a widely used instrumental variable for air pollution in the literature (Arceo et al., 2016; Hicks et al., 2016; Jans et al., 2018; Dechezleprêtre et al., 2019; Sager, 2019; Khanna et al., 2021; Fu et al., 2021; Chen et al., 2022). Thermal inversion is an exogenous meteorological phenomenon. During thermal inversions, the warmer air layers sit above the cooler air layers, acting as a cap on the upward movement of air from the layers below and thus trapping air pollutants near the ground. Our estimates indicate that the instrument is highly predictive and reveals more negative effects on labor productivity and exports than OLS estimates.

We organize our empirical estimations into three parts. First, we estimate the average effect of $PM_{2.5}$ on exporting firms' labor productivity and firm-product level export performance. We find that a 1% increase in $PM_{2.5}$ leads to a 0.95% decrease in labor productivity measured by value-added per worker at the firm level and a 0.89% decline in firm-product level export revenue. At the sample mean level of $PM_{2.5}$, the result implies that a 1 $\mu g/m^3$ rise in $PM_{2.5}$ reduces firm-level labor productivity by approximately 1.33% and firm-product level export by about 1.25% on average.[1] To provide context for the effect's magnitude, at the sample mean of annual firm-product export value, a 1% nationwide increase in annual $PM_{2.5}$ concentration results in approximately $5,596 reduction in export revenue per year at the firm-product level. Across all firm-product export flows, this amounts to around three billion US dollars annually, accounting for about 1.2% of China's total goods export in 2000 and 0.2% of China's total goods export in 2007.

Second, we find that air pollution has a greater negative impact on the exports of relatively more labor-intensive products. For the most labor-intensive quarter of the products, a 1% increase in $PM_{2.5}$ concentration decreases exports by approximately 1%. This negative effect is 17% higher than the effect on products with average labor intensity. In contrast, the impact for the least labor-intensive quarter is approximately 0.73%, which is 14% lower than the effect on products with average labor intensity.

Third, we investigate exporting firms' responses accordingly. Based on firm-product level estimations, firms respond to air pollution shocks by subsequent cessation of exports for relatively more labor-intensive products. Specifically, for the most labor-intensive quarter of the products in the sample, a 1% increase in annual $PM_{2.5}$ exposure increases the linear probability of the firm discontinuing these products by about 0.03% next year.

[1] Our findings regarding the magnitudes of the effects on labor productivity align with previous literature. For instance, Fu et al. (2021) reported a 0.8% reduction in productivity for a 1 $\mu g/m^3$ increase in $PM_{2.5}$ using data from China's above-scale manufacturing firms. Our estimate is slightly larger because we include only exporting firms in the Annual Survey of Manufacturing Enterprises (ASME) database. Exporters in this database exhibit a higher average labor intensity compared to non-exporters (Huang and Ottaviano, 2023), potentially increasing their susceptibility to the impacts of air pollution.

Firm-level estimations of product scope restructuring also confirm this pattern. A 1% increase in air pollution raises the probability of dropping existing products by 0.47%. These effects are mainly driven by transitions away from products with higher labor intensity compared to the exporter's previous labor intensity.

Additionally, according to the model predictions that the impacts of air pollution are heterogeneous by firms, the empirical results reveal significant heterogeneity in impacts based on firm size and ownership. Above-median-sized exporters experience only 33% of the negative impact compared to below-median-sized exporters, conditional on the same labor intensity. At last, we do not find any significant impact on firms' entry and exit in export markets, thereby eliminating potential concerns regarding sample selection bias arising from firms' endogenous location choices based on air pollution.

This paper contributes to several strands of literature. First, we contribute to the literature on air pollution's social and economic consequences. While previous research has explored the effects of air pollution on various outcomes such as mortality, obesity, migration, labor market decisions, real GDP, income, and housing values (Chay and Greenstone, 2005; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Deryugina et al., 2019; Dechezleprêtre et al., 2019; Deschenes et al., 2020; Barwick et al., 2022), this study is the first to examine its causal impact on international trade, and shows that air pollution dampens firms' comparative advantage in labor-intensive varieties through its detrimental effect on labor productivity. On the other hand, while a vast amount of literature on international trade has studied how trade affects pollution,[2] pioneered by Grossman and Krueger (1991), studies on how pollution affects trade are scarce. Understanding this causal relationship is crucial, as trade can serve as a conduit for environmental effects that are regionally localized to have macro-level consequences like comparative disadvantage. In other words, pollution in one region can affect the trade competitiveness of

[2] This is an incomplete list of these papers: Antweiler et al. (2001); Copeland and Taylor (2004); Frankel and Rose (2005); Chintrakarn and Millimet (2006); Levinson (2009); Cherniwchan (2017); Wang et al. (2017); Shapiro and Walker (2018); LaPlue (2019); Bombardini and Li (2020); Gong et al. (2023)

firms in that region, leading to broader economic consequences. However, one of the key challenges in establishing causality in this context is the simultaneous impact of air pollution and exports on each other. This study fills this void by using thermal inversions, an exogenous meteorological phenomenon, to estimate the causal effect of air pollution on trade.

Second, this study contributes to the literature on firms' responses to labor shocks. A closely related recent study is Adhvaryu et al. (2022), which documents that managers reassign workers to mitigate worker-task level productivity losses caused by air pollution based on the data of an Indian ready-made garment firm. We employ similar air pollution shocks but focus on how firms alter their product varieties with varying labor intensity to buffer the negative impact. Moreover, instead of using data regarding one particular worker type, or small sets of firms, our analysis utilizes highly disaggregated firm-product level export data, allowing for nationwide estimates and a relatively longer-term examination of firms' response to air pollution.

Additionally, Imbert et al. (2022) investigates the impact of labor supply shocks resulting from rural-urban migration, demonstrating that increased immigration leads to more labor-intensive manufacturing production. This shift is characterized by the adoption of labor-oriented technological advancements and a greater share of labor-intensive product varieties. In contrast, Hau et al. (2020) examines labor cost shocks driven by minimum wage policies, highlighting how such policy changes drive the substitution of labor with capital, consequently reducing employment growth. Our study focuses on a distinct type of shock - air pollution, which directly affects labor productivity. We show that when firms experience adverse labor productivity shocks due to air pollution, their exports decline disproportionately for products with varying labor intensity, and they respond by shifting their export product scope towards less labor-intensive products. Importantly, our analysis employs highly disaggregated trade data at the firm-product level, providing a finer-grained understanding of how firms adapt to air pollution-induced productivity shocks in comparison to studies using macro-level or survey data, which may suffer from biases or lack granularity (Jones and Olken, 2010).

Third, this paper relates to the literature on multi-product firms (MPFs) in the international trade and industrial organization literature. Recent theoretical studies in international trade have primarily focused on the number of products firms produce and the importance of core products for firm growth (Feenstra and Ma, 2007; Arkolakis et al., 2021; Dhingra, 2013; Eckel and Neary, 2010; Mayer et al., 2014). Additionally, several MPF studies have examined how trade liberalization affects firms' product diversification and specialization(Feenstra and Ma, 2007; Nocke and Yeaple, 2014; Bernard et al., 2011; Ma et al., 2014; Mayer et al., 2021). We contribute to this literature by empirically identifying the role of air pollution in determining the direction of firms' product scope adjustment.

Lastly, our study contributes to the prevailing literature on the interplay between trade and environmental regulations and also has important policy implications. While existing research predominantly focuses on the adverse impact of regulatory policies on trade and economic output, our findings highlight the role of air pollution as a discernible comparative disadvantage for labor-intensive goods, implying that environmental protection policies may instead stimulate trade by promoting labor productivity, particularly in labor-abundant economies. Thus, the implications of our study also extend to policy considerations, specifically for developing nations aiming to balance export growth and environmental preservation.

The rest of this paper is structured as follows. Section 2 presents the theoretical explanation. Section 3 details the empirical strategy. Section 4 describes the data and measurements. Section 5 presents the estimation results. Section 6 concludes.

2 A Simple Model on Pollution and Trade

To guide our empirical analysis, we present a simple, partial equilibrium model to analyze the impact of air pollution on exports. The model is a variant of the multi-product Melitz type of heterogeneous firm model similar to Bernard et al. (2007, 2010, 2011) and Ma et al. (2014). The environment is a world consisting of two countries: Home (H) and Foreign (F), and heterogeneous firms produce multiple products with two factors: capital and labor. Below we start with the consumer side.

2.1 Preferences

Consumers in two countries consume a continuum of products with identical preferences, and thus we ignore the notation of country in this subsection. The utility function is given by:

$$U = \left[\int_0^1 Q_s^{\nu} ds \right]^{\frac{1}{\nu}}, \tag{1}$$

where $\kappa \equiv 1/(1-\nu) > 1$ is the elasticity of substitution between products. Within a product, firms produce horizontally differentiated varieties, facing their demand. The consumption index for product s, Q_s, takes the following form:

$$Q_s = \left[\int_{\omega \in \Omega_s} (\lambda_s(\omega) q_s(\omega))^{\rho} \, d\omega \right]^{\frac{1}{\rho}}, 0 < \rho < 1 \tag{2}$$

where $\sigma \equiv 1/(1-\rho) > 1$ is the elasticity of substitution between varieties within a product. We assume that the elasticity of substitution between varieties within a product is larger than that between products ($\sigma > \kappa > 1$). $\lambda_s(\omega) \geq 0$ is the represented consumer's tastes for a firm's variety ω within product s.[3]

[3]One interpretation of the parameter $\lambda_s(\omega)$ is product quality, though it also captures other more subjective characteristics of a firm's variety that influence the representative consumer's demand for that variety.

Consumer utility maximization yields the expenditure on each variety:

$$x_s(\omega) = p_s(\omega)^{1-\sigma} \cdot \lambda_s(\omega)^{\sigma-1} \cdot P_s^{\sigma-1} R_s \tag{3}$$

where R_s stands for domestic expenditure spent on product s:

$$R_s = \left[\frac{P_s^{\frac{-\nu}{1-\nu}}}{\int_0^1 P_s^{\frac{-\nu}{1-\nu}} ds} \right] \cdot R \tag{4}$$

where R is the total expenditure of the economy, $P_s = \left[\int_{\omega \in \Omega_s} \left(\frac{p_s(\omega)}{\lambda_s(\omega)} \right)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}}$ is the ideal price index for product s, $P = [\int_0^1 P(s)^{\frac{-\nu}{1-\nu}} ds]^{\frac{1-\nu}{-\nu}}$ is the ideal price index for the economy.

2.2 Production

Firms are heterogeneous in their level of productivity by drawing their productivity φ from the distribution $G(\varphi)$. φ is firm-specific and is constant across countries and products. Each firm produces multiple products with varying factor intensities. The market structure of each product is a monopolistic competition. Products are imperfect substitutes in demand and, within each product, firms supply horizontally differentiated varieties of the product facing random consumer taste shocks. More specifically, each firm draws a set of "consumer taste" attributes for each potential product produced, $\lambda_s \in [0, \infty)$ from a distribution $H(\lambda_s)$. The set of λ_s is firm-product specific and is constant across countries.

Firms use both capital and labor to produce product s with the Cobb-Douglas production form. More specifically, the firm with productivity φ has the following cost function for output q_s of product s:

$$TC_s(\varphi) = \frac{q_s}{\varphi} \left(\frac{w}{A(z)}\right)^{\beta_s} r^{1-\beta_s} + f_s \tag{5}$$

where q_s is the firm's output of product variety s, w and r are the wage rate and the rental rate, respectively. We choose the rental rate as the numeraire (i.e., $r = 1$). f_s is the fixed cost of production for product s, measured as units of the numeraire. Therefore, $TC_s(\varphi) = \frac{q_s}{\varphi}(\frac{w}{A(z)})^{\beta_s} + f_s$. $\beta(s)$ represents labor intensity for product s. Without loss of generality, we rank product index $s \in [0, 1]$ so that $\beta(0) = 0, \beta(1) = 1$, and $\beta'(s) > 0$ (i.e., labor intensity is increasing in product index s).

$A(z)$ is the labor-augmenting technology, which decreases in the level of air pollution z, i.e., $A'(z) < 0$. A large literature has documented that air pollution has detrimental physical and mental health effects on workers (Graff Zivin and Neidell, 2012; Chang et al., 2016, 2019; He et al., 2019; Adhvaryu et al., 2022). The recent study Fu et al. (2021) also shows that air pollution reduces the labor productivity of manufacturing firms in China. More specifically, we assume $A(z) = \alpha z^{-\theta}$, where $\alpha > 0$, $\theta > 0$. We also normalize the minimum level of air pollution as 1, i.e., $z \geq 1$. θ measures the (absolute) elasticity of labor-augmenting technology w.r.t the level of air pollution. Thus, a higher value of θ indicates a more severe effect of air pollution on labor-augmenting productivity.

2.3 Air pollution and firm exports

To serve the foreign market, firms must incur a fixed cost of F_s and an iceberg variable trade cost such that $\tau > 1$ units must be shipped from home country for one unit to arrive in foreign country, which is assumed to be identical for all products for simplicity. Given the CES preference, firm's profit maximization implies a constant mark-up over the marginal cost, thus, the optimal exporting price is given by:

$$p_s^F(\varphi) = \frac{\sigma}{\sigma - 1} \cdot \frac{\tau \cdot (\frac{w}{A(z)})^{\beta_s}}{\varphi} \tag{6}$$

Plugging equation (6) into equation (3), we can obtain firm's export revenue by selling its variety of product s to the foreign country:

$$x_s^F\left(\varphi,\lambda_s^F\right)=R_s^F\cdot\left[\frac{\rho P_s^F\varphi\cdot\lambda_s^F}{\tau\cdot\left(\frac{w}{A(z)}\right)^{\beta_s}}\right]^{\sigma-1} \tag{7}$$

where R_s^F denotes aggregate expenditure on product s in foreign country and P_s^F denote the corresponding price index. Taking logarithm at both sides of equation (7), and plugging in $A(z)=\alpha z^{-\theta}$ yields:

$$\ln x_s^F=\ln R_s^F+(\sigma-1)\ln\left(\rho P_s^F\varphi\lambda_s^F\right)-(\sigma-1)\ln\tau-(\sigma-1)\beta_s\ln w+(\sigma-1)\beta_s\ln\alpha-(\sigma-1)\beta_s\theta\ln z \tag{8}$$

By taking the derivative of $\ln x_s^F$ with respect to $\ln z$, we obtain the impact of air pollution on firm's export of product s:

$$\frac{\partial\ln x_s^F}{\partial\ln z}=\frac{\partial\ln x_s^F}{\partial\ln A(z)}\frac{\partial\ln A(z)}{\partial\ln z}=-(\sigma-1)\beta_s\theta \tag{9}$$

Proposition 1.

- $\frac{\partial\ln x_s^F}{\partial\ln z}<0$. *Thus, ceteris paribus, an increase in air pollution lowers labor productivity and thus the firm's exports of product* s.
- $\frac{\partial^2\ln x_s^F}{\partial\ln z\partial\beta_s}=-(\sigma-1)\theta<0$. *This implies that the detrimental impact of air pollution on firm-product exports is stronger for labor-intensive products.*

Note that firms must pay a fixed cost of F_s (measured as units of the numeraire) to serve the foreign market, thus firms' profit of exporting product s is:

$$\pi_s^F\left(\varphi,\lambda_s^F\right)=\frac{x_s^F\left(\varphi,\lambda_s^F\right)}{\sigma}-F_s, \tag{10}$$

Clearly, this profit is increasing in foreign consumer tastes λ_s^F. Thus, it may be non-profitable for firms to export their product varieties if their foreign consumer tastes are lower than some thresholds. We can solve the cutoff of foreign consumer tastes λ_s^{F*} from the zero-profit condition of $\pi_s^F\left(\varphi, \lambda_s^{F*}\right) = 0$, which yields:

$$\lambda_s^{F*}(\varphi, z) = \frac{\tau(\sigma F_s/R_s^F)^{\frac{1}{\sigma-1}}(\frac{w}{A(z)})^{\beta_s}}{\rho P_s^F \varphi}, \tag{11}$$

Note $\lambda_s^{F*}(\varphi, z)$ increases in air pollution z as air pollution raises the marginal production cost. Note that the firm φ will export its variety if its foreign consumer taste $\lambda > \lambda_s^{F*}$, thus its expected exporting probability $1 - H(\lambda_s^{F*})$ will decrease if the air pollution rises. In other words, some varieties with low foreign consumer tastes must exit the foreign market upon air pollution shocks domestically. Meanwhile, $\lambda_s^{F*}(\varphi, z)$ decreases in firm productivity φ as more productive firms charge lower exporting prices, export more, and earn higher profits for given foreign consumer tastes. Thus, for given foreign consumer tastes, more productive firms are more likely to export their product varieties.

Taking derivative of $\ln \lambda_s^{F*}(\varphi, z)$ with respect to $\ln z$ yields:

$$\frac{\partial \ln \lambda_s^{F*}(\varphi, z)}{\partial \ln z} = \frac{\partial \ln \lambda_s^{F*}(\varphi, z)}{\partial \ln A(z)} \frac{\partial \ln A(z)}{\partial \ln z} = \theta \beta_s \tag{12}$$

Based on this result, we can show the second proposition of air pollution on firms' product scope adjustment.

Proposition 2.

- $\frac{\partial \ln \lambda_s^{F*}(\varphi,z)}{\partial \ln z} > 0$. *Thus, an increase in air pollution in the Home country will raise the cutoff threshold of foreign consumer tastes, ceteris paribus, implying that exporters may drop some varieties with low consumer tastes due to the air pollution shock.*

- $\frac{\partial^2 \ln \lambda_s^{F*}(\varphi,z)}{\partial \ln z \partial \beta_s} > 0$. *The foreign consumer tastes threshold will increase more for labor-intensive products upon air pollution shocks at Home. Thus, more export varieties are likely to be dropped in labor-intensive products as air pollution increases.*

2.4 Extension: anti-pollution technology adoption

In the previous section, we assume that the impacts of air pollution on firms' labor productivity are homogeneous, i.e., the value of θ is the same across firms. However, in reality, it is possible that some firms may adopt anti-air pollution technology to mitigate its negative effects on their workers. For example, firms can purchase air cleaners for indoor workers or anti-particulate masks for outdoor workers. A simple and natural approach is to assume that firms can pay a fixed cost f_T (measured as units of the numeraire) to adopt the anti-pollution technology, which better protects their workers from air pollution so as to mitigate the negative effect on labor productivity. Note the fixed cost f_T is at the firm level, which is not specific to a particular market that the firm serves or a particular product that the firm produces.

We assume the genetic value of θ without anti-pollution technology is θ_N, and firms that adopt the anti-pollution technology can mitigate the detrimental impact of air pollution on labor productivity and thus have a lower value of θ_T, i.e., $\theta_N > \theta_T$. Given this setting, the relative labor productivity with anti-pollution technology to without anti-pollution technology is $A_T(Z)/A_N(Z) = z^{\theta_N - \theta_T} \geq 1$ for $z \geq 1$. This suggests that the anti-pollution technology in nature can boost labor productivity, particularly when firms are facing severe air pollution.

It is easy to show that more productive firms will choose to adopt the anti-pollution technology as they have high operating profits to cover the fixed cost of technology adoption. As more productive firms are large in terms of export sales, we have the third following testable proposition.

Proposition 3. *As more productive firms choose to adopt the anti-pollution technology, the negative effects of air pollution on firms' exports will be smaller for more productive or larger firms.*[4]

See the proof in the Appendix.

[4] Given the heterogeneous firm's cost function in equation (5), a more productive firm will have larger output and revenue compared to a less productive one.

In summary, our model predicts that air pollution has negative effects on firms' exports, particularly for labor-intensive products through the channel of lowering labor productivity. As a response, exporters will drop more labor-intensive varieties. Moreover, more productive firms can choose to adopt anti-pollution technologies, thus the negative effects of air pollution on their exports will be smaller. Next, we will proceed to the empirical testing of our theoretical predictions.

3 Empirical Strategy

3.1 Identification strategy

Building on Fu et al. (2021), we investigate the causal impact of air pollution on trade through its effect on labor productivity. The endogeneity concerns arise from the simultaneous impact of air pollution and exports on each other. On the one hand, exports naturally bring more production activities and subsequently generate more air pollutant emissions. Meanwhile, international trade increase local residents' incomes, which in turn encourages them to seek cleaner air and a healthier environment through emissions control or factory pollution monitoring. On the other hand, air pollution is harmful to people's health, diminishes workers' productivity, and hence restrains firms' outputs and exports as predicted by our model. Thus, the issue of simultaneity bias between air pollution and exports would cause an under-or overestimation of the effects of air pollution on firms' exports if we simply regress firms' exports on air pollution using the OLS estimation method.

In addition, other confounding factors, such as economic policies, environmental regulations, and other unobservable time-varying county characteristics, could simultaneously affect air pollution levels and local exporting firms' performance, potentially biasing the estimated results. For instance, counties or prefectures with better local amenities or economic development may have more severe air pollution while also exporting more, which leads to an underestimation of the impact of air pollution on firms' exports. In addition, time trends of economic development or environmental regulations can affect both firm export performance and air pollution.

To address the simultaneity and omitted variable bias mentioned above, we employ an instrumental variable approach to estimate of the causal effect of air pollution on firm export performance. The instrument, thermal inversion, is a meteorological phenomenon that can influence air pollution while being uncorrelated with local firms' export performance and behaviors, except through its impact on air pollution, after accounting for various weather conditions. Normally, as altitude increases, air temperature decreases. However, during a thermal inversion episode, air temperatures rise with increasing altitude in the Earth's atmosphere. One significant consequence of thermal inversion is the occurrence of haze or smog, due to the warmer air layers trapping dust and air pollutants near the ground.[5] This identification strategy, utilizing thermal inversion as an instrument for air pollution, has been employed in several studies to estimate the effects of air pollution on various outcomes, including infant mortality, pro-cyclical mortality, child health, real GDP, road safety, migration, and firm productivity (Arceo et al., 2016; Hicks et al., 2016; Jans et al., 2018; Dechezleprêtre et al., 2019; Sager, 2019; Khanna et al., 2021; Fu et al., 2021; Chen et al., 2022).

Since thermal inversions are meteorological phenomena that occur in the upper atmosphere, their formation can be presumed independent of economic activities. Figure 1a plots the average number of thermal inversion days per year in China over the period 1995-2010, with vertical dashed lines highlighting the selected sample period of 2000-2007. Unlike air pollutants, there is no clear time trend in the occurrence of thermal inversions. This became particularly relevant after 2001 when the sharp increase in air pollutants was accompanied by the rapid export growth following China's accession to

[5] It is important to note that thermal inversions can affect other pollutants as well and may not be solely correlated with $PM_{2.5}$. Therefore, our estimates can represent the effects of air pollution more generally and not exclusively attributed to $PM_{2.5}$, as noted in Fu et al. (2021).

the WTO. Figure 1b further supports this point by illustrating annual export revenue and the average annual cumulative thermal inversions across all counties in China from 1995 to 2010. Export revenue exhibits a clear positive trend, while the number of thermal inversions per year experiences high fluctuations but does not have a discernible time trend. Two panels in Figure 1 together provide evidence that thermal inversions create country-level fluctuations in air pollution that are not influenced by structural sources, such as export development.

Figure 2 provides additional evidence that thermal inversions are not correlated with export at the county level. It depicts the log difference in export revenue (X-axis) and the log difference in inversions (Y-axis) for each county in China between 2000 and 2007. Counties with the highest increase in export do not necessarily experience the highest increase or decrease in thermal inversions. The fitted line representing the relationship between the change in export and thermal inversions appears nearly horizontal, indicating an insignificant association with an R-squared value of 0.00693. Together, Figures 1 and 2 indicate a lack of correlation between exports and thermal inversions at both national and county levels.

To investigate whether the detrimental impact of air pollution on firm-product exports is stronger for labor-intensive products as implied by Proposition 1, we then utilize the rich six-digit HS product information with significant variations in labor intensities in the customs trade data. To measure the labor intensity for each HS product, we merge the Annual Survey of Manufacturing Enterprises data collected by the National Bureau of Statistics (hereafter referred to as ASME data set) with firm-product-year level customs trade data, following the procedure of Ma et al. (2014) and Yu (2015). Using the merged data set in 2000, we construct several measures of the labor intensity of each HS6 product, such as the log ratio of labor to capital, the total labor costs in value-added, and the employment share of unskilled workers (workers without high school degrees). The computation methods are similar to the approach used in Bernard et al. (2010) and Ma et al. (2014), and are discussed in detail shortly in Section 4.3. Using product variations in labor intensity, we can directly test whether air pollution instrumented by the thermal inversion has stronger negative effects on the firm exports of labor-intensive products and thus exit more in those products in foreign markets.

3.2 Econometric specification

To implement our identification strategy, we adopt the following baseline specification:

$$\ln Y_{fht} = \beta_0 + \beta_1 \ln PM_{ct} + \gamma' W_{ct} + \alpha_{fh} + \alpha_t + \varepsilon_{fht}, \tag{13}$$

where f indexes firm, h indexes 6-digit HS code, c indexes the county where the firm locates, and t indexes year. $\ln Y_{fht}$ is the dependent variable of interest in the natural logarithm (e.g., firm-product level export revenue or quantity). α_{fh} and α_t are firm$\times$product fixed effects and year fixed effects.[6] PM_{ct} is the $PM_{2.5}$ concentration at the county-year level, measured in micrograms per cubic meter ($\mu g/m^3$). W_{ct} denotes a set of weather conditions, and ε is the error term. The main coefficient of interest is β_1, representing the effects of air pollutants on firm-product level export revenues, which is expected to be negative. The standard error of the regression is clustered by county to allow for possible correlation within the county.

As we discussed above, the OLS estimation of this specification would lead to biased estimates due to the endogeneity issue of air pollution. Thus, we adopt the two-stage least squares (2SLS) estimation by using the thermal inversion TI_{ct}, measured by the number of thermal inversion days in the firm f's locating county c in year t, as the instrument of air pollution PM_{ct}. As thermal inversion often correlates with weather conditions, we control for the vector of weather variables W_{ct} in both stages to ensure the exclusion

[6] Firms that have reallocated across counties (about 9% of the sample) are excluded from the sample. Thus, each firm (f) is uniquely matched with a county c, and all time-invariant county-specific factors can also be absorbed by α_{fh}.

restriction(Arceo et al., 2016). In particular, we use the number of days within each 20-quantile bin of temperature, relative humidity, wind speed, sunshine duration, pressure, and cumulative precipitation to account for the heterogeneous effect of extreme weather events (Deschenes et al., 2017; Fu et al., 2021).

There are two additional issues relevant to the validity of our instrument and the identification of causal effects. Firstly, thermal inversion can change the effectiveness of fertilizer and pesticides, so it could affect the output of agriculture directly, rather than via air pollution, which violates the orthogonality requirement for instrument variables. Therefore, we exclude all agricultural products from the sample. Secondly, during the sample period, over 20% of Chinese exports were through trading intermediaries (Ahn et al., 2011), for which the exact county of the original production cannot be identified. Therefore, we exclude all trade intermediaries from the sample.

Next, to explore the heterogeneous effects of air pollution on firms' exports across products with varying labor intensities, we include the interaction term of air pollution and product labor intensity as follows:

$$\ln Y_{fht} = \beta_0 + \beta_1 \ln P_{ct} + \beta_2 L/K_h \cdot \ln P_{ct} + \gamma' W_{ct} + \alpha_{fh} + \alpha_t + \varepsilon_{ft} \tag{14}$$

where L/K_h denotes the demeaned labor intensity for each HS 6-digit product h at the initial year of 2000. As we center L/K_h in the interaction term around its mean, β_1 captures the effect of air pollution on firm exports for products with average labor intensity, which is expected to be negative. Moreover, the key coefficient of interest, β_2, captures the heterogeneous effect of air pollution on firm export based on the labor intensity of products. According to Proposition 1 of our model, we anticipate that air pollution will have a stronger negative impact on the exports of labor-intensive products. Hence, we expect β_2 to be negative. Note one additional advantage of using the variations in labor intensity across products is that we can also include the county-year fixed effects α_{ct} to capture all time-varying and time-invariant county factors.

Lastly, we adopt a linear probability model to study how air pollution affects exporters' decisions in dropping or continuing their products in the foreign market. We define the dependent variable $Drop_{fht}$ equal to one if and only if firm f exports product h at time $t-1$ but not at time t, and adopt the similar specification as follows:

$$Drop_{fht} = \theta_0 + \theta_1 P_{ct-1} + \theta_2 L/K_h \cdot P_{ct-1} + \gamma' W_{ct-1} + \lambda' X_{fht} + \alpha_{fh} + \alpha_t + \varepsilon_{fht} \tag{15}$$

We use air pollution with a one-year lag as firms' decisions on dropping or continuing exporting after air pollution shocks are only observed accurately in the next year. Moreover, following Bernard et al. (2010), we also include a vector of other firm-product level control variables X_{fht}: relative firm-product tenure, and the relative size of a specific product to the firm's export revenue. Specifically, firm-product tenure is the length of time the firm has exported the product, measured relative to their averages via log differencing each year. We expect that a rise in air pollution increases exporters' probability of dropping a more labor-intensive product, and thus θ_2 is expected to be positive.

Although we show that thermal inversions can lead to fluctuations in air pollution in the first stage, an important feature of the variation in air pollution caused by thermal inversions is its eventual return to the mean, as partly shown in Figures 1 and 2. This raises the question of why exporting firms would adjust their product scope in response to a transitory shock. One plausible explanation is exporting firms have imperfect information on the sources of air pollution. In practice, firms lack the ability to distinguish between permanent and transitory changes in air pollution and, therefore, might rely on past observations to update predictions regarding future pollution levels. This procedure is similar to a Bayesian updating process (Harrison and Stevens, 1976).

The hypothetical Figure 3 visually demonstrates this updating mechanism. For two distinct counties, the solid dark lines represent air pollution fluctuations attributed to factors other than thermal inversions, while the solid light lines represent full air pollution fluctuations. The gap between each pair of solid lines represents variations solely induced by thermal inversions. However, exporters can only perceive the effect caused by air pollution regardless of the sources, which is represented by the light lines. And no publicly available information that specifies the portion of observed air pollution arising from transitory meteorological factors, such as thermal inversions. When exporters perceive an air pollution change caused by a thermal inversion, they will update their expectations as illustrated by dashed lines, even if the change is transitory in nature. This explains why exporters would react to air pollution induced by thermal inversions.

4 Data and Measurements

4.1 Firm-product level export data

Our study relies on a highly disaggregated firm-product level export dataset from China's General Administration of Customs, encompassing all export flows from 2000 to 2007. This dataset provides detailed information on Chinese export transactions, including export values, quantities, quantity units, HS 6-digit categorization, and firm-specific information such as registered name, address, and ownership. Each observation in our sample represents a unique firm–HS6–year trade flow. We carefully verify the consistency of quantity units across all transaction records within each firm-HS6-year trade flow, ensuring that the traded quantities can be accurately aggregated. Furthermore, we enhance the dataset by obtaining geospatial information for each firm using the GaodeMap API. Using the registered name, address, and prefecture information in each firm's registration code, we can pinpoint the location of each exporting firm at the county level. This geocoding process allows us to match the firm data effectively with the corresponding county-year-level environmental data. The success rate of geocoding China's customs data is reported in Table A1. In total, 88% of exporting firms listed in the Customs database from

2000 to 2007 were successfully geocoded, accounting for 98% of the total export value.

4.2 County-level air pollution, thermal inversions, and weather data

We obtain the air pollution and thermal inversion data from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) maintained by the National Aeronautics and Space Administration (NASA) of the U.S.[7] The data are reported at each $0.5° \times 0.625°$ latitude by longitude grid (around 50 km × 60 km). We transform the grid-level data to county-level for our analysis.[8]

Air pollution data are collected by remote-sensing satellite-based Aerosol Optical Depth (AOD) retrieval techniques. AOD measures the amount of sunlight duration absorbed, reflected, and scattered by particulate matter in the air. It provides accurate measures of ground-level $PM_{2.5}$. The AOD-based pollution data closely aligns with data collected by ground-based monitoring stations (Gupta et al., 2006; Kumar et al., 2011; Chen et al., 2022). We use AOD data because it covers the entire country, in contrast to ground-based data, which is confined to a few cities. In our empirical estimations, we compute annual county-level surface $PM_{2.5}$ concentrations by averaging monthly data, following Buchard et al. (2016).

As for thermal inversions, the measurement is computed according to Fu et al. (2021). A thermal inversion is identified for each 6-hour interval when the temperature of the second layer of the atmosphere (320 meters) is higher than that of the first layer (110 meters). We aggregate the number of days with at least one thermal inversion per year for each county to construct the county-year thermal inversion data.

The weather data are collected by the National Meteorological Information Center of

[7]The air pollution data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary. The thermal inversion data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2I6NPANA_V5.12.4/summary.

[8]We first downscale the 50*60-km grid to 10*12-km grid using the bilinear method (Hijmans et al., 2015) to better accommodate counties that are smaller than 50*60-km. We then take the spatial average for all downscaled grids within each county (see Fu et al. (2021)).

China, which operates over 800 weather stations nationwide. The set of weather control variables includes barometric pressure (hectopascal), relative humidity (%), precipitation (mm), sunshine duration (hour), temperature (degree centigrade °C), and wind speed (m/s). To match with other data in our analysis, we first convert the original station-level weather data to county-level using the inverse-distance weighting (IDW) method (Deschênes and Greenstone, 2011). This method assigns greater weight to stations closer to the geographic centroid. Next, we convert the daily weather data to an annual frequency by dividing it into 20 quantiles for each weather variable and counting the days in the year that fall within each quantile bin. This approach allows us to account for the differential effects of extreme and normal weather events (Deschenes et al., 2017).

4.3 Product level labor intensity

To compute HS6 product level labor intensity measures, we merge the firm-level Annual Survey of Manufacturing Enterprises (ASME) data with the transaction-level customs export data. The ASME data provides information on firm-level input factor costs, such as total employment, total wage bills, unemployment insurance, bonuses, welfare funds, the original value of fixed assets, and the net value of fixed assets. However, the ASME data does not include information on firms' product scope. On the other hand, the customs export data contains complete information on firms' export performance and the product scope of each exporter but lacks firm-level input factor information. These two data sets can be matched through a set of firm information, including firm name, corporate representative name, zip code, location, and contacts. The matching method and statistics are similar to those employed in previous studies that combine these two datasets (Ma et al., 2014; Yu, 2015).

The process of computing HS6 product level labor intensity measures involves several steps. First, we compute the labor intensity at the firm level using the ASME dataset. We employ three different measures, which we will discuss in detail later. Second, we match these firm-level labor intensity measures calculated in the ASME data with the customs export data, which provides information on the product scope of each exporter. Next, we compute the HS6 product level labor intensity by computing the weighted average of the labor intensity of all firms that export a particular product, with weights based on each firm's export revenue. This approach is similar to the method employed in Bernard et al. (2010) and Ma et al. (2014).

The key step of computing HS6 level labor intensity measures is calculating each firm's labor intensity. We adopt three measures of firm-level labor intensity: (1) the employment-to-real-capital ratio in logarithmic format. Total employment is measured by the annual average employed workers. Real capital is calculated using the perpetual inventory approach as described by Brandt et al. (2012), since the related variables in the ASME data are reported in nominal terms and cannot be regarded as a firm's capital stock directly. We adopt this as our baseline measure of factor intensity, similar to that in Ma et al. (2014) and Imbert et al. (2022). (2) The share of total labor cost in value-added. Total labor cost includes wage bills, unemployment insurance, bonuses, and welfare funds. This measure of labor intensity is consistent with the labor income share (β_s) defined in our theoretical model, which enables us to estimate a key parameter (θ) of the model. In addition, this alternative measure of labor intensity complements the first measure by accounting for labor quality employed by firms, since we use total labor cost instead of employment to measure labor input (Qian and Zhu, 2012). (3) The percentage of workers without a high school degree to total employment. Air pollution may affect less skilled workers more than skilled workers. This could be related to the increased vulnerability of less skilled workers to health problems caused by greater exposure to air pollutants, often due to their less favorable working conditions. Therefore, we use the percentage of the least-skilled workers in total employment as an alternative measure for labor intensity. Note that we compute all three measures of labor intensities at the HS6 product level using data in the initial year of our sample, 2000, to avoid any potential concerns about the impact of pollution on the firms' decisions regarding labor and capital allocation.

4.4 Sample construction and summary statistics

The empirical estimation is mainly based on the combination of the above three data sets. To ensure the accuracy and validity of our analysis, we take two essential steps in the sample construction stage. Firstly, following Ahn et al. (2011), we identify trade intermediary firms based on several key Chinese characters in the firm name, and exclude them from our sample as their locations may not be the locations of production. Secondly, we exclude firms that have relocated across counties to deal with potential concerns of spatial sorting, endogenous choices of firm location, and self-selection biases. The impact of removing these observations is limited as more than 91% of exporters stay in the same county during the sample period. For more detailed statistics on firms' relocation within the sample period, please refer to Table A2.

Table 1 reports the key statistics of three different samples that we constructed for the empirical estimations. The full sample comprises the firm-product level China's custom export data from 2000 to 2007, combined with county-level air pollution data and product-level labor intensity data. This is the main sample we used in the estimations. The product scope adjustment sample is a subset of the full sample. Note that the variable $Drop_{fht}$ indicating firms' decision of discontinuation of exports, only applies to the existing products of the surviving firms. Therefore, it does not apply to the varieties exported for the first time or observations in 2000, the sample's initial year. For the ASME-exporter sample, which is at the firm-year level, we include all exporting firms documented in the ASME database between 2000 and 2007. This sample supplements our analysis, providing supporting evidence for the impact of air pollution on firms' labor productivity.

5 Estimation and Results

We first show that air pollution has detrimental effects on the labor productivity of exporters as it offers the premier for our analysis of the effects of air pollution on firm exports. Next, we demonstrate the negative effects of air pollution on firm-product level exports, which is stronger for labor-intensive varieties. As a response, firms adjust their product scope by withdrawing their labor-intensive products in foreign markets. Moreover, we show that the impact of air pollution on firm exports is mitigated for larger exporters and foreign-owned enterprises or state-owned enterprises. Finally, we show that air pollution has no significant impact on firm entry and exit, and export quality.

5.1 The impact on labor productivity

Building on Fu et al. (2021), to provide empirical evidence on the main channel through which air pollution affects export performance, we estimate the average effect of air pollution on exporting firms' labor productivity. Firm-level labor productivity is measured by value-added per worker in the logarithm. As the customs trade dataset lacks information on value-added and labor employment, we use exporters in the ASME dataset from 2000 to 2007 to estimate the impact of air pollution on labor productivity. Table 2 presents the estimation result by employing two estimation methods: OLS and two-stage least squares (2SLS) estimation.

In Table 2, column (1) presents the OLS estimate, which may be subject to simultaneity and omitted variable biases, resulting in an underestimated coefficient. To address this issue, we then turn to the 2SLS estimation in column (2). The bottom half of column (2) presents the first-stage estimations, providing evidence that thermal inversion is a valid instrument for $PM_{2.5}$. The estimations show that, on average, a 1% increase in annual days of thermal inversion increases annual $PM_{2.5}$ pollution by 0.056%, controlling for weather conditions. The coefficient is statistically significant, and the Kleibergen-Paap Wald F statistic for weak IV exceeds the critical value of 16.38, rejecting the null hypothesis of a weak instrument problem. Given the sample mean of annual thermal inversion days (123 days) and $PM_{2.5}$ concentration (71.27 $\mu g/m^3$), we can estimate that approximately one additional day of thermal inversion increases $PM_{2.5}$ by 0.046%, or about 0.033 $\mu g/m^3$. It is important to note that thermal inversions may affect other pollutants, such as SO_2 and CO, in addition to $PM_{2.5}$ (Arceo et al., 2016). Therefore, the estimated coefficient can be interpreted as the impact of broader air pollution rather than solely the effect of $PM_{2.5}$, as noted in Fu et al. (2021).

The first stage demonstrates that thermal inversion is a reliable predictor of air pollution. The second stage estimation yields a statistically significant coefficient of -0.946, indicating that a 1% increase in air pollution concentration corresponds to a labor productivity decrease of 0.95%. Through these estimations, we establish a causal relationship between air pollution and labor productivity.

Considering the sample mean of $PM_{2.5}$ concentrations (71 $\mu g/m^3$), the estimated coefficient in column (2) (-0.946) suggests that a 1 $\mu g/m^3$ in $PM_{2.5}$ concentrations (equivalent to 1.41% of the sample mean) corresponds to an approximate 1.33% reduction in labor productivity for exporting firms in the ASME database. This estimate is a bit larger in magnitude compared with the findings of Fu et al. (2021), who reported a 0.8% decline in productivity for a 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations, employing data from China's above-scale manufacturing firms. A possible reason for our larger estimates in Table 2 is that we focus on exporters in China, which tend to be more labor-intensive than non-exporters on average (Huang and Ottaviano, 2023), potentially rendering them more susceptible to air pollution. In addition, our estimates exhibit larger effects compared to studies that focus on particular worker types, or small sets of firms, such as Adhvaryu et al. (2022); Chang et al. (2016, 2019). For instance, Chang et al. (2016) used employee data from a call center in China and found that for a 1 $\mu g/m^3$ increase in $PM_{2.5}$, worker productivity, as measured by earnings per hour, decrease by roughly 0.8%. And Adhvaryu et al.

(2022) reported a 0.1% reduction in hourly worker productivity for a 1 $\mu g/m^3$ increase in fine particulate matter using data from an Indian garment firm. A possible reason for our larger estimates is that we estimate annual cumulative effects rather than the shorter-term effects examined in these studies.

In columns (3) and (4), we examine the heterogeneous effect of air pollution on firm size by incorporating the variable $LargeFirm$ and its interaction with instrumented air pollution. The variable $LargeFirm$ is a dummy variable indicating firms above the sample median in terms of size, measured by either output or value added. The results demonstrate that larger firms experience less negative impact from air pollution on labor productivity. In column (3), for above-median-size firms, a 1% increase in $PM_{2.5}$ reduces firm-level labor productivity by 0.78%. The effect is approximately 30% smaller than that observed for below-median-size firms. This result aligns with our model prediction in Proposition 3, suggesting that larger firms, characterized by higher productivity, can better afford the fixed costs of adopting technology or equipment to mitigate the detrimental impact of air pollution on productivity. Consequently, the adverse effect of air pollution on export performance is expected to be less severe for larger firms compared to smaller ones, which we will explore further in Section 5.5.

5.2 Causal effects of air pollution on firm exports

Next, we study how air pollution in China affects firm exports and how firms respond. Table 3 displays the average effects of air pollution on firm-product level export value and quantity, both measured in logarithms. We also present two estimation methods to examine these effects. All columns include common covariates: firm$\times$HS6 product fixed effects, year fixed effects, and a vector of weather controls. In addition, robust standard errors are corrected for clustering at the county level in parentheses.

The OLS estimates in columns (1) and (3) reveal a negative correlation between firm-product export and county-level air pollution. The effect of the OLS estimates is smaller than that of the 2SLS estimates. This discrepancy can be attributed to the simultaneity problem, as increased production activity is likely to result in higher air pollution emissions. We introduce thermal inversion as an instrument for $PM_{2.5}$ to address the simultaneity and omitted variable biases. The 2SLS estimates with thermal inversion as an instrument are reported in columns (2) and (4). This specification, as outlined in equation (13), serves as our baseline model.

The bottom half of columns (2) and (4) present the first-stage estimations, similar to that of Table 2, providing evidence that thermal inversion is a valid instrument for $PM_{2.5}$. The top half of columns (2) and (4) in Table 3 present the second-stage results revealing the effects of $PM_{2.5}$ on firm-product level export value and quantity. We find that a 1% increase in $PM_{2.5}$ leads to a decrease of about 0.89% in firm-product level export value, and a reduction of approximately 1% in firm-product level export quantity. Evaluating this at the sample mean of $PM_{2.5}$ concentration (71 $\mu g/m^3$), we find that, on average, a 1 $\mu g/m^3$ increase in $PM_{2.5}$ (i.e., 1.4% increase at the sample mean) results in a reduction of firm-product level export by about 1.25%. The magnitude of these estimates align with the findings of Dechezleprêtre et al. (2019), who reported a 0.8% reduction in real GDP in Europe for each 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations.

In terms of the aggregate impact of air pollution on Chinese exports, we consider the average annual export revenue for each firm-product observation in the sample, which is 629,151 US dollars. A 1% nationwide increase in annual $PM_{2.5}$ concentration would reduce export revenue at the firm-product level by approximately $5,596 per year. With an average of 599,147 different firm-product varieties exported in each year of the sample, the reduction in annual export revenue amounts to approximately three billion US dollars. This accounts for about 1.2% and 0.2% of China's total goods exports in 2000 and 2007 respectively.[9]

The findings presented in Table 3 also demonstrate a degree of similarity in the impact

[9]The total value of China's exports (FoB) was 249,203 million US dollars in 2000, and 1,220,060 million US dollars in 2007.

of air pollution on both export value and quantity. The outcomes for unit value, as exhibited in Table 10, however, lack statistical significance. To elaborate, it can be concluded that air pollution exerts a diminishing influence on export outputs at the firm-product level, yet fails to induce a corresponding escalation in export prices. Consequently, our subsequent discourse will be primarily centered around the examination of export values.

5.3 Heterogeneous effect across products with varying labor intensity

Next, we utilize the variation of labor intensity across products to examine whether the detrimental effects of air pollution on firm exports are stronger for labor-intensive products. Table 4 reports regression results of equation (14), which includes the interaction term of product-level labor intensity with air pollution in the baseline regression, experimenting with various sets of control variables and fixed effects. Note the labor intensity at HS6 product level is computed as the weighted average of the labor intensity of firms producing that particular product in 2000, where the baseline measure of labor intensity is measured by the (log) ratio of employees to real capital. We will show shortly that the results are robust by using alternative measures.

We first briefly discuss our specifications in Table 4. First, all columns report the IV estimates, where $\text{PM}_{2.5}$ and its interaction with product labor intensity are instrumented by the thermal inversion and the corresponding interactions. Second, all columns except for those with county-year fixed effects control for the same set of weather variables, and the standard errors are clustered at the county level to account for possible serial correlation within the county. Third, similar to the baseline specification in Table 3, column (1) includes firm$\times$HS6 and year-fixed effects, while column (2) introduces additional control variables to capture sector-region factors that may affect export and air pollution. Moreover, columns (3) and (4) adopt county-year fixed effects to account for the unobserved time-varying county-level factors.

Since labor intensity is demeaned in the interaction term of air pollution and product labor intensity, the coefficient on air pollution captures its effect on firm exports for products with the average labor intensity, while the interaction term measures the heterogeneous effects of air pollution on firm exports across products with varying labor intensities. Therefore, the coefficients of interest in Table 4 are those of the interaction terms, which are negative and statistically significant across all columns with different sets of control variables and fixed effects. It implies that the negative effect of air pollution on exports is more pronounced for products with relatively higher labor intensity. The results provide empirical support for model Proposition 1 and demonstrate the heterogeneous effects based on the labor intensity of products.

In column (1) of Table 4, the coefficient on $PM_{2.5}$ is -0.86, indicating that a 1% increase in $PM_{2.5}$ concentration leads to a 0.86% reduction in firm-product level exports when the labor intensity of products is at the sample mean level. This magnitude is consistent with the overall effect reported in Table 3. Moreover, the negative coefficient on the interaction term of $PM_{2.5}$ and labor intensity implies that air pollution has a stronger detrimental effect on firms' exports of more labor-intensive products. In particular, for the most labor-intensive quarter of the products (75th percentile) in the sample, a 1% increase in $PM_{2.5}$ concentration reduces firm-product level export by approximately 1%, which is 17% more than the effect for products with labor intensity at the sample mean level. On the other hand, for the least labor-intensive quarter of the products (25th percentile) in the sample, a 1% increase in $PM_{2.5}$ concentration decreases firm-product level export by around 0.73%, which is 14% less than the effect for products with labor intensity at the sample mean level.[10]

In column (2) of Table 4, we introduce additional control variables at the sector-region level to address potential identification concerns related to air pollution-induced migration and regulatory policies. These controls serve as proxies for labor endowments and the strength of air pollution-related regulations at the provincial or prefecture level. As

[10] In Table 4, the sample mean of ln(L/K) is -4.302. While the 75th percentile is -3.754, and the 25th percentile is -4.775.

shown, the results are not sensitive to the inclusion of such controls, reflecting the validity and orthogonality of the instrument. The specific control variables included in column (2) are as follows: (i) provincial air pollution-related regulation strength,[11] (ii) an interaction term between the strength of provincial level regulation and an indicator for pollution-intensive industry,[12] (iii) the logarithm of prefecture-level population, (iv) provincial non-college labor share, (v) an interaction term between product labor intensity and variables related to labor endowments.

In column (3), with product heterogeneity in labor intensity, we can include county$\times$year fixed effects to account for the possibility of unobserved omitted variable bias arising from time-varying county-level shocks at the same variation of thermal inversions. This makes an even tighter identification as it further utilizes the variation of labor intensity across products and captures unobserved county factors. In column (4), we include county$\times$year fixed effects and the set of sector-region level control variables simultaneously. Again, this has little impact on the results. In columns (3) and (4), as the variation of $PM_{2.5}$ and its instrument—thermal inversion—is at the county-year level, thus is dropped due to the inclusion of county$\times$year fixed effects. Our focus in these columns is the coefficient of the interaction term, which captures the heterogeneous effects of air pollution on exports based on labor intensity. However, we find that the estimated coefficients of the interaction terms in columns (3) and (4) are similar to the one in column (1), indicating that the omitted variables bias from unobserved county-year factors is rather limited.

In columns (5) to (8), we re-estimate the specification in columns (1) to (4) with firm-

[11]The strength of provincial restrictions on air pollutant emissions is measured by the percentage of air pollution-related word count in the provincial government work report. We count the number of Chinese characters that have the English-equivalent meaning of: "PM_{10}", "$PM_{2.5}$", "SO_2", "CO_2", "air pollution", "air quality", "dust", "particulate matter", "haze", "clear sky". Specifically, in pinyin (Romanized Chinese), these phrases are: "er4yang3hua4liu2", "er4yang3hua4tan4", "kong1qi4wu1ran3", "da4qi4wu1ran3", "kong1qi4zhi4liang4", "yang2chen2", "jiang4chen2", "ke1li4wu4", "kong1qi4", "wu4mai2", "lan2tian1". Then we de-scale the air pollution-related word count by the total words of the provincial government work report.

[12]The classification of the pollution-intensive industry is drawn from Mani and Wheeler (1998). We converted the ISIC2 in the classification into HS 6-digit by concordance provided by WITS at https://wits.worldbank.org/referencedata.html.

product level export quantity as the dependent variables. The results are close in magnitude and significance level to those of export value. Given the similarity in results and the focus of our analysis, we focus on the export value for the subsequent analysis by using alternative measures of product labor intensity.

Alternative measures of labor intensity.— In Table 5, we provide additional regression results using two alternative measures of product labor intensity: the labor cost share and the employment share of unskilled workers. We follow the same fixed effects and control variables combinations as presented in Table 4. The results consistently demonstrate negative and statistically significant impacts of $PM_{2.5}$ on firm-product level exports and a stronger effect for products with higher labor intensity, confirming the pattern observed in the previous analysis. These findings provide robust evidence that air pollution has a detrimental effect on firm-product level exports, particularly for labor-intensive products, regardless of the specific measure used to capture labor intensity.

The first alternative measure of product labor intensity is the weighted average of the ratio of total labor cost to value-added of all firms producing that product. This measurement has the advantage of directly mapping to the theoretical structural parameter of labor income share, which is represented by the parameter β_s in our theoretical model. However, to construct this measurement, we need to accurately estimate the value-added for each firm. In columns (1) to (4) of Table 5, the coefficients of the interaction term of air pollution and the product's labor cost share range from -1.05 to -0.84. By plugging these estimated coefficients into the double partial derivatives in Proposition 1 and assuming a commonly accepted value of the substitution elasticity $\sigma = 5$ from the literature (Costinot and Rodríguez-Clare, 2014), we can calculate the parameter θ that governs the elasticity of air pollution's effect on labor productivity. Our estimated values of θ fall within the range of 0.21 to 0.26, which are comparable to those found in related literature, such as the study by Fu et al. (2021).

Air pollution can potentially exert disparate impacts on the health and productivity of different segments of the labor force, with unskilled labor potentially bearing a disproportionately heavier burden. This could be attributed to their heightened susceptibility to adverse health effects stemming from greater exposure to air pollutants, owing to their typically disadvantaged working conditions. Thus, we use the employment share of workers without a high school degree as the second alternative measurement of product labor intensity. The outcomes of the empirical analysis, presented in columns (5) to (8) of Table 5, underscore the robustness of employing this particular measure of labor intensity. The results corroborate earlier findings and affirm that the chosen proxy effectively depicts the intricate relationship between labor intensity and its interplay with air pollution.

5.4 Product scope adjustment

This section characterizes the restructuring of export product scope following air pollution shocks. Our analysis involves two parts. First, at the firm-product level, we investigate whether exporters are inclined to cease the export of products that are relatively more labor-intensive compared to other products in the entire product spectrum. Second, we conduct firm-level estimations to examine whether the product bundle dropped by the firms exhibits a relatively higher labor intensity compared to the firm's average labor intensity.

Firm-product level estimation.—-Table 6 presents the estimated results of firms' product scope adjustment in response to air pollution shocks. The dependent variable of interest is a binary variable that takes the value one if a product is dropped from the export product scope of the firms, and zero otherwise. The specification in the table is based on equation (12) and relies on Proposition 2 of the model. We use a linear probability model to incorporate multiple fixed effects and 2SLS estimation with the instrument variable.

Table 6 presents results from various specifications for robustness. In all columns of Table 6, as in all results tables, we include firm$\times$HS6 fixed effects to control for any firm-product characteristics that may affect the decision to drop a product. In columns (1) and (2), we use year fixed effects to control for annual shocks. In columns (3) and (4), we further incorporate county$\times$year fixed effects to account for potential omitted variables whose variation coincides with air pollution and thermal inversion.

Two different measures of product-level labor intensity are used in the analysis. Columns (1) and (3) measure labor intensity by the (log) ratio of employees to real capital. Columns (2) and (4) use the ratio of labor costs to value-added, winsorized to the value of (0.1,0.9). Labor intensity is demeaned as in the previous estimations. The coefficient on the main air pollution variable reflects its impact on the likelihood of dropping products with average labor intensity. The coefficient on the interaction term captures the stronger effect for labor-intensive products. The regression additionally controls for the relative tenure and size of firm-HS6 products. The relative tenure of firm-HS6 products measures the firm's experience in exporting a particular product relative to the average across firms for that product. The relative size of the product is the share of the product in the firm's total export revenue, which captures the importance of the product to the firm. These relative terms are computed using log differencing. Similar specifications for examining firms' product discontinuation decisions can be found in Bernard et al. (2010) as a reference.

The results in Table 6 consistently show that air pollution positively and statistically significantly affects the subsequent cessation of exports for relatively more labor-intensive products. In column (1), the coefficient on the interaction term is about 0.03. It implies that, for the most labor-intensive quarter of the products in the sample, a one standard deviation increase in annual $PM_{2.5}$ exposure increases the linear probability of the firm discontinuing these products by about 0.48% next year.[13] The coefficient estimates indicate that air pollution prompts exporters to stop exporting products that are relatively more labor-intensive compared to other products in the entire product spectrum..

[13]The 75th percentile of labor intensity $ln(L/K)$ is -3.754. The sample mean $ln(L/K)$ is -4.3. One standard deviation of $PM_{2.5}$ is 21.12, accounting for about 29.6% of $PM_{2.5}$ sample mean. The effect is (-3.754-(-4.3))*0.03*29.6=0.48%.

Firm level estimation.—-We investigate whether exporting firms alter their export product scope through dropping varieties, and how much they shift away from their previous labor-intensity. We proxy the labor intensity of each HS6 product by the average labor-to-capital ratio in the logarithm among firms that produce this product, in the same way as in Section 5.3.

We estimate the firm-level specification using data from 2001 to 2007, controlling for both firm fixed effects and year fixed effects. We first detect changes in the product scope across years within firms, and then we explore the direction of changes. The dependent variable, denoted as "*Any variety dropped*", is a binary variable equal to one if there is any removal (columns 1-2) from the firm's export product scope. The other dependent variable, namely "*More labor-intensive varieties dropped*", is a binary variable that is equal to one if the dropped group of products has a higher labor intensity than the firm's average labor intensity in the previous year (columns 3-4). In other words, it indicates that the firm's product scope shifts away from labor-intensive varieties compared with its own status in the previous year, and focuses more on capital-intensive products. Similar to previous sections, we estimate the causal effect of $ln(PM_{2.5})$ using thermal inversions in the log term as an instrument variable.

Table 7 presents the results. Firms in counties that experience more severe air pollution are more likely to drop varieties to their exporting product scopes (columns 1-2). Specifically, a 1% increase in air pollution raises the probability of dropping existing products by 0.47%. These effects are mostly driven by transitions away from products with higher labor intensity (columns 3-4). We provide further results with additional firm-year control variables, including firm age, total export revenue, and the range of product scope. Our conclusion remains robust with these alternative specifications: there is an adjustment of product scope away from labor-intensive goods. Note that our sample in this part is exclusively composed of the incumbent exporters. Since we do not observe the product scope of new exporters in trade data before they start exporting, we cannot detect the change in firms' product scope in the first year of exporting and in 2000, which is the first year of our sample period. Therefore, the estimated coefficients capture the effect on a firm's product scope adjustment conditional on firm survival.

5.5 Firm heterogeneity

In this section, we examine Proposition 3 of the extended theoretical model. In this model extension, we consider the possibility that certain firms may adopt anti-air pollution technologies to mitigate the detrimental effects of pollution on their workers. These technologies include air purifiers for indoor workers and anti-particulate masks for outdoor workers. According to Proposition 3, as more productive firms choose to adopt the anti-pollution technology, the negative effects of air pollution on firms' exports will be smaller for more productive or larger firms. However, the customs data does not contain the information needed to estimate the productivity for exporters. Instead, we use firm export size to proxy exporters' productivity levels, as a large literature has documented that firm size and productivity tend to be positively correlated (Melitz, 2003; Bernard et al., 2012, etc.). In particular, firm size is measured by a binary variable indicating the rank of the firms' export revenue in the current year. We employed sample median and quantiles as thresholds to measure the ranking of the exporter size, which exhibits relatively stable patterns over the years. In addition, state-owned enterprises and foreign-owned enterprises may pay more attention to the working environment and thus provide more protection for workers from air pollution. Thus, we also explore the heterogeneous effects of air pollution on exports across firm ownerships.

Table 8 presents the findings of heterogeneous effect based on firm size and ownership, controlling for the labor intensity of exported goods. In Table 8, the variable $SizeMedian$ is a binary variable indicating whether the firm size is above the sample median for the current year. In column (1), when considering exported goods with labor intensity at the sample mean, the results show that an increase of 1% in air pollution leads to a decrease in export revenue of 0.35% for firms with above-median size, and a decrease of 1.06% for firms with below-median size. This suggests that the adverse impact of air pollution on above-median-sized exporters is only 33% of that on below-median-sized exporters.

Column (2) introduces an interaction term between $\mathrm{PM}_{2.5}$ and a dummy variable representing private-owned enterprises (POEs).[14] The results in column (2) indicate that the negative effect of air pollution on POEs is statistically stronger than on state-owned and foreign-owned firms. This stronger adverse effect persists even after controlling for product-level labor intensity and firm size, suggesting that the working environment or anti-air-pollution protection measures for workers in POEs may be less favorable compared to those in state-owned and foreign-owned firms.

Columns (3) and (4) of Table 8 use three binary variables indicating the position in different quantiles of firm size, instead of simply considering above or below the median. The findings reveal that the top 25% largest firms experience the mildest negative effect of air pollution, while the top 25% smallest firms encounter the strongest negative effect, controlling for the labor intensity of their exported products and firm ownership.

5.6 Discussions

Effect on firm entry and exit.— In order to test for the potential sample selection bias arising from firms' endogenous location choices based on air pollution, we estimate the effect of air pollution on firm entry and exit. The results are shown in Table 9. In columns (1) and (2), we examine the effect of air pollution on firm entry. The dependent variable $Entry_{ft}$ equals one if the firm exports in period t but not in $t-1$, and zero otherwise. We expand the sample to a firm-year balanced panel to estimate the impact on firm entry. In columns (3) and (4), we investigate the effect of air pollution on firm exit. The dependent

[14]We note that there is no significant difference between the impact of air pollution on state-owned enterprises (SOEs) and foreign-owned enterprises (FOEs). Hence, we group SOEs and FOEs together and introduce an indicator for POEs only.

variable $Exit_{ft}$ equals one if the firm exports in period $t-1$, but not in t, and zero otherwise. These findings reveal no statistically significant influence of air pollution on firm's entry or exit.

Effect on quality and price.— Table 10 presents air pollution's effect on firm-product export quality and price. We estimate firm-product-level effective quality using an empirical demand equation following methods in (Khandelwal et al., 2013). In columns (1) to (3), we employ different assumptions on σ to estimate firm-product-level effective quality. Column (4) presents the results of the quality-adjusted price, which is calculated as the observed log price minus the estimated effective quality. Additionally, column (5) presents the results for the unit price. Across all columns, we find no statistically significant effects of air pollution on exporters' product quality or prices.

6 Conclusion

Global climate change and environmental pollution have imposed great challenges on firms. This paper investigates how air pollution affects Chinese firms' export performance and their comparative advantage in the global market, as well as how exporters respond to pollution shocks. As air pollution has adverse effects on health conditions and the productivity of labor, this paper further shows that it also has eroded China's traditional comparative advantage in labor-intensive products, by using highly disaggregated firm-product level trade data and county-level air pollution data. In response to air pollution shocks, exporters also adjust their product scope by discontinuing labor-intensive varieties and focusing more on capital-intensive products. Moreover, more productive firms are inclined to invest in technologies that mitigate the impact of pollution, likely driven by a strategic intent to safeguard their workforce's well-being amidst polluted conditions.

The prevailing body of literature concerning the interplay between trade and environmental regulations predominantly emphasizes the adverse impact of regulatory policies on trade and overall economic output. In contrast, our study pivots to underscore the pivotal role of environmental protection policies in stimulating trade, particularly in economies abundant in labor resources. This is rooted in the recognition that air pollution operates as a discernible comparative disadvantage for labor-intensive goods. Consequently, our research accentuates the potential of environmental regulations aimed at enhancing air quality to catalyze the comparative advantage of labor-intensive products in labor-abundant developing economies.

The implications of our study extend to policy considerations, particularly for developing nations striving to navigate the delicate equilibrium between bolstering export growth and ensuring environmental preservation. By spotlighting the potential gains derived from aligning environmental protection measures with trade promotion objectives, our findings offer valuable insights that could inform the policy discourse in these countries.

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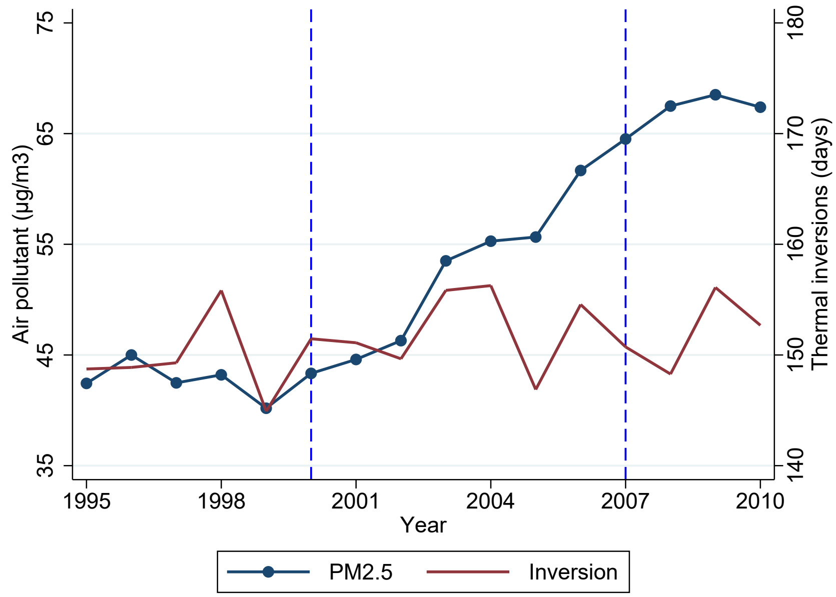
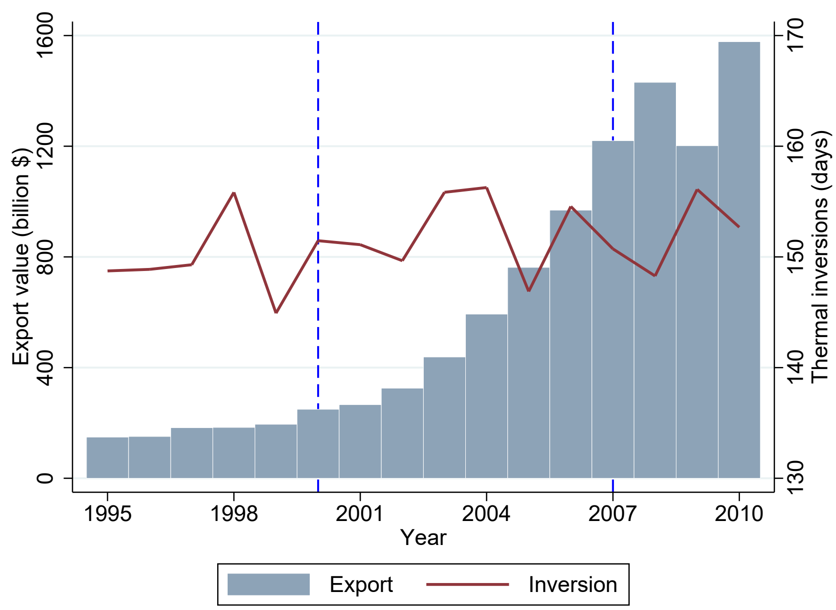
Figure 1: Time Trend of National Average of $PM_{2.5}$, Thermal Inversions, and Total Export Value in China (1995–2010).



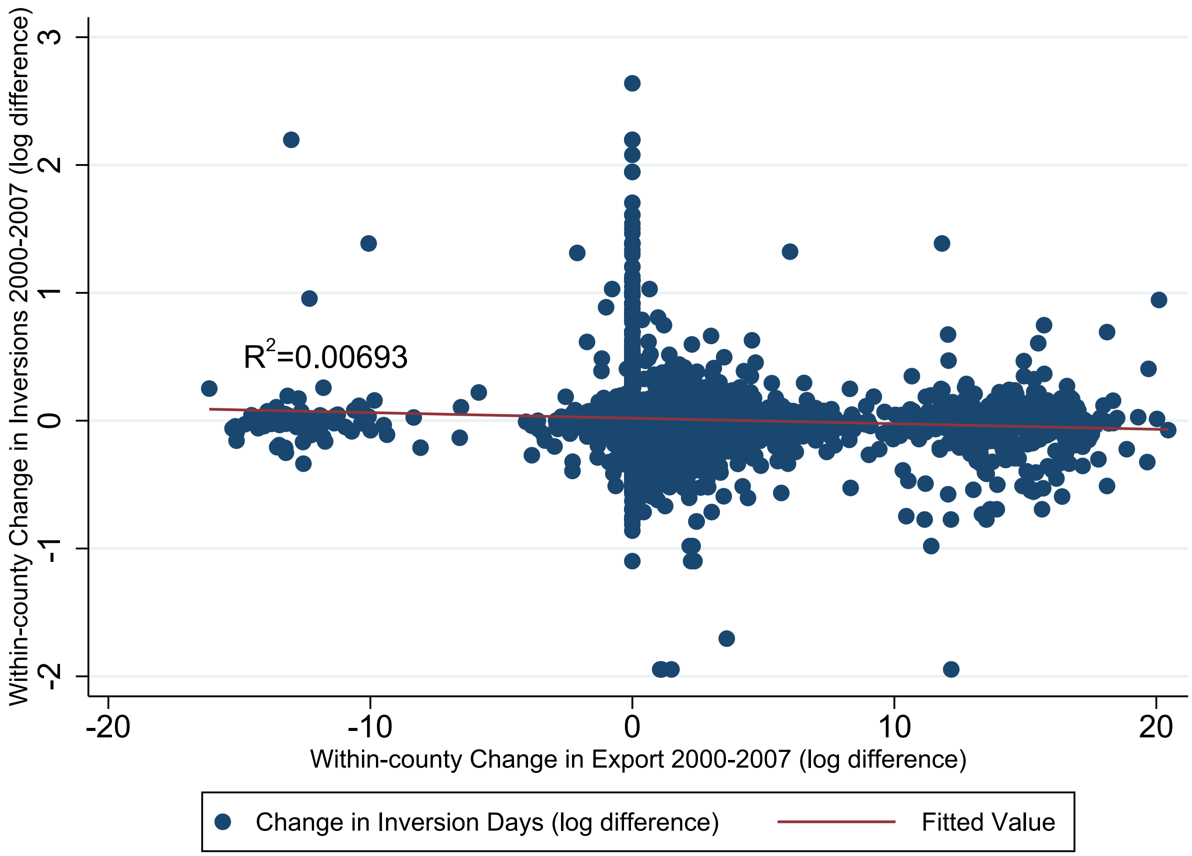
(a) $PM_{2.5}$ and Thermal Inversion



(b) Export Revenue and Thermal Inversion

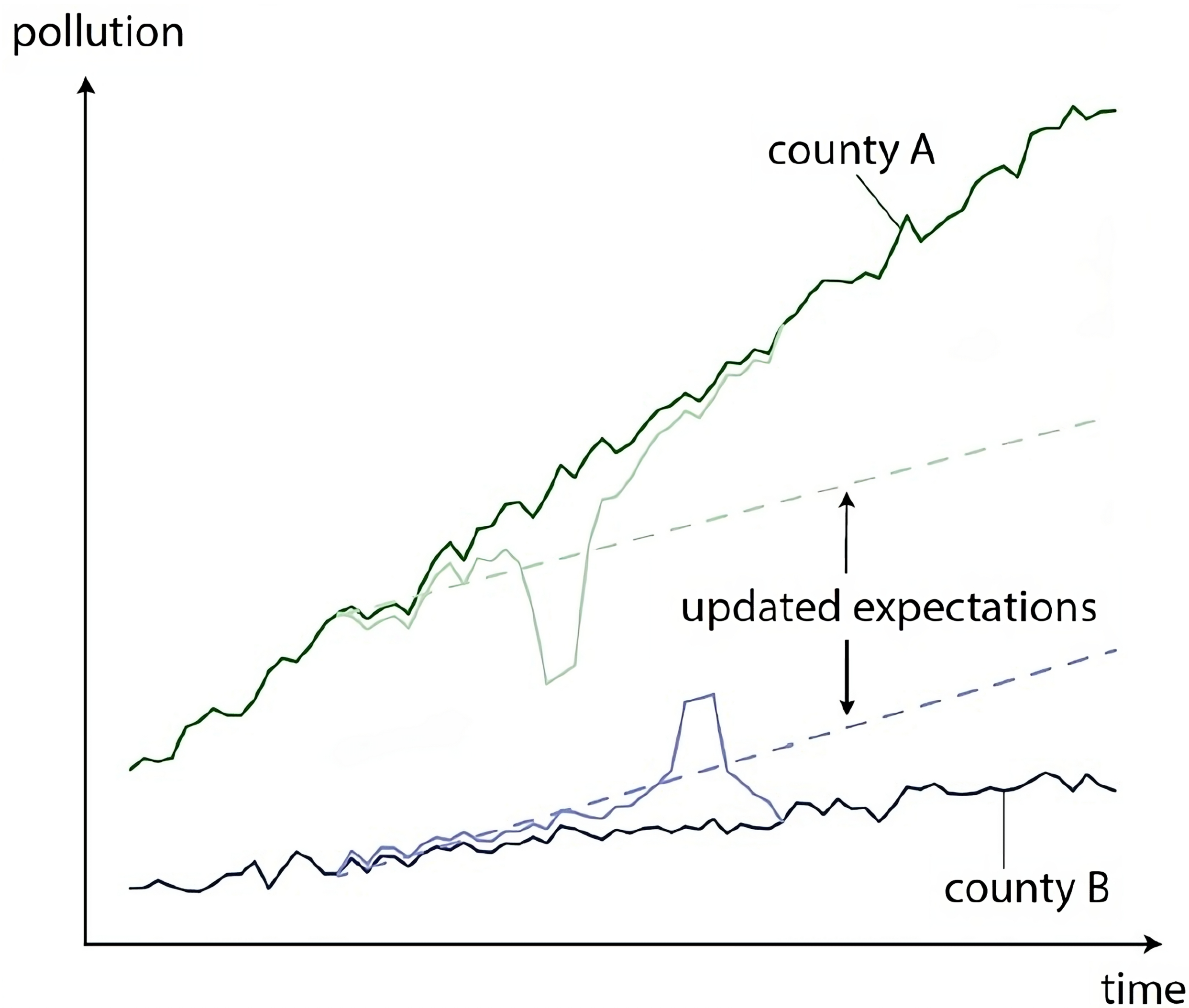
Notes: This figure depicts the national average of PM2.5 and thermal inversions in Panel (a) and export value and thermal inversions in Panel (b) in each year from 1995 to 2010. Two vertical dash lines highlight our study period: 2000–2007. $PM_{2.5}$ is measured in micrograms per cubic meter (μg/m3).

Figure 2: Within-County Change in Export and Thermal Inversions Between 2000-2007 (Log Difference)



Notes: This figure illustrates the correlation between the log difference in export value and the number of annual thermal inversion days for each of the 2,839 counties in China from 2000 to 2007. Each dot represents a county-level observation.

Figure 3: Exporters' Formation of Expectations About Air Pollution



Notes: This figure explains why exporters would react to air pollution induced by transitory shocks such as thermal inversions. For two distinct counties, the solid dark lines represent air pollution fluctuations attributed to factors other than thermal inversions, while the solid light lines represent full air pollution fluctuations. However, exporters can only perceive the effect caused by air pollution regardless of the sources, which is represented by the light lines. When exporters perceive an air pollution change caused by a thermal inversion, they will update their expectations as illustrated by dashed lines, even if the change is transitory in nature.

Table 1: Summary statistics

Full sample (firm-HS6-year): N=4,552,957							
Variables	**Mean**	**S.D.**	**Min**	**p25**	**Median**	**p75**	**Max**
Export value (1 USD)	629,151	1.49E+07	124	3,071	16,547	100,302	8.16E+09
Export quantity	757,514	4.68E+07	1	819	5,713	37,680	2.69E+10
Export price (1 USD)	2,223	206,642	7.29E-05	1.03	2.88	8.67	1.40E+08
$PM_{2.5}$ ($\mu g/m^3$)	71.27	21.12	3.47	55.17	70.01	86.07	134.80
Thermal inversion (day)	123	59	0	80	121	159	325
ln(employment/real capital)	-4.30	0.81	-8.62	-4.78	-4.17	-3.75	-0.62
Labor cost/value added	0.27	0.33	0.00	0.19	0.25	0.32	1.00
Unskill labor share	0.56	0.17	0.00	0.45	0.61	0.69	0.99

Product scope adjustment sample (firm-HS6-year): N=3,350,597						
Variables	**Mean**	**S.D.**	**Median**	**Mean**	**S.D.**	**Median**
	Drop=1 N=1,415,280			Drop=0 N=1,935,317		
Export value$_{t-1}$ (1 USD)	92,047	4.90E+06	5,526	998,567	1.67E+07	47,040
Export quantity$_{t-1}$	113,079	1.16E+07	2,150	1.30E+06	6.09E+07	14,604
$PM_{2.5,t-1}$ ($\mu g/m^3$)	67.71	20.09	68.03	68.67	20.01	68.13
Thermal inversion$_{t-1}$ (day)	122	63	119	126	58	124
ln(employment/real capital)	-4.31	0.82	-4.18	-4.28	0.79	-4.16
Labor cost/value added	0.28	0.15	0.25	0.27	0.13	0.25

ASME-exporter sample (firm-year): N=391,024							
Variables	**Mean**	**S.D.**	**Min**	**p25**	**Median**	**p75**	**Max**
Employment	301	388	10	85	164	347	3,010
Value-added (1000 CNY)	18,073	30,436	103	3,320	7,251	18,248	357,934
ln(value added per worker)	3.85	0.93	-0.96	3.20	3.75	4.41	9.28
$PM_{2.5}$ ($\mu g/m^3$)	70.66	20.63	4.31	55.36	69.07	85.64	134.80
Thermal inversion (day)	138	58	0	96	130	170	333

Notes: Each observation is at the firm-HS6-year level in the full sample and product scope adjustment sample, while at the firm-year level in the ASME-exporters sample. The period for the full sample and ASME-exporter sample is from 2000 to 2007. The period for the product scope adjustment sample is from 2001 to 2007. Export quantity is measured in consistent units for each firm-HS6 trade flow across years. Unskilled labor share is measured by the proportion of workers without a high school degree.

Table 2: The effect of air pollution on exporters' labor productivity

	ln(value added per worker)			
	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
$\ln(PM_{2.5})$	-0.4059***	-0.9461**	-1.1016***	-1.1188***
	(0.0960)	(0.3854)	(0.3543)	(0.3107)
$\ln(PM_{2.5})\times$Large Firm$_{output}$			0.3259**	
			(0.1275)	
$\ln(PM_{2.5})\times$Large Firm$_{va}$				0.2706**
				(0.1112)
		First stage		
ln(TI)		0.0561***		
		(0.0102)		
KP F-statistic		30.41	15.17	15.24
Weather controls	+	+	+	+
Firm FE	+	+	+	+
Year FE	+	+	+	+
Firm size dummy	-	-	+	+
R^2	0.0099	0.0086	0.0697	0.1842
N	363,627	363,616	363,616	363,616

Notes: The results are estimated based on exporting firms in the ASME database. The sample period is 2000-2007. Columns 3-4 include both a dummy variable $LargeFirms$, and its interaction term with instrumented air pollution. $LargeFirms$ equals one if the firm size (measured in output or value added) is above the sample median. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3: The average effects of air pollution on Chinese firms' exports

Dependent variable:	ln(export value)		ln(export quantity)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
ln($PM_{2.5}$)	-0.3909***	-0.8895**	-0.3898***	-1.0134**
	(0.090)	(0.418)	(0.086)	(0.444)
		First stage		First stage
ln(TI)		0.0653***		0.0654***
		(0.007)		(0.007)
KP F-statistic		87.66		87.75
Weather controls	+	+	+	+
Firm×HS6 FE	+	+	+	+
Year FE	+	+	+	+
R^2	0.796	0.001	0.848	0.001
N	3,022,089	3,021,888	3,018,880	3,018,679

Notes: This table reports the average effect of air pollution on firm-product level export performance. See Section 3 and equation (13) for a description of the IV specification. The sample period is 2000-2007. The dependent variable is winsorized at the 5th percentile. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: The heterogeneous effects of air pollution by product labor intensity

Dependent variable:	ln(export value)				ln(export quantity)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln($PM_{2.5}$)	-0.8560**	-0.8977**			-0.9828**	-0.8754*		
	(0.415)	(0.453)			(0.443)	(0.505)		
ln($PM_{2.5}$)×Labor intensity	-0.2583***	-0.2351***	-0.2503***	-0.2102***	-0.2762***	-0.2359***	-0.2771***	-0.2233***
	(0.051)	(0.057)	(0.051)	(0.057)	(0.045)	(0.048)	(0.044)	(0.048)
Weather controls	+	+	-	-	+	+	-	-
Firm×HS6 FE	+	+	+	+	+	+	+	+
Year FE	+	+	-	-	+	+	-	-
County×year FE	-	-	+	+	-	-	+	+
Covariates for sensitivity analysis	-	+	-	+	-	+	-	+
KP F-statistic	45.70	15.78	68.02	43.72	45.72	15.79	68.05	43.71
R^2	0.002	0.002	0.001	0.001	0.002	0.003	0.001	0.001
N	3,031,425	2,599,212	3,029,606	2,598,065	3,028,245	2,596,443	3,026,431	2,595,299

Notes: This table reports regression results of equation (14). All columns report the second-stage estimates of 2SLS. $PM_{2.5}$ and its interaction with product labor intensity are instrumented by the thermal inversion and the corresponding interactions. Labor intensity is measured by the (log) ratio of employee to real capital, and is demeaned in the interaction term. Covariates for sensitivity analysis are control variables at the sector-region level, including provincial air pollution-related regulation strength, the interaction term of indicator of pollution-intensive industry and strength of regulation, population, non-college labor share, the interaction term of labor intensity and population, and the interaction term of labor intensity and non-college labor share. The sample period is 2000-2007. The dependent variable is winsorized at the 5th percentile. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Alternative measures of product labor intensity

Dependent variable:	ln(export value)							
Labor intensity measure:	labor cost/value added				unskilled labor share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln($PM_{2.5}$)	-0.9273**	-0.9397**			-0.8551**	-0.8735**		
	(0.412)	(0.454)			(0.402)	(0.442)		
ln($PM_{2.5}$)×Labor intensity	-0.9257***	-1.0545***	-0.8390***	-0.9739***	-1.0491***	-0.7971***	-1.1709***	-0.8582***
	(0.266)	(0.301)	(0.249)	(0.286)	(0.283)	(0.306)	(0.253)	(0.301)
Weather controls	+	+	-	-	+	+	-	-
Firm×HS6 FE	+	+	+	+	+	+	+	+
Year FE	+	+	-	-	+	+	-	-
County×year FE	-	-	+	+	-	-	+	+
Covariates for sensitivity analysis	-	+	-	+	-	+	-	+
KP F-statistic	44.18	15.70	58.31	39.93	44.74	15.68	56.40	35.57
R^2	0.001	0.002	0.000	0.000	0.002	0.003	0.001	0.001
N	3,046,936	2,612,570	3,045,123	2,611,437	3,043,456	2,610,457	3,041,642	2,609,322

Notes: This table reports estimation results of the same specification as in Table 4 with alternative measures of product labor intensity. The first alternative measure is the ratio of total labor cost to value-added, which is winsorized at the value of (0.1,0.9). The second alternative measure, unskilled labor share, is the share of workers without a high school degree to total employment. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Product scope restructuring: firm-product level estimation

Dependent variable:	Indicator of export variety drop			
Labor intensity measure:	L/K	L/Y	L/K	L/Y
	(1)	(2)	(3)	(4)
$\ln(\mathrm{PM}_{2.5})_{t-1}$	-0.2196	-0.1995		
	(0.189)	(0.194)		
$\ln(\mathrm{PM}_{2.5})_{t-1}\times$Labor intensity	0.0328**	0.1108*	0.0284**	0.0937*
	(0.016)	(0.058)	(0.014)	(0.056)
Weather controls	+	+	-	-
Firm×HS6 FE	+	+	+	+
Year FE	+	+	-	-
County×year FE	-	-	+	+
KP F-statistic	26.18	26.23	63.17	61.58
R^2	0.170	0.169	0.167	0.166
N	2,249,842	2,260,849	2,248,245	2,259,243

Notes: The dependent variable of interest is a binary variable that takes the value one if the product is dropped from the export product scope of the firms, and zero otherwise. All columns report the second-stage estimates of 2SLS. L/K denotes the (log) ratio of employees to real capital. L/Y denotes the ratio of labor costs to value-added, winsorized to the value of (0.1,0.9). Both labor intensity measures are demeaned as in the previous estimations. The regression additionally controls for the relative tenure of firm-HS6 products and the (log) share of the product in the firms' total export revenue. The sample does not include new entrants. The sample period is 2001-2007. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Product scope restructuring: firm-level estimation

	(1)	(2)	(3)	(4)
Dependent variable:	Any variety dropped		More labor-intensive varieties dropped	
$\ln(\text{PM}_{2.5})_{t-1}$	0.4704***	0.5088***	0.2597**	0.2752**
	(0.140)	(0.147)	(0.107)	(0.108)
Weather controls	+	+	+	+
Firm FE	+	+	+	+
Year FE	+	+	+	+
Firm-year covariates	-	+	-	+
KP F-statistic	76.71	75.74	76.71	75.74
R^2	0.000	0.012	0.000	0.004
N	380,106	376,978	380,106	376,978

Notes: This table reports the firm-level estimation results: $Y_{ft} = \beta_0 + \beta_1 \ln PM_{ct} + \gamma' W_{ct} + \alpha_f + \alpha_t + \varepsilon_{ft}$. All columns report the second-stage estimates of 2SLS. The first-stage coefficients are 0.0651, with a significance level of 1%. The dependent variables are dummy variables equal to one if any products are dropped from the firm's export product scope (columns 1-2), and if the dropped group of products has a higher labor intensity than the firm's average labor intensity in the previous year (columns 3-4). Firms included in the sample are similar to Table 6. Firm-year covariates include firm age, size (in log), and the range of product scope (in log). Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: The heterogeneous effects by firm size and ownership

Dependent variable:	ln(export value)			
	(1)	(2)	(3)	(4)
ln($PM_{2.5}$)	-1.0604***	-0.9289***	-1.0693***	-0.9805***
	(0.327)	(0.342)	(0.381)	(0.379)
ln($PM_{2.5}$)×Labor intensity	-0.2611***	-0.2572***	-0.2178***	-0.2151***
	(0.047)	(0.049)	(0.040)	(0.041)
ln($PM_{2.5}$)×SizeMedian	0.7062***	0.7107***		
	(0.145)	(0.147)		
ln($PM_{2.5}$)×SizeQ2			0.5623***	0.5646***
			(0.158)	(0.159)
ln($PM_{2.5}$)×SizeQ3			0.9664***	0.9711***
			(0.281)	(0.283)
ln($PM_{2.5}$)×SizeQ4			1.1773***	1.1830***
			(0.296)	(0.296)
ln($PM_{2.5}$)×POE		-0.2982**		-0.2045*
		-0.151		(0.114)
Weather controls	+	+	+	+
Corresponding firm size dummy	+	+	+	+
Firm×HS6 FE	+	+	+	+
Year FE	+	+	+	+
KP F-statistic	30.37	23.82	18.32	21.70
R^2	0.053	0.053	0.101	0.050
N	3,031,425	3,031,425	3,031,425	3,029,606

Notes: All columns report the second-stage estimates of 2SLS. *SizeMedian* is a dummy indicating that the firm size is above the sample median for the current year. *SizeQ2* indicates that the firm size is in the second quantile. *SizeQ3* indicates that the firm's size is in the third quantile. *SizeQ4* indicates that the firm's size is in the fourth quantile. *POE* indicates private-owned enterprises. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: The effects on firm entry and exit in foreign markets

Dependent variable:	Firm entry		Firm exit	
	(1)	(2)	(3)	(4)
$\ln(\mathrm{PM}_{2.5})_{t-1}$	-0.1659	-0.1762	-0.1146	-0.2279
	(0.191)	(0.211)	(0.133)	(0.149)
	First stage		First stage	
$\ln(\mathrm{TI})_{t-1}$	0.0701***	0.0730***	0.0647***	0.0597***
	(0.007)	(0.008)	(0.007)	(0.008)
KP F-statistic	104.6	84.11	83.29	58.62
Weather controls	+	+	+	+
Firm FE	+	+	+	+
Year FE	+	+	+	+
Covariates for sensitivity analysis	-	+	-	+
R^2	0.001	0.001	0.002	0.025
N	727,361	569,007	460,440	425,618

Notes: The dependent variables are dummy variables indicating firm entry and exit. We exclude firms that enter and exit the export market in the same year from the sample. Covariates for sensitivity analysis include firm age (not applicable for entry specification), provincial air pollution-related regulation strength, non-college labor share, and population. Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10: The effect on estimated quality and price

Dependent variable:	ln(export quality)			ln(quality-adjusted price)	ln(unit price)
	σ=σ_i	$\sigma = 5$	$\sigma = 10$	σ=σ_i	
	(1)	(2)	(3)	(4)	(5)
ln(PM$_{2.5}$)	-0.4670	-0.1864	0.5979	0.0988	0.1329
	(0.502)	(0.503)	(0.888)	(0.417)	(0.101)
ln(PM$_{2.5}$)$\times$Labor intensity	-0.0998	-0.1796	-0.0719	0.1031	0.0201
	(0.093)	(0.113)	(0.208)	(0.089)	(0.020)
Weather controls	+	+	+	+	+
Firm$\times$HS6 FE	+	+	+	+	+
Year FE	+	+	+	+	+
KP F-statistic	45.06	45.06	45.06	43.77	45.72
R^2	0.001	0.001	0.002	0.001	0.002
N	3,001,796	3,001,796	3,001,796	2,262,332	3,028,245

Notes: All columns report the second-stage estimates of 2SLS. The dependent variables in columns (1) to (3) are the estimated (effective) quality at the firm-HS6 level, given different values of the elasticity of substitution (σ) following the method in Khandelwal et al. (2013). The industry-variant σ_i is based on Broda and Weinstein (2006). Robust standard errors are corrected for clustering at the county level in parentheses. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% level, respectively.

Online Appendix
Not for Publication

A1 Proof of Proposition 3

We assume the genetic value of θ without anti-pollution technology is θ_N, and firms that adopt the anti-pollution technology can mitigate the detrimental impact of air pollution on labor productivity and thus have a lower value of θ_T, i.e., $\theta_N > \theta_T$. Given this setting, the relative labor productivity with anti-pollution technology to without anti-pollution technology $A_T(Z)/A_N(Z) = z^{\theta_N - \theta_T} \geq 1$ for $z \geq 1$. This suggests that the anti-pollution technology in nature can boost labor productivity, particularly when firms are facing severe air pollution.

The expression for the firm-level profit of not adopting anti-pollution technology can be rewritten in $\pi_N(\varphi)$ as follows:

$$
\begin{aligned}
\pi_N(\varphi) &= \pi_N^H(\varphi) + \pi_N^F(\varphi) \\
&= \int_0^1 \left[\int_{\lambda_{s,N}^{H*}}^{\bar{\lambda}} \pi_{s,N}^H \left(\varphi, \lambda_s^H\right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds + \int_0^1 \left[\int_{\lambda_{s,N}^{F*}}^{\bar{\lambda}} \pi_{s,N}^F \left(\varphi, \lambda_s^F\right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
&= \int_0^1 \left[\int_{\lambda_{s,N}^{H*}}^{\bar{\lambda}} \left(R_s^H \cdot \left(\frac{\rho P_s^H \lambda_s^H \cdot \varphi}{\left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} - f_s \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
&\quad + \int_0^1 \left[\int_{\lambda_{s,N}^{F*}}^{\bar{\lambda}} \left(R_s^F \cdot \left(\frac{\rho P_s^F \lambda_s^F \cdot \varphi}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} - F_s \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds
\end{aligned}
$$

Note that f_s is the fixed cost of production for product s, measured as units of the numeraire. Firms must pay a fixed cost of F_s (measured as units of the numeraire) to serve the foreign market.

The expression for the firm-level profit of adopting anti-pollution technology can be rewritten in $\pi_T(\varphi)$ as follows:

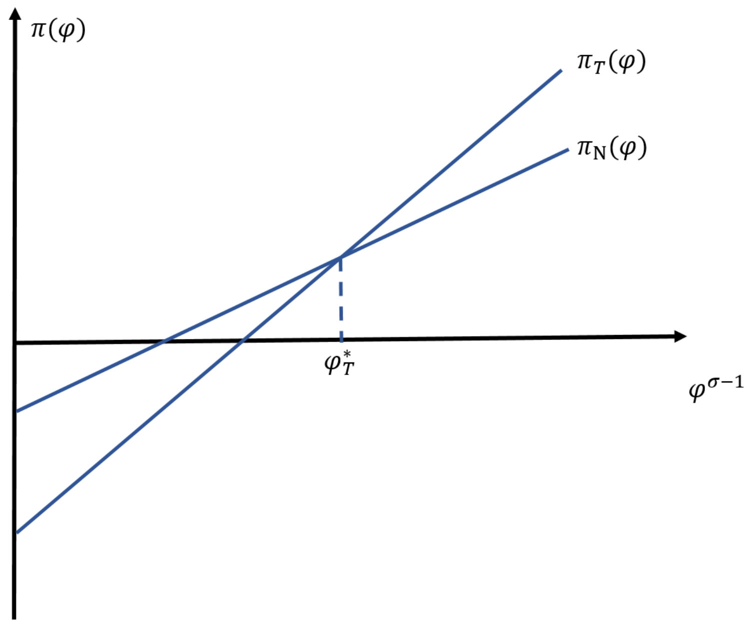
$$
\begin{aligned}
\pi_T(\varphi) &= \pi_T^H(\varphi) + \pi_T^F(\varphi) - f_T \\
&= \int_0^1 \left[\int_{\lambda_{s,T}^{H*}}^{\bar{\lambda}} \pi_{s,T}^H\left(\varphi, \lambda_s^H\right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds + \int_0^1 \left[\int_{\lambda_{s,T}^{F*}}^{\bar{\lambda}} \pi_{s,T}^F\left(\varphi, \lambda_s^F\right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds - f_T \\
&= \int_0^1 \left[\int_{\lambda_{s,T}^{H*}}^{\bar{\lambda}} \left(R_s^H \cdot \left(\frac{\rho P_s^H \lambda_s^H \cdot \varphi}{\left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} - f_s \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
&\quad + \int_0^1 \left[\int_{\lambda_{s,T}^{F*}}^{\bar{\lambda}} \left(R_s^F \cdot \left(\frac{\rho P_s^F \lambda_s^F \cdot \varphi}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} - F_s \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
&\quad - f_T,
\end{aligned}
$$

where f_T is a fixed cost paid by firms (measured as units of the numeraire) to adopt the anti-pollution technology, which better protects their workers from air pollution to mitigate the negative effect on labor productivity.

$\pi_N(\varphi)$ and $\pi_T(\varphi)$ can be illustrated by Figure A1. In order to prove Proposition 3, we need to prove that there exists an anti-pollution technology adoption cutoff φ_T^* such that for firms with productivity higher than the tech-adoption cutoff (i.e., $\varphi > \varphi_T^*$), firms' expected profit of adopting technology will be larger than firms' expected profit of not adopting such technology (i.e. $\pi_T(\varphi) > \pi_N(\varphi)$). On the other side, for firms with productivity lower than the tech-adoption cutoff (i.e., $\varphi \leq \varphi_T^*$), firms' expected profit of adopting technology will be smaller than firms' expected profit of not adopting such technology (i.e., $\pi_T(\varphi) \leq \pi_N(\varphi)$). In other words, for firms with higher productivity, firms choose to pay the fixed cost to adopt anti-pollution technology. For firms with lower productivity, they choose not to. In this way, firms with higher productivity suffer less from air pollution.

As illustrated by Figure A1, we show that: (1) the intercept of $\pi_T(\varphi)$ is strictly smaller than the intercept of $\pi_N(\varphi)$. And both of them are negative; (2) the slope of $\pi_N(\varphi)$ is strictly smaller than $\pi_T(\varphi)$. When both (1) and (2) are satisfied, there must exist a φ_T^* such that for $\varphi > \varphi_T^*$, $\pi_T(\varphi) > \pi_N(\varphi)$, and for $\varphi \leq \varphi_T^*$, $\pi_T(\varphi) \leq \pi_N(\varphi)$.

Figure A1: Illustration for the proof of the existence of φ_T^*



Notes: This figure illustrates firm-level profit of not adopting anti-pollution technology $\pi_N(\varphi)$ and adopting anti-pollution technology $\pi_T(\varphi)$.

$$\text{The intercept of } \pi_N(\varphi) = -\int_0^1 f_s \cdot \left(1 - H\left(\lambda_{s,N}^{H*}\right)\right) ds - \int_0^1 F_s \cdot \left(1 - H\left(\lambda_{s,N}^{F*}\right)\right) ds$$

$$\text{The intercept of } \pi_T(\varphi) = -\int_0^1 f_s \cdot \left(1 - H\left(\lambda_{s,T}^{H*}\right)\right) ds - \int_0^1 F_s \cdot \left(1 - H\left(\lambda_{s,T}^{F*}\right)\right) ds - f_T$$

The first term in the above two equations is the aggregation of fixed production costs f_s for all varieties produced. The second term is the aggregation of fixed export cost F_s for all varieties exported, for not adopting (N) and adopting anti-pollution technology (T), respectively.

Given $\theta_N > \theta_T$, i.e., the relative labor productivity with anti-pollution technology is higher than or equal to that of without anti-pollution technology $A_T(Z)/A_N(Z) = z^{\theta_N - \theta_T} \geq 1$ for $z \geq 1$, we have:

$$\lambda_{s,T}^{H^*} \leq \lambda_{s,N}^{H^*}, \quad \text{and} \quad 1 - H\left(\lambda_{s,T}^{H^*}\right) \geq 1 - H\left(\lambda_{s,N}^{H^*}\right)$$

$$\lambda_{s,T}^{F^*} \leq \lambda_{s,N}^{F^*}, \quad \text{and} \quad 1 - H\left(\lambda_{s,T}^{F^*}\right) \geq 1 - H\left(\lambda_{s,N}^{F^*}\right)$$

To put it in words, firms' product scope for both domestic and foreign markets is larger if they adopt anti-pollution technology. Therefore, given $f_T > 0$, the intercept of $\pi_T(\varphi)$ is strictly smaller than the intercept of $\pi_N(\varphi)$.

Then we show that for each product s, the slope of $\pi_{s,T}(\varphi)$ is strictly smaller than the slope of $\pi_{s,N}(\varphi)$.

$$\begin{aligned}
\text{The slope of } \pi_N(\varphi) = & \int_0^1 \left[\int_{\lambda_{s,N}^{H^*}}^{\bar{\lambda}} \left(R_s^H \cdot \left(\frac{\rho P_s^H \lambda_s^H}{\left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
& + \int_0^1 \left[\int_{\lambda_{s,N}^{F^*}}^{\bar{\lambda}} \left(R_s^F \cdot \left(\frac{\rho P_s^F \lambda_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
= & \int_0^1 \left[R_s^H \cdot \left(\frac{\rho P_s^H}{\left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \int_{\lambda_{s,N}^{H^*}}^{\bar{\lambda}} \left(\lambda_s^H\right)^{\sigma-1} h\left(\lambda_s\right) d\lambda_s \right] ds \\
& + \int_0^1 \left[R_s^F \cdot \left(\frac{\rho P_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \int_{\lambda_{s,N}^{F^*}}^{\bar{\lambda}} \left(\lambda_s^F\right)^{\sigma-1} h\left(\lambda_s\right) d\lambda_s \right] ds
\end{aligned}$$

$$\begin{aligned}
\text{The slope of } \pi_T(\varphi) = & \int_0^1 \left[\int_{\lambda_{s,T}^{H^*}}^{\bar{\lambda}} \left(R_s^H \cdot \left(\frac{\rho P_s^H \lambda_s^H}{\left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
& + \int_0^1 \left[\int_{\lambda_{s,T}^{F^*}}^{\bar{\lambda}} \left(R_s^F \cdot \left(\frac{\rho P_s^F \lambda_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \right) \cdot h\left(\lambda_s\right) d\lambda_s \right] ds \\
= & \int_0^1 \left[R_s^H \cdot \left(\frac{\rho P_s^H}{\left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \int_{\lambda_{s,T}^{H^*}}^{\bar{\lambda}} \left(\lambda_s^H\right)^{\sigma-1} h\left(\lambda_s\right) d\lambda_s \right] ds \\
& + \int_0^1 \left[R_s^F \cdot \left(\frac{\rho P_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \int_{\lambda_{s,T}^{F^*}}^{\bar{\lambda}} \left(\lambda_s^F\right)^{\sigma-1} h\left(\lambda_s\right) d\lambda_s \right] ds
\end{aligned}$$

Note that each firm draws a set of "consumer taste" attributes for each potential product produced, $\lambda_s \in [0, \infty)$ from a Pareto distribution $H(\lambda_s)$. The set of λ_s is firm-product specific and is constant across countries. The shape parameter of Pareto distribution $H(\lambda_s)$ is γ, and $\gamma > \sigma - 1$.[1] Therefore, the slopes of $\pi_N(\varphi)$ and $\pi_T(\varphi)$ can be rewritten as follows:

$$\begin{aligned}\text{The slope of } \pi_N(\varphi) = & \int_0^1 \left[R_s^H \cdot \left(\frac{\rho P_s^H}{\left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \frac{\gamma \cdot \left(\lambda_{s,N}^{H*}\right)^{-\gamma+\sigma-1}}{\gamma - (\sigma - 1)} \right] ds \\ & + \int_0^1 \left[R_s^F \cdot \left(\frac{\rho P_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_N}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \frac{\gamma \cdot \left(\lambda_{s,N}^{F*}\right)^{-\gamma+\sigma-1}}{\gamma - (\sigma - 1)} \right] ds\end{aligned}$$

$$\begin{aligned}\text{The slope of } \pi_T(\varphi) = & \int_0^1 \left[R_s^H \cdot \left(\frac{\rho P_s^H}{\left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \frac{\gamma \cdot \left(\lambda_{s,T}^{H*}\right)^{-\gamma+\sigma-1}}{\gamma - (\sigma - 1)} \right] ds \\ & + \int_0^1 \left[R_s^F \cdot \left(\frac{\rho P_s^F}{\tau \cdot \left(\frac{w}{\alpha z^{-\theta_T}}\right)^{\beta_s}} \right)^{\sigma-1} \cdot \frac{\gamma \cdot \left(\lambda_{s,T}^{F*}\right)^{-\gamma+\sigma-1}}{\gamma - (\sigma - 1)} \right] ds\end{aligned}$$

Given $\theta_T < \theta_N$, we have $\lambda_{s,T}^{H*} \leq \lambda_{s,N}^{H*}$, and $\lambda_{s,T}^{F*} \leq \lambda_{s,N}^{F*}$. Therefore, the slope of $\pi_N(\varphi)$ is strictly smaller than $\pi_T(\varphi)$.

As illustrated by Figure A1, we have shown: (1) The intercept of $\pi_T(\varphi)$ is strictly smaller than the intercept of $\pi_N(\varphi)$. And both of them are negative; (2) The slope of $\pi_N(\varphi)$ is strictly smaller than $\pi_T(\varphi)$. Therefore, there must exists a φ_T^* such that for $\varphi > \varphi_T^*$, $\pi_T(\varphi) > \pi_N(\varphi)$, and for $\varphi \leq \varphi_T^*$, $\pi_T(\varphi) \leq \pi_N(\varphi)$.

[1] $\gamma > \sigma - 1$ ensures a positively sloped profit function of firms' productivity.

Table A1: Information about geocoding China's customs export data

	(1) Observation number	(2) Percentage	(3) Export Value	(4) Percentage	(5) Firm Number	(6) Percentage
Total	13,427,498	100%	4,414,934,457,775	100%	279,953	100%
Geocoding process: success	11,845,233	88.22%	4,314,079,657,289	97.72%	245,819	87.81%
Geocoding process: fail	1,582,265	11.78%	100,854,800,486	2.28%	34,134	12.19%

Notes: Geocoding is the process of converting firm addresses into geographic coordinates, through which we can identify each firm's locating county. This table reports the success rate of geocoding China's customs data. Each observation in the data is at the firm-product-year level. The sample period is from 2000 to 2007.

Table A2: Statistics on firms that have relocated in the sample period

Number of distinct counties each firms have located in	Number of firms	Share among all firms	Number of f-h-t observations	Share among all f-h-t observations
1	255017	91.09%	11661239	86.85%
2	23957	8.56%	1683131	12.53%
3	960	0.34%	78224	0.58%
4	19	0.01%	4904	0.04%
Number of distinct prefectures each firms have located in	**Number of firms**	**Share among all firms**	**Number of f-h-t observations**	**Share among all f-h-t observations**
1	274293	97.98%	13215785	98.42%
2	5650	2.02%	211652	1.58%
3	10	0.00%	61	0.00%

Notes: Each observation in the data is at the firm-HS6 product-year level. The sample period is from 2000 to 2007.