Can Trade Integration Reduce Production Emissions? The Role of Within-Firm Product Composition

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Abstract

We develop a stylized trade model showing that lower trade costs can reduce firm-level emissions by encouraging firms to specialize in their most productive intermediate products. This mechanism operates through changes in within-firm product composition rather than industry-level reallocation. Using firm-level data from China (1998–2012), we provide empirical support for this mechanism in the context of domestic trade. Increased trade integration, driven by railway expansion, significantly reduces sulfur dioxide, carbon dioxide, and other pollutant emissions by lowering emission intensity. Consistent with our theoretical conditions for emission reduction, we find that emission reductions occur primarily in cities where a firm's productivity advantage aligns with a location-specific cost advantage, and only for firms with large within-firm productivity dispersion. A calculation based on our estimates suggests that without the 1.88% (1,203-kilometer) railway expansion in 2005——midway through our sample period——sulfur dioxide emissions would have been 0.43% higher at the national level.

JEL classification: F1, R4, Q5
Keywords: emissions, market access, railway network, Chinese manufacturing firms

1 Introduction

Concerned individuals and economists are interested in the environmental consequences of economic activities, including those related to trade. Economic theory suggests that

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All the authors made equal contributions to the paper. All errors are our own.

the impact of trade on pollution or emissions can be decomposed into the scale effect, technique effect, and composition effect (Grossman and Krueger, 1993). The first two refer to the tendency of pollution to increase with the scale of production and the tendency of it to decrease as better technology is adopted during economic development. The composition effect at the industry level is ambiguous, as trade-induced specialization can make a country's industry composition dirtier or cleaner.

Focusing on the composition effect, Copeland and Taylor (1994) point out that lax regulations can induce polluting industries to relocate across countries, creating a "pollution haven". Empirical tests of the pollution haven hypothesis (PHH) at the industry level have yielded varying degrees of support (Antweiler et al., 2001; Cole and Elliott, 2003; Levinson, 2009). Recently studies suggest several firm-level channels through which trade may reduce emissions: the reallocation of production to more productive and cleaner firms (Holladay, 2016), export market-induced adoption of cleaner technology (Shapiro and Walker, 2018), and better access to imported emission-intensive inputs (Cherniwchan et al., 2017; Cherniwchan, 2017). However, with the notable exceptions of Barrows and Ollivier (2018) and Akerman et al. (2024), the question of whether and how trade-induced within-firm adjustments affect pollution remains largely unexplored.

This paper examines whether trade influences emissions by altering within-firm product composition.[1] We develop a stylized Ricardian model with multi-product firms to illustrate the mechanism. Firms in each of two locations produce a non-tradable final good from intermediate products using Leontief technology to satisfy local demand. These firms can either produce intermediate products by combining an emission-intensive input (dirty input) and an emission-light input (clean input), or purchase them from firms in the other location. Crucially, productivity differences in the production of intermediate products exist both within firms and across locations. A firm will outsource intermediate products externally if the purchased intermediates are cheaper than those produced in-house. As trade costs decrease, multi-product firms concentrate their production on intermediate

[1]Because our empirical work focuses on emissions, an important form of pollution, we will use the term "emission" throughout the remainder of the paper for consistency, even though our theory applies to pollution more broadly.

products in which they have a greater productivity advantage.

We demonstrate that post-trade integration, adjustments in within-firm product composition can lower a firm's total emissions under two conditions. The first is productivity advantage and input cost alignment: firms in the location where the relative price of the emission-intensive input is lower must also have higher productivity in producing intermediate products that use the input intensively. This is a substantial assumption, as it requires that a firm's productivity advantage in an intermediate product coincides with the location-specific cost advantage of the input used intensively in producing that intermediate product. Theoretically, this is plausible because a location's input cost advantage can enable firms to gain a long-term productivity advantage through learning by doing or accumulating local knowledge about production of these products. Empirically, we present supportive evidence in subsection 4.3 that productivity advantage and input cost advantage are positively correlated in the data.

The second is large productivity dispersion within firms: the within-firm productivity gap between discontinued and retained products must be sufficiently large. This significant difference in productivity ensures that, for a firm, the reduction in emissions from outsourcing its least efficient intermediate products outweighs the increase in emissions from processing its most efficient intermediate products for firms in the other location. When both conditions are met in both locations, emissions can decrease in both, differing from the PHH, which typically involves the migration of emissions.

Using detailed firm-level data from China, the largest emitter of carbon dioxide (CO_2) and many other pollutants, we test the theory in the context of domestic trade between cities. Following Donaldson and Hornbeck (2016), we examine domestic trade integration—measured by market access (MA)—which is driven by the expansion of the railway network. We find that increases in MA are negatively correlated with emissions in a sample of Chinese manufacturing firms from 1998 to 2012. To address the endogeneity of railway construction, we adopt the control function approach of Borusyak and Hull (2023). Specifically: (1) We follow Faber (2014) and Banerjee et al. (2020) to construct artificial transportation networks based on geographic and historical factors, and use the corresponding counterfactual MA indices as instrumental variables (IVs) for the actual MA index. (2) In the second stage of the two-stage least-squares (2SLS) regressions, we control for a city's expected market access (EMA) to address biases from centrally located cities being more connected by railways.

We have two sets of main empirical results. First, MA significantly reduces firm-level emissions of sulfur dioxide (SO_2), CO_2, dust, and waste gas. Almost all of the drop in emissions can be attributed to decreases in emission intensity. In terms of explanatory power, after controlling for firm fixed effects, industry-year fixed effects, and city characteristics, 56.24% and 51.67% of the interquartile range of firm-level SO_2 emissions and emission intensity, respectively, can be explained by the interquartile range of MA. Additionally, city-level emissions of SO_2 also decline following an increase in MA. Based on the estimates, had the length of China's railway not expanded by 1.88% or 1,204 kilometers in 2005——the year in the middle of our sample period, as an example——additional industrial SO_2 emissions would have increased national emissions by 0.43%.

Second, by conducting extensive testing of the predictions of the product-composition channel, we show that product composition is empirically important for understanding the reduction in firm-level emissions in China. Consistent with our premise on the joint role of productivity patterns and factor costs in determining product composition and emissions across different locations, we find that MA reduces emissions in cities where a firm's productivity advantage aligns with a location-specific cost advantage, but not in other cities. Furthermore, the change in product composition in the data is strongly related to productivity advantage; i.e., increases in MA prompt firms to discontinue intermediate products with low productivity and increase the output of remaining intermediate products. Most crucially, as predicted by our theory, it is only for firms that exhibit large dispersion in within-firm productivity, such changes in product composition are accompanied by a reduction in emissions.

Furthermore, following increases in MA, firm-level emissions do not rise in cities with lax environmental regulations or abundant local coal supplies. In the context of our analysis, which focuses on short-term changes in emissions related to product composition, we find no evidence supporting the PHH.

Our results remain robust when controlling for the adoption of abatement technology. They are also unaffected when we account for the effects of infrastructure-related or emission-related policies, the four-trillion yuan stimulus in 2009—which had a substantial focus on infrastructure, a national policy to tackle SO_2 pollution and acid rain introduced in 1998, trade liberalization associated with China's admission to the World Trade Organization (WTO) in 2001, and the use of imported inputs.

This study argues that trade-induced adjustments in within-firm product composition can reduce overall emissions, contributing to the literature on trade and pollution.[2] Existing research primarily focuses on industry-level and firm-level adjustments. At the industry level, the pollution haven hypothesis (PHH) has been widely studied, with evidence varying by pollutants and countries (Antweiler et al., 2001; Cole and Elliott, 2003; Levinson, 2009; Managi et al., 2009; Brunel, 2017). At the firm level, studies highlight how trade reduces emissions through production reallocation to more productive firms (Martin, 2012; Kreickemeier and Richter, 2014; Holladay, 2016), investment in cleaner technologies (Cui et al., 2016; Shapiro and Walker, 2018; Forslid et al., 2018; Gutiérrez and Teshima, 2018), or imports of dirty inputs (Cherniwchan et al., 2017; Cherniwchan, 2017; Akerman et al., 2024). In contrast, our focus on within-firm adjustments in product composition represents a distinct perspective in this literature.

Focusing on adjustment in product scope, we are particularly related to Cherniwchan et al. (2017), Barrows and Ollivier (2018), and Akerman et al. (2024). Our production setup follows Cherniwchan et al. (2017), where firms can source intermediate products or produce them in-house. However, while their trade patterns are driven by firm-level productivity heterogeneity (Melitz, 2003), our model relies on location-specific productivity as in the Ricardian framework. Our focus on product composition aligns with Barrows and Ollivier (2018), who show that competition reduces a firm's product scope to its "core competency," with emissions falling only if core products are cleaner. In contrast, our model links emission reductions to specialization based on productivity advantages,

[2] See Copeland and Taylor (2004), Cherniwchan et al. (2017), and Copeland (2020) for reviews on trade and the environment.

independent of product cleanliness. Akerman et al. (2024) empirically demonstrate that imported intermediate inputs reduce emissions via the composition effect. Our study extends this line of analysis by offering a theoretical framework linking trade-induced changes in product composition to emissions, and by analyzing domestic trade in China, the world's largest emitter. This allows us to explore emission reduction mechanisms in a different and significant context.

In the context of China, the relationship between international trade and emissions is complex. On the positive side, following China's accession to the World Trade Organization (WTO), tariff reduction prompts firms to improve production process and reduce emission (Cui et al., 2020), and exporting significantly reduces emissions from Chinese manufacturing firms (Rodrigue et al., 2024). However, trade also reallocates production to dirty firm (Rodrigue et al., 2022). From both theoretical and empirical perspectives, our analysis of within-firm product composition provides new insights into the trade-emissions relationship, complementing existing research on firm-level production reallocation.

Our work is also related to literature that assess the environmental impact of transportation infrastructure. The literature in this area has focused on the emissions associated with different modes of transportation (Parry et al., 2007; Chen and Whalley, 2012; Lalive et al., 2018; Lin et al., 2021; Jia et al., 2021; Gendron-Carrier et al., 2022). A consistent finding is that rail transit reduces air pollution, while automobile transportation and congestion lead to more pollution. Distinguishing between public and private transportation, there is evidence that the substitution of cleaner public transport for automobiles can reduce air pollution (Bauernschuster et al., 2017; Lin et al., 2021). We complements this branch of literature on emissions generated during transportation by showing how transportation infrastructure can reduce emissions at production sites.[3]

More broadly speaking, we add to the general literature that examines the potential benefits of transportation infrastructure. The findings are generally positive, as infrastructure is shown to promote economic growth (Démurger, 2001; Donaldson and Hornbeck, 2016; Faber, 2014; Banerjee et al., 2020), employment (Michaels, 2008; Duran-

[3]Shapiro (2016) finds that trade leads to a 5% increase in global carbon emissions, with the emissions from production and transport each contributing to roughly half of the increase in emissions.

ton and Turner, 2012), trade (Duranton et al., 2014; Coşar and Demir, 2016; Donaldson, 2018), and firm productivity (Ghani et al., 2016; Holl, 2016). Additionally, infrastructure enhances urban decentralization (Baum-Snow, 2007; Baum-Snow et al., 2017), labor migration (Morten and Oliveira, 2018), capital flow (Banerjee et al., 2020), and ultimately, welfare (Allen and Arkolakis, 2022).

The rest of the paper proceeds as follows. In section 2, we develop a model to illustrate how trade integration and within-firm productivity differences influence product composition and emissions. section 3 presents the empirical design and data description, followed by the empirical results on the effects of MA on emissions in section 4. Finally, we conclude in section 5.

2 Theory

We introduce within-firm productivity difference in the production of intermediate products into a Ricardian model of trade and pollution along the line of Copeland and Taylor (1994), and study the change in firm emissions following a reduction in trade costs.

2.1 Model Setup

Consider an economy consisting of two locations. As our empirical application involves domestic trade, for continuity in discussion we refer to the two locations as a home city and an outside one, with the understanding that the two locations can be two countries in other applications. To focus on the analysis of intermediate goods, we make the simplifying assumption that each city demands one unit of a final good which is not tradable across cities. In each city, a firm assembles the final good y using a Leontief technology with a continuum of intermediate products $x_j,\ j \in [0, 1]$:

$$y = \min_{j \in [0,1]} \{x_j\}.$$

The firm can produce x_j in house or purchase it from the other city subject to a per unit trade cost of τ. The in-house production of x_j is governed by a constant elasticity of substitution (CES) technology:

$$x_j = A_j[a_j^{1-\delta} L_j^{\delta} + b_j^{1-\delta} D_j^{\delta}]^{\frac{1}{\delta}}, \tag{1}$$

where A_j denotes the home firm's product-specific productivity on j, and $\delta < 1$ is the elasticity of substitution. The parameters $a_j > 0$ and $b_j > 0$ are the share parameters of the two factors of production, L the emission-light input (or the clean input) and D the emission-intensive input (or the dirty input). For simplicity, we assume that L entails no emission. Meanwhile, the use of D will generate emission that is proportional to output, $z_j = gD_j$, where $0 \leq g \leq 1$ represents the emission intensity of the dirty input. Together, a_j and b_j determine the cleanness of product x_j, i.e. products with a higher value of b_j/a_j are dirtier.

The factor prices of L and D, denoted w and r, are exogenously given. The firm pays an emission tax of t for each unit of emission. Based on the CES production function, the unit cost of in-house production of x_j is:

$$c_j^s = \frac{1}{A_j}[a_j w^{1-\sigma} + b_j(r+tg)^{1-\sigma}]^{\frac{1}{1-\sigma}}, \tag{2}$$

where $\sigma = 1/(1-\delta) > 0$. From equations (1) and (2), the factor demands for labor and dirty input to produce x_j are given by:

$$L_j(x_j) = \frac{x_j}{A_j} a_j^{\frac{1}{1-\sigma}} [1 + \frac{b_j}{a_j}(\frac{r+tg}{w})^{1-\sigma}]^{\frac{\sigma}{1-\sigma}},$$

$$D_j(x_j) = \frac{x_j}{A_j} b_j^{\frac{1}{1-\sigma}} [1 + \frac{a_j}{b_j}(\frac{w}{r+tg})^{1-\sigma}]^{\frac{\sigma}{1-\sigma}}.$$

It follows that the corresponding input ratio can be written as:

$$\frac{D_j(x_j)}{L_j(x_j)} = \frac{b_j}{a_j}(\frac{w}{r+tg})^{\sigma},$$

which measures demand intensity for input D relative to L in the production of product j . Note that this relative demand intensity is independent of output level and firm's productivity in intermediate product j. We order the intermediate products such that b_j/a_j is increasing with j, that is, products with lower j are cleaner in the sense it uses more of the clean input.

Assume that the market for the final good is perfectly competitive in both cities, then the constant to return technologies imply that there is a representative firm in each city. The home and outside representative firms are asymmetric in terms of productivity (A_j), costs of labor and the dirty input (w and r), and environmental regulation (t).[4]

The relative productivity A_j/A_j^* varies across products, which is a crucial and novel feature in our model. If the relative productivity is constant for all j, then the productivity pattern in our setup is reduced to that of Copeland and Taylor (1994) and Cherniwchan et al. (2017).

If the home firm outsources j to the external city, then the unit cost is:

$$c_j^* = \frac{1+\tau}{A_j^*}[a_j(w^*)^{1-\sigma} + b_j(r^* + t^*g)^{1-\sigma}]^{\frac{1}{1-\sigma}}, \tag{3}$$

where the superscript $*$ denotes variables associated with the external city.

2.2 Trading Equilibrium

Now we analyze a trading equilibrium in which factor prices are taken as given. Define T_j as the relative unit cost (net of trade cost) of outsourcing to local production. Using equations (2) and (3), the relative unit cost can be written as:

$$T_j \equiv \frac{A_j}{A_j^*}[\frac{(w^*)^{1-\sigma} + \frac{b_j}{a_j}(r^* + t^*g)^{1-\sigma}}{w^{1-\sigma} + \frac{b_j}{a_j}(r + tg)^{1-\sigma}}]^{\frac{1}{1-\sigma}}.$$

For each intermediate product j, the home firm outsources it to the other city if the in-house unit cost is greater than the cost of purchasing the same product from the other city, $c_j^s > c_j^*$. Using the definition of T_j, this outsourcing condition can be stated as:

$$T_j < \frac{1}{1+\tau},$$

which says that the relative unit cost advantage of the external city dominates the trade cost. By symmetry, the representative firm in the external city source product j from the home city if $T_j > 1+\tau$.

[4]In the long term, the relocation of firms and labor can significantly affect the geographic distribution of production and pollution. However, in the current study, we focus on how immediate adjustments in product composition affect emissions and make the simplifying assumption that firms and labor are not mobile across cities. In our empirical analysis, the sample consists of large manufacturing firms that do not report changes in their primary location.

In the trading equilibrium, outsourcing by the home firm creates external demand for the firm in the external city to produce intermediate products, and vice versa. The trade cost τ affects the range of intermediate products traded in equilibrium. A large trade cost may block all possible trade and each firm will produce all x_j for (and only for) itself. Under moderate trade costs, the trade pattern varies with factor costs and productivities.

Given the level of cleanness (b_j/a_j) for a specific intermediate product j, the relative unit cost T_j is determined by two factors, the relative cost of the dirty input $(\frac{r+tg}{w}/\frac{r^*+t^*g}{w^*})$ and variation in the relative productivity (A_j/A_j^*). The former is the main driver of trade pattern in the model of Copeland and Taylor (1994) and Cherniwchan et al. (2017). The latter term, i.e. the relative productivity (A_j/A_j^*), is the crucial and new factor introduced by our study.

Without additional assumption about the relative input cost and relative productivity, it is not possible to tract the pattern of specialization and trade. In order to obtain testable prediction about the relation between trade cost, specialization and emissions, we make the following assumption.

Assumption 1. *In the city where the relative price of emission-intensive input is cheaper (more expensive, respectively), firms have higher productivity in producing intermediate products using the input more (less, respectively) intensively. Without loss of generality, let the external city be the one with lower cost of emission-intensive input. Mathematically, the assumption is* $\frac{r+tg}{w} > \frac{r^*+t^*g}{w^*}$ *and* $\frac{\partial}{\partial j}(\frac{A_j}{A_j^*}) < 0$.

Under Assumption 1, both cross-city comparison of factor cost and comparison of productivity indicate that the home firm has a comparative advantage in cleaner goods, i.e. goods with smaller values of j. Consequently, T_j is decreasing monotonically with j and there is a unique trading equilibrium in which the firm in the home city will specialize in intermediate products with smaller j values, while the firm in the other city specialize in goods with larger j values. Subsequently, we show in Proposition 1 that firms will further specialize after a drop in trade cost, and in Proposition 2 that firm-level emissions can decrease under suitable conditions.

Without Assumption 1, the pattern of specialization and trade is not tractable because the distribution of relative productivity could offset or even reverse the cost advantage. Thus, we would have no prediction about the relationship between trade costs and emissions. We recognize that Assumption 1 is substantial, as it requires the productivity advantage and input cost advantage to overlap at the city level. We argue that this is plausible because firms are likely to specialize in products that intensively use the locally abundant factor. If there exists learning by doing or local knowledge about technology, then over time, firms would develop or strengthen their productivity advantage in these products. Therefore, productivity advantage would coincide with the cost advantage of the locally abundant factor. Ultimately, in subsection 4.3, we test this assumption empirically and find supportive evidence.

Because Assumption 1 implies that T_j is decreasing monotonically with j, there exist $j_0 \leq j_1$ such that $T_{j_0} = 1 + \tau$ and $T_{j_1} = \frac{1}{1+\tau}$. Given the user costs of factors $\{w, r + tg, w^*, r^* + tg^*\}$ and final demands in local and outside markets, we obtain a trading equilibrium in which both firms outsource their inefficient intermediate products to each other. As shown Figure 1, in equilibrium, the home firm produces its productive products of $j \in [0, j_1]$ while outsourcing the less productive products of $j \in [j_1, 1]$. Furthermore, it also processes products in $[0, j_0]$ over which it commands productivity advantage, to satisfy the demand of the external city. The production pattern for the firm in the external city is symmetric. There exists an interval of $j \in [j_0, j_1]$ such that intermediates in the range are produced in both locations as trade cost prevents trade from occurring. The product scope of the home firm and the foreign firm are $[0, j_1]$ and $[j_0, 1]$, respectively. [5]

2.3 Effects of Trade Cost Reduction on Product Composition and Emission

In this subsection, we first present a proposition regarding the effects of trade cost reduction on product composition and production volume of firms. The proposition is largely a statement of an implicit result of Dornbusch et al. (1977) in the current setup.

[5] We ignore the trivial case that j_0 and (or) j_1 lie outside the interval $[0, 1]$. For example, when $j_1 > 1$, the home firm can produce all goods for itself and outsource nothing. In a more extreme case such that $j_0 > 1$, the home firm has an overwhelming advantage and provides all products j for both locations, and hence there is no longer any firm in the external city.

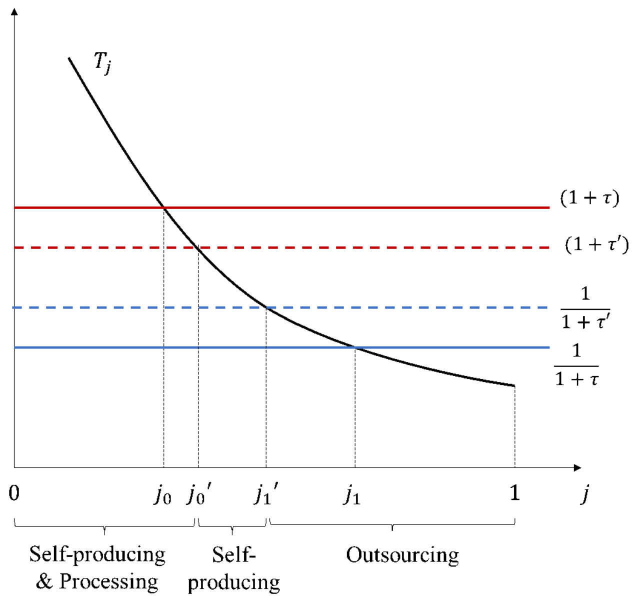

Figure 1: Effects of Trade Costs on the Production Pattern of the Home Firm

Proposition 1. *In the trading equilibrium, after a reduction in trade costs, all firms narrow the product scope and specialize in their most productive products, and increase the average output of the products that they keep.*

Proof:

In the trading equilibrium, a decline in trade cost τ results in a wider range of products being outsourced. As illustrated in Figure 1, when τ drops to τ', the varieties of outsourced intermediates expand from $[j_1, 1]$ to $[j_1', 1]$ for the home firm, while the range of goods that it processes for the foreign firm also expands from $[0, j_0]$ to $[0, j_0']$. Since T_j is monotonically decreasing in j, it can be shown that $\frac{\partial j_0}{\partial \tau} < 0$ and $\frac{\partial j_1}{\partial \tau} > 0$. Therefore, the home firm's product scope $[0, j_1]$ is positively related with trade cost τ.

Corresponding to the changes in product scope, we then examine the average output per variety of intermediate product. Given the final good output level y and y^* and the Leontief technology in the production of final good, the total intermediate output[6] of the

[6] The trade costs in our benchmark model are monetary expenses. In Appendix A, we discuss the scenario where additional products are used to cover iceberg costs.

home firm is:

$$\int_0^{j_1} y dj + \int_0^{j_0} y^* dj = j_1 y + j_0 y^*.$$

We define the average output of intermediate products in the home city as:

$$\overline{x} = \frac{j_1 y + j_0 y^*}{j_1}.$$

By symmetry, the total intermediate output and average output of intermediate products in the external city are:

$$(1 - j_0)y^* + (1 - j_1)y,$$

and

$$\overline{x^*} = \frac{(1 - j_0)y^* + (1 - j_1)y}{1 - j_0}.$$

Because a reduction in trade cost τ increases j_0 and lowers j_1, it follows that $\partial\overline{x}/\partial\tau < 0$ and $\partial\overline{x^*}/\partial\tau < 0$. Thus, average output increases in both cities after a reduction in trade costs. ■

Next, in proving Proposition 2, we demonstrate that a decrease in domestic trade cost can lead to reduction in firm-level emissions under two conditions.

Proposition 2. *Emissions by a firm in either city decrease with a reduction in trade costs if (i) Assumption 1 holds, and (ii) the productivity difference across intermediate products within the firm is sufficiently large.*

Proof:

The home firm's emission from producing x_j is given by:

$$z_j(x_j) = gD_j(x_j) = g\frac{x_j h_j}{A_j},$$

where $h_j \equiv b_j^{\frac{1}{1-\sigma}}[1 + \frac{a_j}{b_j}(\frac{w}{r+tg})^{1-\sigma}]^{\frac{\sigma}{1-\sigma}}$ is a measure of relative input price. Thus, the total emission of the home firm can be written as:

$$z = g(y^* \int_0^{j_0} \frac{h_j}{A_j} dj + y \int_0^{j_1} \frac{h_j}{A_j} dj). \tag{4}$$

The derivative of the total emission of the home firm with respect to trade cost τ is:

$$\frac{\partial z}{\partial \tau} = g[\frac{\partial j_1}{\partial \tau}\frac{yh_{j_1}}{A_{j_1}} + \frac{\partial j_0}{\partial \tau}\frac{y^* h_{j_0}}{A_{j_0}}].$$

A reduction in trade costs lowers emission reduction if $\frac{\partial z}{\partial \tau} > 0$, i.e.

$$\frac{\partial j_1}{\partial \tau}\frac{yh_{j_1}}{A_{j_1}} > -\frac{\partial j_0}{\partial \tau}\frac{y^* h_{j_0}}{A_{j_0}}. \tag{5}$$

The last line states that the emission reduction from outsourcing intermediate products (the left hand side of the equation) is larger in magnitude than the increase in emission associated with processing additional intermediate products for the foreign firm (the right hand side). Rearrangement of the inequality (5) yields:

$$\frac{-y^* \frac{\partial j_0}{\partial \tau}}{y \frac{\partial j_1}{\partial \tau}} < \frac{A_{j_0}/h_{j_0}}{A_{j_1}/h_{j_1}}. \tag{6}$$

in which A_{j_0}/h_{j_0} and A_{j_1}/h_{j_1} can be regarded as the factor price-adjusted productivity.

The left hand side of (6) measures the production of intermediate products (and emissions) acquired by the home firm from the other city subsequent to a reduction in trade cost, relative to the intermediate products it outsources to the other city. The right hand side is the productivity of the marginal intermediate product for which the home firm gains production relative to the productivity of the marginal intermediate product it loses. When the productivity gap between the two marginal varieties are large enough, then the increase in emission associated with additional intermediate products processed by the home firm will be smaller in magnitude than the reduction in emission associated with the additional outsourcing enabled by a lower trade cost. In this case, net emission of the home firm will decrease. ■

It is important to note that Proposition 2 applies for all firms, including those specializing in emission-intensive products. In Copeland and Taylor (1994), all producers are final good producers, and they use identical technology for producing the clean good and dirty good. The firms must use more dirty inputs when they switch production from clean products to dirty products. The industry-level composition effect of trade, therefore, necessarily transfers emission from one location to another in a zero-sum framework.

In the current setup, we retain the feature of production specialization and reallocation, but emission does not necessarily rise in the city that hosts more production of emission-intensive goods. Whether emission rises or drop, depends on whether firms have sufficient dispersion in within-firm productivity of intermediate goods. In other words, while industry-level reallocation of production triggered by an increase in trade can still result in pollution havens, the within-firm composition effect of trade in our setup can mitigate or even reverse the pollution havens effect. Because the emission reduction criterion can apply simultaneously to firms in different locations, we have the following corollary to Proposition 2 regarding the possibility of emission reduction in both locations.

Corollary 1. *After a reduction in trade costs, firms in both the home city and external city will experience reduction in emission levels if the following two conditions are satisfied in both locations. (i) Assumption 1 holds. (ii) There exists sufficiently large within-firm difference in productivity of intermediate products.*

For a detailed discussion of the conditions under which emissions are reduced in both locations, please refer to Appendix B.

3 Empirical Specification and Data

3.1 Regression Model

To examine the effects of domestic trade integration on emission at the firm level, we estimate the following regression model:

$$\begin{aligned} ln(SO2_{ijct}) = \beta_0 + \beta_1 \cdot ln(MA_{ct}) + \beta_2 \cdot ln(EMA_{ct}) + \beta_3 \cdot enviro.\ regulation_{ct} \\ + W_c \cdot \eta_t + \psi_i + \omega_{jt} + \mu_{ijct} \end{aligned} \tag{7}$$

where $SO2_{ijct}$ is the tons of sulfur dioxide emitted by firm i in industry j in city c in year t. Industries are defined at the 4-digit level according classification of the National Bureau of Statistics of China. The cities are cities hold at least the administrative rank of prefectures. We choose sulfur dioxide (SO_2) as the main measure of emission because it is commonly used in studies of air pollution. Furthermore, SO_2 is particularly important for air quality in China because the burning of coal, the most important source of energy in the country, entails emission of SO_2. We also use emission intensity, defined as the log of tons of SO_2 emission per thousand yuan of industrial value-added, as the dependent variable in the regression. In extended analysis, we examine additional pollutants that include dust, Chemical Oxygen Demand (COD), industrial waste gas and carbon dioxide (CO_2), and obtain similar results.

MA_{ct} is the city-level market access index that we construct by following the method of Donaldson and Hornbeck (2016). Details about construction of the MA index are discussed in subsection 3.2. To capture the tendency that centrally-located cities are expected to have better railway connections, we control for the expected level of MA, EMA_{ct}, which is constructed with the procedure outlined in Borusyak and Hull (2023). As pointed out by Borusyak and Hull (2023), while we can regard the opening status of new railways to be random, leaving out the expected level of MA would bias estimates in OLS or 2SLS regressions.

The variable *envir. regulation* measures the strength of city-level emission regulation. We construct the variable by following the method of Chen et al. (2018) which exploits the pollution-reduction targets set by the Eleventh Five-year Plan of China (covering the period of 2006-2010). To be specific, the central government of China sets the cap on SO_2 emission for each province at the end of the Eleventh Five-year plan. We compute the city-specific target for emission reduction as the product of provincial emission reduction target and the share of each city in the province's total SO_2 emissions in 2005. Because the emission targets were introduced in November 2006, we construct the measure of strength of regulation by multiplying an indicator for years post 2006 with the ratio of city-specific target for emission reduction to the level of actual emission in 2006.[7]

The vector W_c contains other city-level variables at the initial period: log coal output per capita, highway density measured as kilometers of highway per square kilometer,[8] log

[7]The variable for strength of regulation takes the value zero for all cities prior to 2006. The values can be positive post 2010, the year of of evaluation, because measured emission levels went up in some cities after meeting the targets in 2010.

[8]Due to the lack of historical road network data at the city level, we use province-level road density as a proxy to capture MA associated with roads.

of GDP, log of GDP per capita, and log of applications for invention patents related to environmental protection. We interact them with the year indicators η_t to capture city-specific trends correlated with initial features of the cities. The variables ψ_i, ω_{jt}, and μ_{ijct} represent firm fixed effects, industry-year fixed effects, and the error term, respectively.

3.2 Construction of the MA Index

Using data from the *China Railway Yearbook*, Chinese Research Data Services Platform (CNRDS), and *China City Statistical Yearbook*, we construct a MA index based on connectivity to freight railway for 291 cities in China from 1998 to 2012 by applying the method of Donaldson and Hornbeck (2016). The cities have three different administrative ranks, listed in descending order: four are municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing), fifteen are vice-provincial cities, and the remainder are prefecture-level cities. Similar to Donaldson and Hornbeck (2016), our construction makes use of the national railway network vector maps. We focus on railway-related MA because railway transportation is arguably the most important factor in determining inter-city MA. While roads accounted for a larger share of national land-based freight turnover (64.76% in 2012 compared to 31.75% for railways), the average distance per trip for railway freight (747.55 kilometers) far exceeded that of road transportation (186.72 kilometers). Thus, despite roads handling more freight overall, railway transportation played an essential role in long-distance transportation and was crucial for inter-city MA in China.

Following Donaldson and Hornbeck (2016), we define railway MA index as:

$$MA_{ct} = \sum_{c' \neq c} \tau_{cc',t}^{-\theta} Y_{c',t} \tag{8}$$

where c and t are the indices of city and time, respectively. In the formula, we use $Y_{c',t}$, the GDP of destination city c', to measure the size of target markets. τ is an index of railway transportation cost per ton of goods shipped. θ is the price elasticity of trade, which measures the substitution between output of different cities. Following Donaldson (2018), we set the elasticity value to 3.8.

The specification of railway transportation cost follows the method of Baum-Snow et al. (2016). The cost is given by

$$\tau_{cc',t} = 1 + p_t \left(d_{cc',t}\right)^{\rho} \tag{9}$$

where p_t is the annual average freight rate. We obtain the average freight rate by dividing the total revenue of railway transportation deflated with production price index by the total freight volume in tons. The variable $d_{cc',t}$ is the shortest railway distance between two cities, calculated based on the national railway network vector maps constructed by Gao and Tang (2024). The parameter ρ captures the concave relationship between shipping cost and railway distance, and it is set to 0.8 (Baum-Snow et al., 2016).

3.3 Firm-level Data

Firm-level information is obtained from two datasets, the Annual Survey of Industrial Firms (ASIF) and China's Environmental Statistics Database (CESD). The source of the former is the National Bureau of Statistics of China, and it covers private firms that report sales greater than 5 million yuan (equivalent to around $760,000 at current exchange rate) and all state-owned enterprises. The latter dataset is from the Ministry of Environmental Protection of China, and it covers firms that collectively account for 85% of emissions of key pollutants in their respective counties. The CESD is main source of comprehensive information on emission of large industrial firms in China during our sample period. The merged data is an unbalanced panel of 337,882 firm-year observations, and the sample period is 1998-2012.[9] Summary of key variables can be found in Table 1.

3.4 Visual Summary of Data

In the left (right, respectively) panel of Figure 2, we plot the time series of the mean of firm-level emissions (emission intensity, respectively). In 1999, firms experienced a significant reduction in emission levels. The reason, which is well documented in the literature (Hao

[9]In merging the datasets, we follow the procedure of Brandt et al. (2012) and Wang et al. (2018). In addition, we use the combination of the abbreviated firm name and province name to match firms from the two datasets. Abnormal observations are removed by applying the procedures outlined in Feenstra et al. (2014) and Yu (2015).

et al., 2001; Cai et al., 2016), is that a government policy called 'Two Control Zones' (TCZ) caused a sharp drop in SO_2 emissions. In response to severe acid rain and SO_2 pollution in 175 cities, China's State Council introduced the TCZ policy, which set emission reduction targets for the years 2000 and 2010. Because we include year fixed effects and city fixed effects in all regressions, the identification of the effect of domestic trade integration on emissions is not affected by the TCZ policy. Between 1999 and 2012, there is no notable reduction in emission levels. Meanwhile, because the output level of firms had been rising, the right panel shows that emission intensity had been decreasing over time.

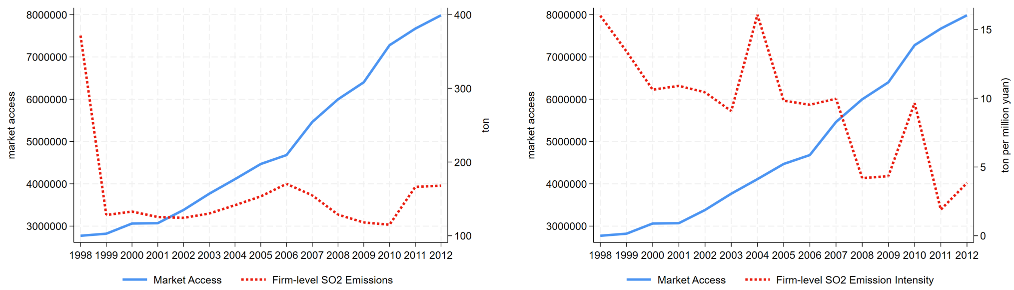

Figure 2: Trends in MA and the Mean of Firm-level SO_2 Emissions
Source: authors' calculations.

Figure 3 presents maps of the levels of MA in cities in 1998 and 2012, relative to the national average of MA in 1998. It can be seen that there is a general increase in MA in most cities. We demonstrate the spatial pattern of MA and emissions at the city level in 2012 in four combinations in Figure 4. There are a large number of cities (coded in navy) in eastern and central China that report a high level of MA and a low level of emissions. Meanwhile, a number of cities in northeastern and western China (coded in brown) report a low level of MA and a high level of emissions.

4 Regression Results

4.1 Benchmark Results: Firm-level Emissions

The OLS estimate in Column (1) of Table 2 suggests a clear negative relation between MA and SO_2 emission at the firm level. A 1% increase in MA is associated with 1.840% decrease in SO_2 emission, which significant in both statistical and practical sense. When

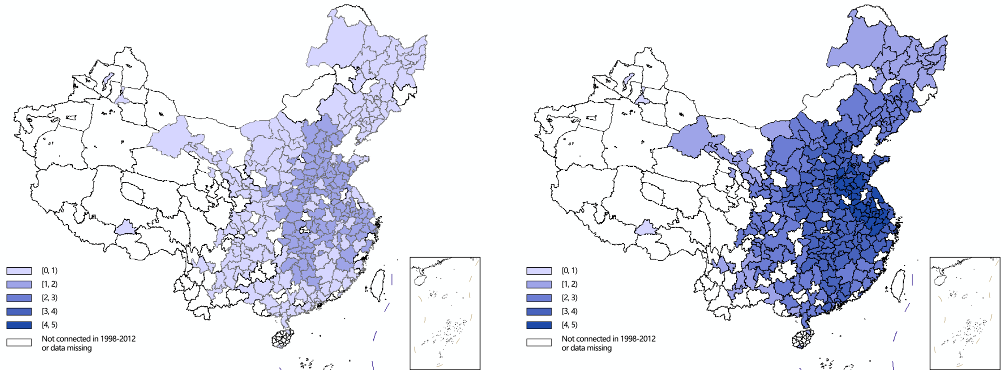

Figure 3: The Spatial Distribution of MA in 1998 and 2012

Source: authors' calculations. The values in the left (right, respectively) map are the ratio of MA of each city in 1998 (2012, respectively) to the mean level of MA in 1998. The blank cities are those that are not connected to the railway throughout the sample period or those for which data are missing. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

we add the control variables, trends, time fixed effects, and firm fixed effects, the estimated effect of MA reported in Column (2) remains statistically significant. In the third column, we replace year fixed effects with industry-year fixed effects to account for the potential effects of industry-specific policies and productivity trends. In particular, the industry-year fixed effects can capture the technique effect which also contributes to reduction in emissions. In Columns (2) and (3), the estimated coefficients on MA are -1.782 and -2.110 which are similar to Column (1).

The bin scatter plots in Figure 5 demonstrates visually the correlation between residualized emission and MA in the panel that give rise to the estimates in the OLS regression in column (2) of Table 2. The residualized version of both variables is obtained from regressions of the respective variable on all other right hand side variables in equation (7). Clearly, conditioned on the other control variables and fixed effects, the log of MA is negatively correlated with and log of firm-level SO_2 emissions and emission intensity.[10]

Whether a city is connected to railways can be affected by endogenous factors. Railway lines often connect cities with larger economies and better growth prospects. On the other hand, it is known that the Chinese government has purposely used railway lines as

[10]There are 50 bins the scatter plots.

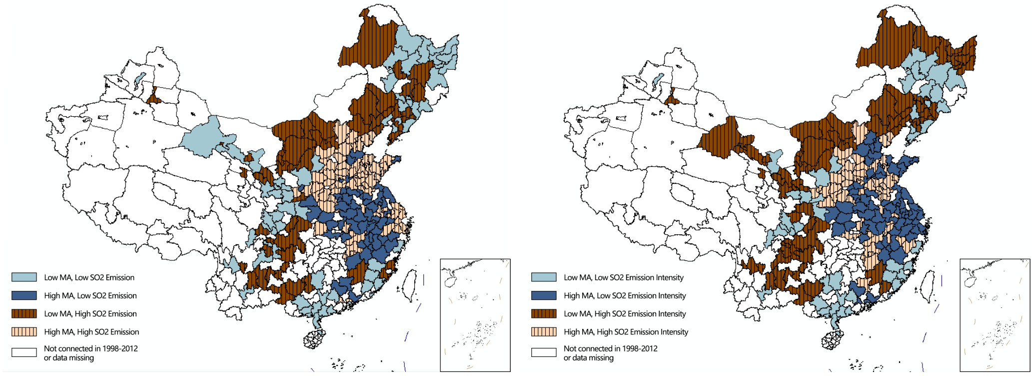

Figure 4: The Spatial Distribution of MA and SO_2 Emissions in 2012

Source: authors' calculations. The blank cities are those that are not connected to the railway throughout the sample period or those for which data are missing. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

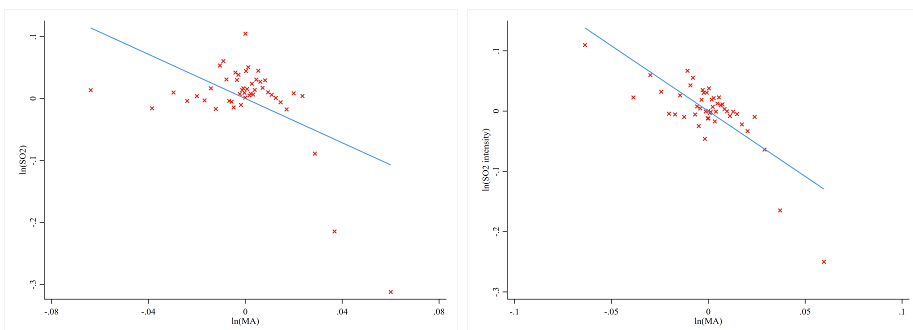

Figure 5: Scatter Plot of MA and Firm-level SO_2 Emissions

Source: authors' calculations.

a tool to alleviate poverty, which implies that some poorer cities are connected to railways intentionally. Given the complex forces shaping the expansion of railway network, it is difficult to conjecture the direction and magnitude of bias when OLS is used to estimate the effect of MA on emissions.

To address the endogeneity of MA, we adopt the control function approach proposed by Borusyak and Hull (2023): (1) we use an instrumental variable (IV) to identify exogenous variation in railway construction and the corresponding exogenous variation in MA, and (2) include the expected level of MA in the second-stage regression. As demonstrated in Borusyak and Hull (2023), the conventional 2SLS approach alone cannot identify the effect of MA because the expected level of MA is correlated with the city's geographic location. Intuitively, cities in more central locations tend to be better connected within the railway network and thus exhibit higher levels of MA. A solution to this issue is to include the expected MA in the second-stage regression.

Our instrumental variables are constructed from artificial transportation networks that are determined by exogenous factors. To span the artificial networks, we select 36 key cities that must be connected. They are the 27 provincial capitals in Mainland China (which are either city-level cities or vice-provincial cities), four municipalities directly under the Central Government (Beijing, Shanghai, Tianjin, and Chongqing), and five additional key cities (Dalian, Ningbo, Qingdao, Shenzhen, and Xiamen). These five cities hold the rank of vice-provincial cities in China but are not themselves provincial capitals.[11]

We construct two artificial transportation networks to link these 36 key cities. First, we follow the strategy of Faber (2014) to use the algorithm in the ArcGIS software to construct the least costly path between two cities. As in Fan et al. (2021), the development cost of each pixel in ArcGIS (a 1-meter-by-1-meter area) is posited to be proportional to the sum of the average gradient and 25 times the indicator function for presence of water body. The ArcGIS program computes the sum of development cost of all pixels associated with a path between two cities, and identify the least costly path which we take as the artificial transportation path. Second, following Banerjee et al. (2020), we use the straight-line segments between the cities as an artificial transportation network. Because the locations of the 36 key cities are determined by historical factors, if any other city-level cities in the sample happens to be located near the artificial transportation network, it is more likely to be connected to the actual railway network due to exogenous geographical factors.

The left and right panels in Figure 6 correspond to the first and the second artificial network, respectively. In both panels, the denser network illustrated with thinner lines is the actual railway network in 2012. The artificial networks are clearly correlated with the actual network. Based on the shortest railway distance on artificial networks and the second lag of the city-level GDP, we compute two counterfactual MA measures and use them as the IVs for the actual MA index.

[11]In one of the robustness checks, we exclude these 36 key cities in regressions and examine the effects of exogenous change in MA on emissions in the non-key cities.

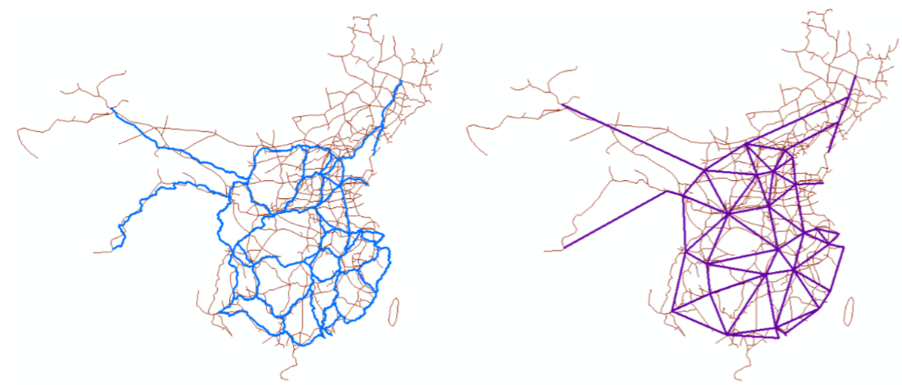

Figure 6: Artificial Transportation Networks Predicted by Exogenous Factors
Source: authors' calculations. Note: The blue network in the left panel and the purple network in the right panel are the artificial transportation newtorks.

Based on the MA index, we follow Borusyak and Hull (2023) to construct the EMA index, which measures the expected level of MA for each city. Starting with the initial MA level for each city, we randomly simulate 1,000 counterfactual MA shocks, corresponding to the random opening of new railway lines. By adding the average of these 1,000 MA shocks to the initial MA level, we obtain a measure of the expected MA level for the subsequent period.

The 2SLS regression results in Table 3 confirm the findings from the OLS regressions, and the estimated effect of MA is slightly larger in magnitude than the OLS estimate in Column (3) of Table 2. In the first and second columns of Table 3, we use the first and second IV individually, while both IVs are used in the third column. In the three cases, a 1% increase in MA is estimated to lower SO_2 emissions by 2.746%, 2.392%, and 2.692%, respectively.

To understand whether the reduction in emission is driven by change in output or emission intensity, in Column (4), we use the SO_2 emission intensity as dependent variable and employ the first IV in estimation. The coefficient on MA (-3.014) in Column (4) is slightly larger than the coefficient (-2.746) in Column (1) where total emission is the dependent variable. In Columns (5) and (6), when we repeat the IV regressions of emission intensity with the second IV and both IVs, respectively, the coefficients on MA are also slightly larger than the counterparts in Columns (2) and (3). Clearly, alomost all of the decrease in emissions is explained by the drop in emission intensity.

In all first-stage regressions, the K-P rk LM statistic and K-P rk Wald F statistic indicate that we do not suffer from the weak IV problem.[12] When the model is over-identified, the Hansen J statistics do not reject the null that the IVs are valid. Between the two IVs, we prefer the first one as it makes use of more geographical information. Following Angrist and Kolesár (2024), who recommend a single-variable just-identified instrumental variables estimator, we rely on the first IV alone for identification in further 2SLS regressions.

Besides SO_2, the CESD dataset also contains information on the emission of dust, COD, and waste gas. We use the emissions of these pollutants and their intensity as the dependent variables. From Columns (1) and (2) of Table 4, we can see that a 1% improvement in MA is estimated to reduce the emission of dust by 2.838% and the emission intensity by 2.850%. The estimated effects of MA on emission of gas are also negative and significant, while in the COD regressions, the coefficients on MA are negative but not statistically significant.

Because the CESD dataset reports information on the consumption of coal, oil and gas, we follow the method of Liu et al. (2015) and Shan et al. (2018) to impute the fuel-related emission of CO_2 at the firm level. The regression results associated with the CO_2, reported in Columns (7) and (8) in Table 4, suggest that a one percent increase in MA reduces the emission of CO_2 by 2.514% and the emission intensity by 2.632%. Therefore, MA also contributes to reduction in the emission of greenhouse gases. Overall, by inducing more efficient product compositions within firms, market can be a positive force in mitigating pollution and climate change.

To assess the explanatory power of MA, we follow Korovkin and Makarin (2023) to compute the following statistics:

$$\Delta SO2\ explained = 100 \cdot \frac{[ln(MA_{p75}) - ln(MA_{p25})] \cdot |\beta_{SO2}|}{ln(SO2_{p75}) - ln(SO2_{p25})} \tag{10}$$

$$\Delta SO2\ intensity\ explained = 100 \cdot \frac{[ln(MA_{p75}) - ln(MA_{p25})] \cdot |\beta_{SO2\ intensity}|}{ln(SO2\ intensity_{p75}) - ln(SO2\ intensity_{p25})} \tag{11}$$

[12] In all two-stage regressions, the K-P rk LM statistic and K-P rk Wald F statistic are always significant at 5% level.

where $ln(MA_{p75})$ and $ln(MA_{p25})$ are the 75th and 25th centiles of the natural logarithm of MA, β_{SO2} the coefficient on MA in the SO_2 regression, and so on. The statistic in last two equations measures the fractions of SO_2 and SO_2 emission intensity differences between the 25th and 75th centiles that can be explained by MA difference between the 25th and 75th centiles. Based on results in Columns (1) and (4) of Table 3, we obtain that $\Delta SO2\ explained = 56.24\%$ and $\Delta SO2\ intensity\ explained = 51.67\%$. Details about the calculation can be found in Table C1 in Appendix C. Therefore, after controlling for firm-level, industry-level, and city-level factors, MA can explain a significant portion of variation in emission of SO_2 and the emission intensity.

4.2 Aggregate Implication: City-level Emissions and Counterfactual Analysis

As our sample covers manufacturing firms with sales above 5 million yuan, we do not observe emission of smaller firms and firms in service industries. It is possible that these firms increase their production and emission after they access a larger market. To alleviate the concern that increase in emissions from smaller firms prevents a reduction in total emission at the city level, we also run regressions of SO_2 emission at the city level. In the first and second columns of Table 5, the dependent variables are SO_2 emission and emission intensity obtained from the *China City Statistical Yearbook*. Following a 1% increase in MA, emission of SO_2 drops by 1.039% and the emission intensity drops by 1.651% in the city level.

To corroborate the results, in Column (3) we run regression of the city-level average concentration level of SO_2 which is computed from the satellite data released by National Aeronautics and Space Administration.[13] The estimated coefficient on MA is -0.497, which is statistically and practically significant. Note that because the unit of dependent variable in the third column (microgram of SO_2 per cubic meter) is different from the

[13] The SO_2 concentration data comes from the NASA satellite M2TMNXAER V5.12.4 and are published by the Goddard Earth Sciences Data and Information Services Center (GAS DISC). See *https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary*. The raw data is in monthly frequency and stored in grids with units of micrograms per cubic meter. We take the mean of SO_2 concentration in dimensions of both ground surface area and time so as to obtain the annual concentration level of SO_2 at the city level.

second column (tons of SO_2 per 10,000 yuan of GDP), sizes of the two coefficients are not comparable. Despite the difference in units, the marginal effects in all three columns are practically large relative to means of the respective dependent variables. Overall, improvement in MA is associated with both reduction of emission at firm level and general reduction in emission at the city level.

Based on the regression results in Table 3, we perform a simple calculation to quantify of the overall effect of MA on emissions of firms in our sample. The analysis is based on the firm-level data from the year 2005, which sits in the middle of our sample period from 1998 to 2012. According to data from the National Bureau of Statistics of China, the length of China's railway expanded by 1,203 kilometers or 1.88% in 2005, bringing the total length of railway in the country to 75,400 kilometers. For each city, we compute the counterfactual MA index (denoted $\tilde{MA}_{2005,c}$) assuming that the 1,203 kilometers of railway had not been completed in 2005.[14] The city-level deviation from the actual MA is computed as $\hat{MA}_{c,2005} = (\tilde{MA}_{2005,c} - MA_{c,2005})/MA_{c,2005}$, where $MA_{c,2005}$ is the actual MA for city c. We find the average of $\hat{MA}_{c,2005}$ to be 0.0092, meaning that on average, the counterfactual MA is 0.92% lower than the actual MA. We compute the counterfactual aggregate difference in SO_2 emissions from the firm-level data:

$$\sum_c \sum_i \hat{MA}_{c,2005} \cdot (-2.746) \cdot SO2_{ic,2005}$$

where -2.746 is the coefficient on MA from column (1) of Table 3, and $SO2_{ic,2005}$ is the actual emission of SO_2 of firm i in city c in 2005. The counterfactual total emission of SO_2 by firms in our sample would have been 123,895 tons higher. The difference is equivalent to 0.43% of China's total emission of SO_2 in 2005, which was 25.49 million tons.[15]

[14] In the calculation of counterfactual MA, we use the same actual city-level GDP that is used in the construction of the actual MA. Therefore, the only difference between the actual and counterfactual MA indices is railway construction in 2005.

[15] Alternatively, we can use the prefecture-level data to compute the counterfactual aggregate difference in SO_2 emissions calculated as $\sum_c \hat{MA}_{c,2005} \cdot (-1.039) \cdot SO2_{c,2005}$, where -1.039 is the regression coefficient from column (1) of Table 5, and $SO2_{c,2005}$ is the actual emission of SO_2 of prefecture c in 2005. The calculation results indicate that had China's railway network not expanded by 1,203 kilometers in 2005, the total emission of SO_2 would have been 191,958 tons higher. The difference is equivalent to 0.52% of China's total emission in the year. Because prefecture-level emissions include those from the transportation process, the counterfactual difference overstates the change in emissions from production. Thus, we favor the counterfactual difference based on firm-level data as it is more conservative.

4.3 Further Analysis: The Product Composition Channel for Emission Reduction

After establishing the emission-reducing effects of MA in the previous two subsections, in this subsection we present evidence in support of Assumption 1 and the mechanism of emission reduction in our theory.

4.3.1 Verifying Assumption 1 and Its Implication

Assumption 1, which posits a positive correlation between the cost advantage of the dirty input and the productivity advantage in intermediate products using the dirty input intensively, is a necessary condition for emission reduction in our theory. To verify whether the assumption is supported by evidence, we run the following regression

$$\begin{aligned} TFP_{jct} = & \gamma_0 + \gamma_1 \cdot \textit{coal per capita}_{pt} + \gamma_2 \cdot \textit{emission intensity}_{jct} \\ & + \gamma_3 \cdot \textit{coal per capita}_{pt} \cdot \textit{emission intensity}_{jct} + \theta_{jc} + \theta_t + \nu_{jct} \end{aligned} \tag{12}$$

where TFP_{jct} is the productivity of product j in city c in year t, $\textit{coal per capita}_{pt}$ the log of tons of coal production per capita in province p (in which city c is located) in year t, and $\textit{emission intensity}_{jct}$ the emission intensity of product j in city c in year t. A positive γ_3 would support Assumption 1.

To estimate the regression, we merge the China Product Output Database (CPOD) with our main dataset. The CPOD records the number of products, five-digit product codes, product names, and quantities of products for more than 200,000 firms annually in China from 2000 to 2009. As detailed in the Appendix of Deng et al. (2024), the five-digit product codes in the CPOD can be mapped into the five-digit product codes in the Central Product Classification published by the United Nations, thus enabling the identification of products as defined in Bernard et al. (2010). The average product scope is 1.859, with a maximum of 42.

In the CPOD data, if a firm is a multi-product producer, there is no information on output and input of each product. Thus it is impossible to calculate product-level productivity for multi-product firms. However, as long as productivity is location specific—as posited in the Ricardian model, we can calculate the Total Factor Productivity (TFP) of product j in city c for year t by using data on firms in city c that exclusively produce product j, and obtain the mean TFP across these firms. Subsequently, we use the city-product-year level mean TFP as a proxy for the TFP of multi-product firms in producing product j in city c during year t. The emission intensity variable $emission\ intensity_{jct}$ is constructed similarly.

In the results reported in Table 6, the coefficient for the interaction term between coal production per capita and emission intensity is positive and significant. This suggests that in provinces with higher level of coal production (and, consequently, likely lower coal cost), firm level productivity for emission-intensive goods are higher. The evidence supports Assumption 1.

We then test the conditional theoretical prediction that MA can reduce emission in cities that satisfy the Assumption 1. To carry out the test, we estimate the benchmark regression model specified in equation (7) for cities that satisfy Assumption 1 and cities that do not satisfy the assumption, respectively. Cities satisfying Assumption 1 are defined as cities with above median level of coal production per capita[16] and positive correlation between product-level TFP and emission-intensity[17], and cities with below median level of coal production per capita and negative correlation between product-level TFP and emission-intensity.

As shown in the first column of Table 7, MA significantly reduces emission in cities that satisfy Assumption 1. The size of coefficient (-4.891) is much larger then the benchmark regression in column (1) of Table 3. In the second column, the effect of MA is insignificant and the magnitude of the coefficient is close to zero. The Fisher's Permutation test statistic indicates that the difference in coefficients in the two columns, -4.803, is statistically different at 1% level. The pair of regressions thus supports the theoretical prediction, that conditional on Assumption 1, MA is more likely constrain emission in

[16]Since coal production is defined at the province level, and there are 30 provinces (including autonomous regions and municipalities that hold province-level administrative status) in our sample, cities with an above- or below-median level of coal production per capita correspond to those in the top or bottom 15 provinces in terms of coal production per capita. When we use alternative cutoff values for high or low coal production per capita—ranging from the top or bottom 8 to 14 provinces—the results remain similar.

[17]The correlation between product-level TFP and emission-intensity in a city is measured by the estimated γ from the city-specific version of regression (12): $TFP_{jt} = \gamma_0 + \gamma \cdot emission\ intensity_{jt} + \theta_j + \theta_t + \nu_{jt}$.

cities where productivity advantage and input cost advantage are aligned.

4.3.2 Testing Mechanisms in Proposition 1 and Proposition 2

After verifying the viability and the implication of of Assumption 1, we proceed to test in three steps whether the mechanisms outlined in Proposition 1 and Proposition 2 are observed in the data. First, we investigate whether there is a reduction in the product scope of firms and an increase in output per product following an increase in MA. In Column (1) of Table 8, we use a 2SLS regression to estimate the effects of MA on log product scope. The results indicate that MA significantly lowers the product scope. Because the mean of log product scope is 0.432, the coefficient of -0.306 is large in practical sense too. When we regress output per product at the firm-level on MA in Column (2), we find that MA significantly increases the average output per product.[18] Thus, both predictions in Proposition 1—namely the reduction in product scope and increase in output of remaining products following an increase in MA—are supported by the data.[19]

Second, we verify whether an increase in MA induces firms to further specialize in products with high productivity. To test this part of mechanism, we introduce product-level TFP and interaction between TFP and MA in regressions in Table 9. In the first column of Table 9, the dependent variable is an indicator variable of whether a product is discontinued by a firm in year t. The coefficients on both TFP and the interaction term between MA and TFP are negative. Thus, a high-productivity product is less likely to be discontinued by a firm on average, and the probability of it being dropped is smaller when the MA improves. The second column employs output per product as the dependent variable. The results there indicate that as MA improves, output per product increases and the increase is larger for high-productivity products. Therefore, the results provide

[18] Because the quantities of products vary in their units, we use a standardized measure of average output per product. Let x_{jict} be output volume of product j by firm i in city c in year t, and μ_{jt} and σ_{jt} the mean and standard deviation of output volume of all producers in all cities that produce product j in year t. The standardized measure of average output per product is calculated as $(x_{jict} - \mu_{jt})/\sigma_{jt}$

[19] As our sample is reduced to 125,260 firm-year observations after merging the main sample with the CPOD, we rerun the benchmark regressions of SO_2 emission and emission intensity with the smaller sample to verify the existence of emission-reduction effect. As shown in Columns (3) and (4) of Table 8, the effects of MA on emission and emission intensity remain negative and significant, and the coefficients of -2.498 and -2.549 are slightly smaller in magnitude than the benchmark 2SLS results of -2.746 and -3.014 in Columns (1) and (4) of Table 3, respectively.

evidence for the mechanism for emission reduction in Proposition 2, namely firms specialize in high-productivity products after an improvement in MA. Because the first two regressions in Table 9 are based on the sample of firms that are continuously observed throughout the sample period, we perform the benchmark regressions for the sample. The results, reported Columns (3) and (4), confirm that MA reduces emissions in this sample.

The third step in our mechanism analysis is to show that a productivity-driven reduction in product scope is indeed associated with reduction in emission. In the first two columns of Table 10, we regress emission and emission intensity on log product scope, using the counterfactual MA as the instrumental variable. Clearly, product scope is positively related with emission and emission intensity.

In completing the third step, we test the key prediction of Proposition 2 that, besides Assumption 1, a large dispersion in within-firm productivity is a necessary condition for trade-induced reductions in product scope to result in a reduction in total emissions. To test this, we include in the regression an indicator for firms that reported a reduction in product scope between periods $t-1$ and t (denoted $\mathbb{1}$(scope reduction)), and its interaction with an indicator for large productivity dispersion (denoted $\mathbb{1}$(productivity dispersion)). To capture the predetermined difference in productivity, the indicator for large productivity dispersion equals one for firms whose within-firm productivity dispersion is above the median level in the initial period, and zero otherwise. As the indicator is time-invariant, the variable itself is absorbed by the fixed effects in the regressions.

In the 2SLS regressions of emissions and emission intensity, as shown in Columns (3) and (4) of Table 10, the coefficients on the interaction terms between the product scope reduction indicator and the large productivity dispersion indicator are both negative and significant.[20] This suggests that for firms with large within-firm productivity dispersion, discontinuing less productive products leads to a reduction in emissions. Meanwhile, the coefficient on the product scope reduction indicator is highly insignificant, indicating that for firms with small productivity dispersion, a reduction in product scope does not lead to a decrease in emissions.

[20]Because $\mathbb{1}$(scope reduction) and $\mathbb{1}$(productivity dispersion) are indicator variables, we use logit regressions in the first stage.

Based on the tests of mechanisms in three steps, reported in Table 8 through Table 10, the empirical evidence supports the central premise of the theory that an increase in MA reduces emissions of firms with large productivity dispersion by inducing firms to adjust their product composition to focus on high-productivity products.

4.4 Analysis Related to the Pollution Haven Hypothesis

While we outline in Corollary 1 the conditions under which adjustments in product composition can lead to reduction in emissions in both cities, hence mitigating the PHH, these conditions are complex and may not hold in reality. In China, there is significant variation in environmental regulation and coal endowment, which is the primary source of energy in the country. When MA improves, these factors can lead to a rise in emissions in some cities as firms further specialize. Such a scenario would give rise to a form of pollution haven phenomenon, even without the relocation of dirty product producers across cities.

To examine whether there is evidence of the PHH from the perspective of product composition, we interact MA with the index of city-level environmental regulation and province-level coal production—both of which were included as control variables in previous regressions. The results provide no supporting evidence for the PHH. In the first three regressions in Table 11, which use the full sample, the interaction terms are consistently insignificant.

In columns (4) and (5), we perform separate regressions for firms in cities that satisfy Assumption 1 and for those in cities that do not. For the former group, our theory predicts that MA does not increase emissions in cities where the regulation is less stringent or the supply of dirty inputs is more abundant. The results reported in column (4) confirm this prediction.[21] For firms in cities that do not satisfy Assumption 1, our theory does not offer a specific prediction regarding emissions and the cost of dirty inputs, leaving open the possibility that the PHH might apply. The regression results in column (5) indicate that for this subset of firms, MA no longer reduces firm-level emissions. The positive

[21] The coefficient on the interaction between MA and regulation negative, which indicates a weaker emission reduction effect of MA in cities with less stringent regulation. However, because the minimum value of the regulation variable is 0, the effect of MA is estimated to be negative and significant in all cities, lending no support to the PHH.

coefficient on MA and coal production is positive but insignificant, providing hints that firm emissions increase more in cities with access to cheap coal after an increase in MA.

Due to data limitations, our study only examines the PHH in the context of the relationship between MA and the short-term changes in emissions of incumbent firms. While we find clear evidence of the PHH in this context, we recognize that it is possible for producers using the dirty input intensively to relocate over time to cities with lax regulations and cheap coal. A comprehensive examination of the PHH is beyond the scope of this study.

4.5 Robustness Results

In this subsection, we show the results remain robust when we control for other policy changes, include MA associated with high-speed rail in the regression, and when we use alternative measures of MA.

Firstly, we include abatement equipment in the regressions in Column (1) in Table 12. In general, abatement technology can be an important determinant of emission. For example, Forslid et al. (2018) demonstrate that abatement investment is effective in reducing emission in Swedish firms. However, as shown in Column (1), in our sample we find that abatement equipment has a small and (surprisingly) positive effect on emissions, while the effect of MA remains negative and significant.[22]

Secondly, we drop observations from the years post the 2008 global financial crisis in Column (2). In response to global financial crisis, China rolled out a large stimulus package with a strong emphasis on infrastructure and real estate in 2009 which might have led to both a higher level of MA and a higher level of emissions. The exclusion of observations after 2008 eliminates the influence of the stimulus.

Thirdly, to ensure our results are not driven by firms in the major cities whose connectivity to railways is rendered necessary by their status, we exclude firms in the 36 major cities in Column (3). As described in Section 4.1, these key cities include the 4

[22]In unreported regressions, we also run regressions of the number of pieces of emission-abatement equipment, and its rate of change on the first lag and the second lag of MA. The coefficients are highly insignificant, indicating that an increase in MA does not cause firms to increase installment of abatement equipment.

municipalities directly under the central government, 27 provincial capitals, and another 5 key cities.

Fourthly, we want to account for the effects of a major policy that aims at reducing acid rain. Because of the need to reduce the impact of SO_2 pollution and acid rain, China has implemented stricter regulation in cities prone to such pollution since 1998.[23] In Column (4), we report the regression which include an indicator variable for city-year observations subject to the regulation.

Fifthly, we control for liberalization of international trade by introducing the interactions between year dummies and industry levels of output tariff, input tariff, and export tariff in Column (5).

Sixthly, since the literature suggests that imported inputs can affect emissions either by outsourcing emissions (Dussaux et al., 2023) or by altering product composition (Akerman et al., 2024), in Column (6), we include the interaction between year dummies and the value of imported inputs in the initial base year. In all six columns, the coefficients on MA remain significant, and their magnitudes are similar to those of the benchmark estimates, indicating the robustness of our benchmark results.

In addition, we examine the potential effect of high-speed rail which is found to be a positive force in reducing emission (Lin et al., 2021). To do so, we construct a MA index using only data on high-speed railway. The variable is insignificant when it is added to the benchmark regression. When we exclude the original MA variable and include only the MA variable associated with high-speed railway , high-speed rail continues to have no effect on the emissions of manufacturing firms.[24] The details of the regressions are reported in Table C2 in Appendix C.

Lastly, we adjust the parameters in equations (8) and (9) and reconstruct the MA indices. We report the regressions with alternative MA indices in Table C3 in Appendix C. The estimated effects of all alternative measures of MA on emission are always negative and significant. Overall, the large number of checks in this subsection provide strong

[23]These cities are collectively referred to as "double-control areas", because the purpose is to control both SO_2 and acid rain.

[24]The sample in the regression in Column (2) is smaller because China started to operate high-speed railway in 2008.

evidence of the robustness of the results.

5 Conclusion

Our study identifies within-firm product composition as a key mechanism through which trade can reduce production emissions. Using a stylized Ricardian model with multi-product firms, we demonstrate that trade integration encourages firms to specialize in intermediate products in which they have a productivity advantage. This specialization reduces emissions under two key conditions: (1) firms in locations with a relative cost advantage in the emission-intensive input must also exhibit higher productivity in producing products that use the input intensively, and (2) there must be a significant productivity difference between the discontinued and retained products within firms.

Empirically, we test these predictions using firm-level data from China, the largest emitter of many pollutants, and analyze the effects of domestic trade integration through railway expansion. Our findings show that increases in market access (MA) significantly reduce firm-level emissions of pollutants such as SO_2, CO_2, dust, and COD. The reduction is primarily driven by decreases in emission intensity, with nearly half of the observed variation in firm-level SO_2 emissions and emission intensity explained by changes in MA. A counterfactual analysis of 2005 data reveals that, without railway expansion that year, additional industrial SO_2 emissions would have increased national emissions by 0.43%.

We further show that this reduction in emissions is closely linked to trade-induced adjustments in product composition. As MA increases, firms discontinue less productive intermediate products while expanding production of more productive ones. Importantly, consistent with our theory, these shifts in product composition lead to emission reductions only in firms with substantial productivity dispersion across their products. Our results are robust when we control for policy effects related to infrastructure, emissions, and trade liberalization.

Overall, our findings underscore the role of trade integration and within-firm product composition adjustments in reducing emissions, offering a new perspective on how MA influences environmental outcomes in the context of domestic trade. While our study focuses on domestic trade in China, the proposed product composition channel of emission reduction is also applicable to international trade. Evaluating this effect in the context of international trade remains an important avenue for future research.

Declaration of generative AI technologies in the writing process

During the preparation of this work the authors used GPT4.0 developed by OpenAI in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Table 1: Summary Statistics

	Unit	Observations	Mean	Min	Max	S.D.
Firm-level variables						
SO_2 emissions	ton	337882	145.00	0.00	2180000.00	3934.81
SO_2 emission intensity	ton per million yuan	316804	9.98	0.00	45690.00	188.24
product varieties	count	125260	1.859	1	42	1.668
average output	standardized index	232078	0.007	-0.212	18.172	1.007
City-level variables						
market access (MA)	\	3369	4960363.70	1456604.80	12175258.00	2177659.20
ln(MA)	\	3369	15.326	14.192	16.315	0.423
expected market access (EMA)	\	3369	4982192.00	1456604.80	10226873.00	1799712.90
ln(EMA)	\	3369	15.356	14.192	16.141	0.363
IV 1 (artificial ln(MA))	\	3369	15.087	14.088	16.065	0.383
IV 2 (artificial ln(MA))	\	3369	15.308	14.242	16.286	0.400
environmental regulation	\	3369	0.486	0.000	13.300	1.154
GDP (1998)	billion yuan	252	31.17	1.605	368.82	36.74
GDP per capita (1998)	yuan per capita	252	8112.12	1349.46	112479.84	8734.71
green invention patent (1998)	count	252	3.698	0	185	12.668
Province-level variables						
coal production per capita (1998)	ton per capita	30	19.638	0.000	198.70	40.496
highway density (1998)	km per km2	30	0.332	0.021	1.000	0.216

Note: Average output is a standardized index of firm's output of each product variety. To eliminate the impact of different counting units of products in the data, the original product-level output is standardized using the sample mean and standard deviation of the outputs from all firms that produce the same product in the current year.

Table 2: Market Access and SO_2 Emissions Level (OLS)

Dependent Variable:		$ln(SO_2)$	
	(1)	(2)	(3)
$ln(MA)$	-1.840**	-1.782*	-2.110**
	(0.759)	(0.915)	(0.831)
$ln(EMA)$		-4.382	-4.419
		(5.288)	(4.540)
envir. regulation		-0.007	-0.008
		(0.025)	(0.025)
Dependent Variable's Mean	8.603	8.603	8.603
$W_c \times \eta_t$	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Industry-year fixed effects	No	No	Yes
Observations	337,882	337,882	337,882
Adjusted R^2	0.784	0.785	0.790

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] The variable $ln(MA)$ is the log of market access index, and $ln(EMA)$ is the log of expected market access index. The variable *envir. regulation* is an index of city's emission regulation as described in Section 3. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 3: Market Access and SO_2 Emissions (2SLS)

	Panel A. Second stage					
Dependent Variables:	$ln(SO_2)$	$ln(SO_2)$	$ln(SO_2)$	$ln(SO_2$ $intensity)$	$ln(SO_2$ $intensity)$	$ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(MA)$	-2.746***	-2.392***	-2.692***	-3.014***	-2.741***	-2.975***
	(0.927)	(0.815)	(0.904)	(0.813)	(0.742)	(0.797)
$ln(EMA)$	-4.273	-4.354	-4.286	-5.686	-5.749	-5.695
	(4.502)	(4.512)	(4.503)	(4.239)	(4.259)	(4.241)
envir. regulation	-0.009	-0.009	-0.009	0.004	0.005	0.004
	(0.025)	(0.025)	(0.025)	(0.022)	(0.022)	(0.022)
Dependent Variable's Mean	8.603	8.603	8.603	-1.040	-1.040	-1.040
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	337,882	337,882	337,882	316,804	316,804	316,804
	Panel B. First stage					
Dependent Variable:	$ln(MA)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$IV1$	0.793***		0.675***	0.794***		0.681***
	(0.037)		(0.083)	(0.037)		(0.084)
$IV2$		0.928***	0.160		0.935***	0.154
		(0.057)	(0.103)		(0.057)	(0.105)
Dependent Variable's Mean	15.413	15.413	15.413	15.385	15.385	15.385
Expected Market Access	Yes	Yes	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	52.356	54.340	54.497	52.343	54.593	54.678
K-P rk Wald F statistic	457.72	269.20	238.40	464.72	270.32	241.82
Hansen J statistic	\	\	1.546	\	\	1.074
Observations	337,882	337,882	337,882	316,804	316,804	316,804

Note: [1] The dependent variable in Columns (1)-(3) in Panel A is the log of sulfur dioxide emission level and that in Columns (4)-(6) is the log of sulfur dioxide emission intensity. [2] $IV1$ is the counterfactural MA that is constructed by the artifitial transportation network connected by the least costly paths, and $IV2$ is the counterfactural MA that is constructed by the artifitial transportation network connected by straight lines. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 4: Market Access and Emission of Other Pollutants (2SLS)

Dependent Variables:	ln(dust)	$ln(dust\ intensity)$	ln(COD)	$ln(COD\ intensity)$	ln(gas)	$ln(gas\ intensity)$	$ln(CO_2)$	$ln(CO_2\ intensity)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(MA)$	-2.838***	-2.850***	-1.395	-1.382	-3.030**	-3.101**	-2.514***	-2.632***
	(1.032)	(0.973)	(1.011)	(1.002)	(1.433)	(1.351)	(0.665)	(0.640)
Dependent Variable's Mean	7.285	-2.141	6.121	-3.388	15.270	5.715	5.491	-3.767
Expected Market Access	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	50.749	50.933	48.772	48.815	51.853	52.005	49.808	49.574
K-P rk Wald F statistic	511.81	517.73	473.27	481.61	483.04	488.64	498.84	501.82
Observations	267,378	261,363	353,157	330,816	303,491	291,396	186,434	184,669

Note: [1] The dependent variables in odd columns are the logs of emission level of dust, chemical oxygen demand (COD), gas, and carbon dioxide (CO_2), respectively. The dependent variables in even columns are the logs of emission intensity of pollutants corresponding to the odd columns. [2] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 5: Market Access and City-level Emissions (2SLS)

Dependent Variables:	$ln(SO_2)$	$ln(SO_2\ intensity)$	$ln(SO_2\ density)$
	(1)	(2)	(3)
$ln(MA)$	-1.039*	-1.651***	-0.497***
	(0.557)	(0.566)	(0.114)
Dependent Variable's Mean	10.719	-4.273	2.731
Expected Market Access	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
K-P rk LM statistic	64.734	64.770	64.000
K-P rk Wald F statistic	647.89	649.51	758.73
Observations	2,371	2,370	3,344

Note: [1] The dependent variables in Columns (1) and (2) are emission level and emission intensity of sulfur dioxide at the city level from City Statistical Yearbook. The dependent variable in Column (3) is average concentration of sulfur dioxide that comes from NASA satellite data (M2TMNXAER V5.12.4) in GAS DISC. The units are tons of SO_2, tons of SO_2 per 10,000 yuan of GDP, and microgram of SO_2 per cubic meter. [2] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 6: Test of Assumption 1 (OLS)

Dependent Variable:	*productivity*	
	(1)	(2)
lncoal	0.026***	0.024***
	(0.005)	(0.004)
lncoal × *emission intensity*		0.057**
		(0.022)
emission intensity		-0.070***
		(0.025)
Dependent Variable's Mean	4.057	4.038
City-product fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	36,120	32,783

Note: [1] The dependent variable is the product-level productivity as described in Section 4.3. *lncoal* is the log of raw coal output per capita at the provincial level. The variable *emission intensity* represents the product emission intensity, which is measured by the average emission intensity of all firms in sample from the same city that produce this product only. [2] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the provincial level and shown in parenthesis.

Table 7: Emission Reduction Conditional on Assumption 1 (2SLS)

Dependent Variable:	$ln(SO_2)$	
	(1)	(2)
$ln(MA)$	-4.891***	-0.088
	(1.133)	(1.609)
Dependent Variable's Mean	8.448	8.785
Expected Market Access	Yes	Yes
envir. regulation	Yes	Yes
$W_c \times \eta_t$	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
K-P rk LM statistic	35.497	32.775
K-P rk Wald F statistic	794.33	116.56
Observations	177,996	157,612
Fisher's Permutation test	4.803***	

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 8: Market Access and Specialization (2SLS)

Dependent Variables:	Product scope	Output/product	$ln(SO_2)$	$ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)
$ln(MA)$	-0.306**	0.731***	-2.498**	-2.549**
	(0.132)	(0.181)	(1.031)	(0.997)
Dependent Variable's Mean	0.432	0.007	9.174	-0.531
Expected Market Access	Yes	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	No	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Firm-product fixed effects	No	Yes	No	No
K-P rk LM statistic	53.589	49.089	53.589	53.672
K-P rk Wald F statistic	448.82	444.54	448.82	451.47
Observations	125,260	232,078	125,260	122,689

Note: [1] The dependent variable in Column (1) is firm's product scope measured by the log of the number of product varieties. The dependent variable in Column (2) is a standardized index of firm's output of each product variety. To eliminate the impact of different counting units of products in the data, the original product-level output is standardized using the sample mean and standard deviation of the outputs from all firms that produce the same product in the current year. [2] Columns (3) and (4) use the same sample as Column (1) to perform the benchmark regressions in Table 3 that estimate the elasticity of emission level and emission intensity of sulfur dioxide to MA. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 9: Specialization in Efficient Products (2SLS)

Dependent Variables:	Product exit	Output/product
	(1)	(2)
$ln(MA)$	0.151	0.457*
	(0.094)	(0.240)
$ln(MA) \times productivity$	-0.031**	0.097**
	(0.016)	(0.046)
$productivity$	-0.014***	0.034**
	(0.005)	(0.016)
Dependent Variable's Mean	0.065	0.056
Expected Market Access	Yes	Yes
envir. regulation	Yes	Yes
$W_c \times \eta_t$	Yes	Yes
Firm fixed effects	No	No
Industry-year fixed effects	Yes	Yes
Firm-product fixed effects	Yes	Yes
K-P rk LM statistic	54.284	53.071
K-P rk Wald F statistic	208.45	189.75
Observations	86,711	101,877

Note: [1] The dependent variable in Column (1) is an indicator for firms that discountinued a product in year t. The dependent variable in Column (2) is a standardized index of firm's output of each product variety. To eliminate the impact of different counting units of products in the data, the original product-level output is standardized using the sample mean and standard deviation of the outputs from all firms that produce the same product in the current year. The variable *productivity* is product-level productivity. [2] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 10: Product Scope, Productivity Dispersion and SO_2 Emissions

Dependent Variables:	$ln(SO_2)$	$ln(SO_2$ $intensity)$	$ln(SO_2)$	$ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)
product scope	8.175**	8.015**		
	(3.971)	(3.862)		
$\mathbb{1}(scope\ reduction)$			0.038	0.005
			(0.230)	(0.245)
$\mathbb{1}(scope\ reduction) \times \mathbb{1}(productivity\ dispersion)$			-0.277**	-0.314**
			(0.141)	(0.150)
Dependent Variable's Mean	9.174	-0.531	9.923	-0.623
Expected Market Access	Yes	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
K-P rk LM statistic	6.237	6.476	/	/
K-P rk Wald F statistic	5.387	5.599	/	/
Wald statistic	/	/	35.93	36.96
Observations	125,260	122,689	10,874	10,766

Note: [1] The dependent variables are firm's emission level and emission intensity of sulfur dioxide. [2] The variable *product scope* is firm's product scope measured by the log of the number of product varieties. The variable $\mathbb{1}(scope\ reduction)$ is an indicator for firms which report a reduction in product scope between period $t-1$ and t, and $\mathbb{1}(productivity\ dispersion)$ is an indicator for firms with large within-firm productivity dispersion in the initial period. [3] Columns (1) and (2) are estimated by the 2SLS. Columns (3) and (4) are estimated by two-stage methods, and the first stages are logit regressions. [4] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 11: Analysis of the Pollution Heaven Hypothesis (2SLS)

Dependent Variable:	$ln(SO_2)$				
	(1)	(2)	(3)	(4)	(5)
$ln(MA)$	-2.570***	-3.011***	-2.801***	-4.417***	-1.252
	(0.913)	(1.004)	(1.043)	(1.268)	(1.992)
$ln(MA) \times envir.\ regulation$	-0.078		-0.057	-0.160**	0.063
	(0.071)		(0.085)	(0.078)	(0.140)
$envir.\ regulation$	0.003	-0.002	0.005	0.021	-0.020
	(0.021)	(0.024)	(0.020)	(0.025)	(0.032)
$ln(MA) \times lncoal$		0.451	0.313	-0.140	0.934
		(0.436)	(0.514)	(0.539)	(0.918)
Dependent Variable's Mean	8.603	8.603	8.603	8.448	8.785
Expected Market Access	Yes	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	52.717	40.614	43.607	25.706	33.590
K-P rk Wald F statistic	250.72	131.54	80.452	219.35	30.485
Observations	337,882	337,882	337,882	177,996	157,612

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] The stand-alone variable *lncoal* is absorbed into $W_c \times \eta_t$. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table 12: Robustness Checks (2SLS)

Dependent Variable:	$ln(SO_2)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(MA)$	-3.032***	-2.175**	-3.530***	-2.770***	-2.446**	-2.417**
	(0.982)	(1.070)	(1.134)	(0.926)	(1.006)	(0.946)
$facility\ per\ worker$	0.015**					
	(0.007)					
Dependent Variable's Mean	8.511	8.409	8.965	8.603	8.603	8.657
Expected Market Access	Yes	Yes	Yes	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
double-control × year dummies	No	No	No	Yes	No	No
Tariff reductions × year dummies	No	No	No	No	Yes	No
K-P rk LM statistic	51.621	52.187	40.697	52.204	47.210	52.357
K-P rk Wald F statistic	434.64	551.67	223.29	449.84	399.57	438.06
Observations	265,985	234,476	236,843	337,882	337,871	304,366

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] The varaible $facility\ per\ worker$ in Column (1) is the number of emission abatement equipment per worker. Column (2) excludes observations after 2008. Column (3) excludes the firms in the 36 major cities as described in Section 4.1. Column (4) controls the interaction between year dummies and an indicator for cities subject to the "double-control area" regulation on acid rain and sulfur dioxide. Column (5) controls the interaction between year dummies and industry levels of output tariff, input tariff, and export tariff. Column (6) includes the interaction between year dummies and the value of imported inputs in the initial year of the sample. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Appendix For Online Publication

A Discussion of Iceberg Trade Cost

In this section, we discuss the scenario where τ is an iceberg cost that is paid for with products and revisit the two properties in the model.

Given Assumption 1, we still have $\frac{\partial j_0}{\partial \tau} < 0$ and $\frac{\partial j_1}{\partial \tau} > 0$. Therefore, both the home and outside firms' product scopes, $[0, j_1]$ and $[1 - j_0, 1]$, are positively related with the trade cost τ. However, under the iceberg cost τ, a firm now must produce $1 + \tau$ units of intermediate products to deliver one unit to the other region. Given the final good output level y and y^*, the total intermediate output of the home firm is:

$$\int_0^{j_1} y dj + \int_0^{j_0} (1+\tau) y^* dj = j_1 y + (1+\tau) j_0 y^*.$$

The average output per variety of intermediate product in the home city is

$$\overline{x} = \frac{j_1 y + (1+\tau) j_0 y^*}{j_1}.$$

By symmetry, the total intermediate output and average output of intermediate goods in the outside city are:

$$(1 - j_0) y^* + (1+\tau)(1 - j_1) y,$$

and

$$\overline{x^*} = \frac{(1 - j_0) y^* + (1+\tau)(1 - j_1) y}{1 - j_0}.$$

Take the derivative of the home firm's average output $\overline{x}$ with respect to τ:

$$\begin{aligned}
\frac{\partial \overline{x}}{\partial \tau} &= y^* \frac{j_0}{j_1} + (1+\tau) y^* \frac{\partial (j_0/j_1)}{\partial \tau} \\
&= \frac{1+\tau}{\tau} \frac{j_0}{j_1} y^* [\frac{\tau}{1+\tau} + \frac{(\partial j_0/\partial \tau)}{j_0/\tau} - \frac{(\partial j_1/\partial \tau)}{j_1/\tau}] \\
&= \frac{1+\tau}{\tau} \frac{j_0}{j_1} y^* (\varepsilon_{1+\tau} + \varepsilon_{j_0} - \varepsilon_{j_1}),
\end{aligned}$$

where $\varepsilon_{1+\tau} \equiv \frac{\tau}{1+\tau}$, $\varepsilon_{j_0} \equiv \frac{(\partial j_0/\partial \tau)}{j_0/\tau}$ and $\varepsilon_{j_1} \equiv \frac{(\partial j_1/\partial \tau)}{j_1/\tau}$ are the elasticity of $1 + \tau$, j_0 and j_1 to τ, respectively. In the benchmark model in Section 2, the changes in product scope of processing and self-production, $\varepsilon_{j_0} < 0$ and $\varepsilon_{j_1} > 0$, ensure that $\frac{\partial \overline{x}}{\partial \tau} = \frac{1+\tau}{\tau}\frac{j_0}{j_1}y^*(\varepsilon_{j_0} - \varepsilon_{j_1}) < 0$ always holds. The intuition is that under a lower trade cost, the home firm increases the output of some existing efficient products (from y to $y + y^*$) and stops producing some less-efficient products (with also relatively low output y). The additional item $\varepsilon_{1+\tau} > 0$ here represents an opposing force. That is, a lower iceberg cost decreases the factory outputs of all outsourcing products by reducing the cargo losses during transportation. In general, after a reduction in trade costs, the condition for an increase in home firm's average output is $\varepsilon_{1+\tau} + \varepsilon_{j_0} - \varepsilon_{j_1} < 0$.

Similarly, we can derive that $\frac{\partial \overline{x^*}}{\partial \tau} < 0$ if $\varepsilon_{1+\tau} + \varepsilon_{1-j_1} - \varepsilon_{1-j_0} < 0$, where $\varepsilon_{1-j_1} < 0$ and $\varepsilon_{1-j_0} > 0$ are the elasticity of $1 - j_1$ and $1 - j_0$ to τ, respectively.

The results in property 1 should now be summarized as, after a reduction in trade costs, (i) all firms narrow the product scope and specialize in their most productive products, and (ii) increase the average output of the products that they keep if the elasticity of product scope to trade costs is greater than the elasticity of transportation losses to trade costs.

Given the expression of total output, the home firm's total emission is:

$$z = g((1+\tau)y^* \int_0^{j_0} \frac{h_j}{A_j} dj + y \int_0^{j_1} \frac{h_j}{A_j} dj). \tag{A.1}$$

Differentiated the total emission of the home firm z with respect to trade cost τ, the derivative is:

$$\frac{\partial z}{\partial \tau} = g[\frac{\partial j_1}{\partial \tau}\frac{y h_{j_1}}{A_{j_1}} + \frac{\partial j_0}{\partial \tau}\frac{y^* h_{j_0}}{A_{j_0}} + y^* \int_0^{j_0} \frac{h_j}{A_j} dj].$$

A reduction in trade cost lowers emission reduction if $\frac{\partial z}{\partial \tau} > 0$, i.e.

$$\frac{\partial j_1}{\partial \tau}\frac{y h_{j_1}}{A_{j_1}} + y^* \int_0^{j_0} \frac{h_j}{A_j} dj > -\frac{\partial j_0}{\partial \tau}\frac{y^* h_{j_0}}{A_{j_0}}. \tag{A.2}$$

As in the condition (5) in Section 2, the first item on the left side of inequality (A.2) represents the emission reduction from outsourcing intermediate goods and the right side is the increase in emission associated with processing additional intermediate goods for the outside city. The item $y^* \int_0^{j_0} \frac{h_j}{A_j} dj$ indicates a direct and mechanical effect of the decline in iceberg costs on emission reduction. Due to the lower losses during transportation, the home firm can reduce emissions brought by processing products for the outside city. This effect benefits the emission reduction of all firms and supplements the results in Property 2: after a reduction in trade costs, a firm's emission declines through a composition effect if the within-firm productivity difference across products is sufficiently large, while the saving effect of cargo losses always helps firms to reduce their emissions.

B Discussion about Emission Reduction in Both Cities

In this Appendix, we first outline the conditions under which emissions will decrease in both cities. Recall that the condition for the home firm to reduce emissions is:

$$\frac{-y^* \frac{\partial j_0}{\partial \tau}}{y \frac{\partial j_1}{\partial \tau}} < \frac{\tilde{A_{j_0}}}{\tilde{A_{j_1}}}. \tag{B.1}$$

Similarly, we can write the condition as in (B.1) for the foreign firm, that is:

$$\frac{y \frac{\partial j_1}{\partial \tau}}{-y^* \frac{\partial j_0}{\partial \tau}} < \frac{\tilde{A_{j_1}^*}}{\tilde{A_{j_0}^*}}. \tag{B.2}$$

Combining (6) and (B.2), we obtain the condition for both firms to reduce emissions after the drop in trade costs:

$$\underbrace{\frac{\tilde{A_{j_1}}}{\tilde{A_{j_0}}}}_{\mathbb{L}} < \underbrace{\frac{y \frac{\partial j_1}{\partial \tau}}{-y^* \frac{\partial j_0}{\partial \tau}}}_{\mathbb{M}} < \underbrace{\frac{\tilde{A_{j_1}^*}}{\tilde{A_{j_0}^*}}}_{\mathbb{R}}. \tag{B.3}$$

The part $\mathbb{M}$ in (B.3) represents the relative output transfer between the two cities, and $\mathbb{L}$ and $\mathbb{R}$ represent the home and foreign firm's (adjusted) efficiency gap between products j_0 and j_1, respectively. When the first inequality holds, i.e., $\mathbb{L} < \mathbb{M}$, the home firm decreases its emissions with lower trade costs, and so does the foreign firm if the second inequality $\mathbb{M} < \mathbb{R}$ holds. Here we show an interesting result that there is possibility of joint emission reduction for both firms. As is typical in Ricardian models, after a decline of trade costs, inter-location competition is intensified and more varieties of intermediate goods are now produced by only one location. In Copeland and Taylor (1994), this result of further specialization creates a composition effect that certainly transfers pollution from the North to the South[25].

The key difference here is that the emission outcome from the output transfer depends not only on the cleanliness of the intermediate products, but is also affected by within-firm productivity differences among these products. A firm may be more productive at producing dirtier products than cleaner products[26], and it could achieve emission reduction by specialization in polluting intermediate goods[27]. In summary, productivity heterogeneity plays two roles in affecting our equilibrium results and comparative statics. The inter-firm productivity differences, together with differences in factor costs, form the firms' cost advantages and thus shape the pattern of production specialization in intermediate goods in equilibrium. The within-firm productivity differences, in comparison, determine how firm emissions respond to such further specialization after a reduction in domestic trade costs.

Consider a change in environmental policy that is embodied by an increase in the emission tax t in the home city. A higher emission tax will increase the unit cost of the home firm, thereby reducing its cost advantage in each variety j, i.e., $\frac{\partial T_j}{\partial t} < 0$. As shown in Figure B1, when t rises to $t^{''}$, the relative unit production cost of the foreign firm and home firm increases from T_j to $T_j^{''}$. As a result, the scope of varieties outsourced by the home firm expands from $[j_1, 1]$ to $[j_1^{''}, 1]$, while the range of locally processed varieties drops from $[0, j_0]$ to $[0, j_0^{''}]$. Both of these two forces decrease the home firm's total output of intermediate products, which leads to a reduction in emissions of the home firm. Correspondingly, the emissions of the foreign firm increase because it now processes more intermediate products and outsources fewer intermediate products. This result is consistent with the Pollution Havens Hypothesis, which states that stricter environmental regulations will promote the outward transfer of pollution emissions. If the Carbon Border

[25] They proved that the composition effect dominates the scale effect and technology effect.

[26] Again, note that the condition here for emission reduction is only about the productivity heterogeneity within a firm, so we do not require a firm to be more efficient at producing dirty products than other firms.

[27] As a contrast, when $\frac{\partial A_j / A_j^*}{\partial j} \equiv 0$, there is no heterogeneity in product-specific productivity and we can prove that only one of inequalities $\mathbb{L} < \mathbb{M}$ and $\mathbb{M} < \mathbb{R}$ can hold, which must lead to the outcome of Pollution Haven.

Adjustment Mechanism (CBAM) of the European Union (EU) raises the emission-related cost of an exporting economy, our model predicts that there will be an increase in the EU's local emissions.

The changes in emission in the exporting economy and the EU are

$$-gy^* \int_{j_0'}^{j_0} \frac{h_j}{A_j} dj - gy \int_{j_1'}^{j_1} \frac{h_j}{A_j} dj$$

and

$$gy^* \int_{j_0'}^{j_0} \frac{h_j^*}{A_j^*} dj + gy \int_{j_1'}^{j_1} \frac{h_j^*}{A_j^*} dj$$

where the variables associated with the EU are denoted with the superscript $*$. The global change in emissions is equal to the sum of the last two lines. Clearly, whether global emissions increase or not depends on the productivities (A_j and A_j^*) and factor costs (h_j and h_j^*). There is no guarantee that a policy such as the CBAM will reduce global emissions.

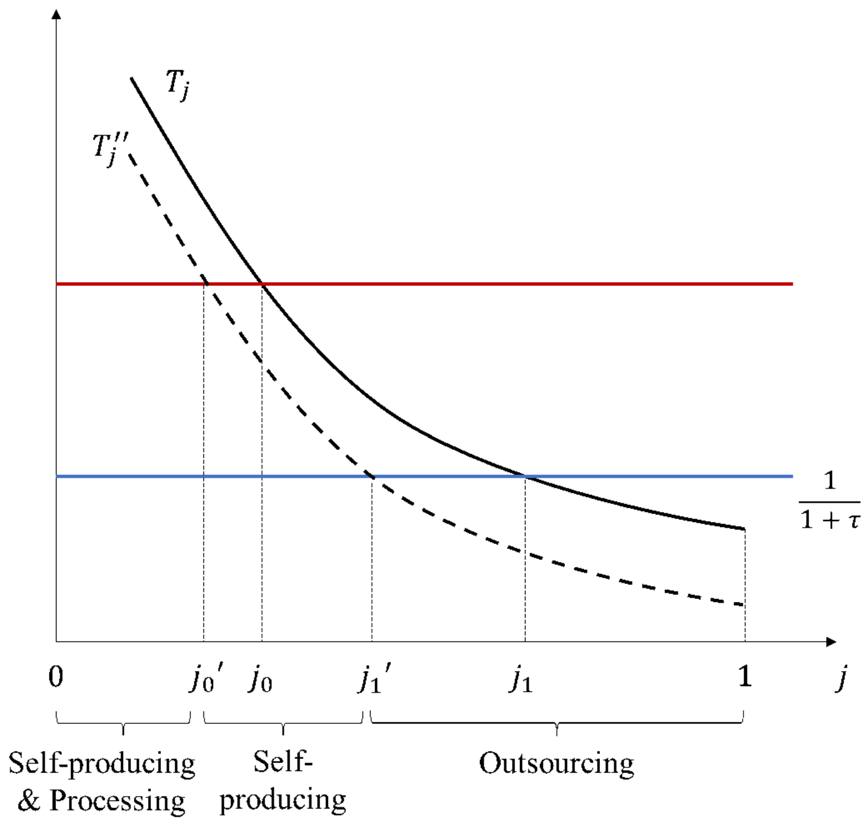

Figure B1: Effects of An Increase in Emission Tax in the Home City

C Additional Tables

Table C1: Explanatory Power of Market Access

Variables	P_{25}	P_{75}	P_{75}-P_{25}	β	Change explained
			A. Emission level		
$ln(MA)$	15.074	15.738	0.664	-2.746	56.24%
$ln(SO_2)$	7.743	10.985	3.242		
			B. Emission intensity		
$ln(MA)$	15.052	15.688	0.636	-3.014	51.67%
$ln(SO_2\ intensity)$	-2.157	1.553	3.710		

Note: The explanatory power statistic in the last column is calculated as (10) and (11). p_{25} and p_{75} represent the 25th and 75th centiles of the corresponding variables in the first column. The estimates of β in Panel A and Panel B are from Columns (1) and (4) in Table 3.

Table C2: Market Access Associated with High Speed Railway (2SLS)

Dependent Variable:	$ln(SO_2)$	
	(1)	(2)
$ln(MA)$	-2.733***	
	(0.934)	
$ln(MAHSR)$	-0.001	-0.002
	(0.004)	(0.004)
Dependent Variable's Mean	8.603	9.164
Expected Market Access	Yes	Yes
envir. regulation	Yes	Yes
$W_c \times \eta_t$	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
K-P rk LM statistic	52.454	66.398
K-P rk Wald F statistic	225.42	13970
Observations	337,882	114,248

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] The variable $ln(MAHSR)$ is a market access index that is constructed based on high-speed railway network. [3] Column (1) uses full sample as in the benchmark regression, while Column (2) only includes observations since 2008, which was the first time high-speed rail was opened in China. [4] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.

Table C3: Robustness Checks: Alternative Parameters of MA (2SLS)

Dependent Variable:	$ln(SO_2)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(MA)$	-2.746***						
	(0.927)						
$ln(MA)\_t2$		-2.559***					
		(0.858)					
$ln(MA)\_t3$			-1.937***				
			(0.598)				
$ln(MA)\_t4$				-1.982***			
				(0.638)			
$ln(MA)\_s2$					-7.164***		
					(2.513)		
$ln(MA)\_s3$						-1.848***	
						(0.578)	
$ln(MA)\_ppi$							-3.390***
							(1.170)
Dependent Variable's Mean	8.603	8.603	8.603	8.603	8.603	8.603	8.603
Expected Market Access	Yes	Yes	Yes	Yes	Yes	Yes	Yes
envir. regulation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W_c \times \eta_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	52.356	52.215	44.009	49.871	53.058	45.999	51.691
K-P rk Wald F statistic	457.72	480.89	251.03	474.14	290.04	313.15	324.30
Observations	337,882	337,882	337,882	337,882	337,882	337,882	337,882

Note: [1] The dependent variable is the log of sulfur dioxide emission level. [2] The variable $ln(MA)$ is the log of baseline market access index. The independent variables in Columns (2)-(6) are logs of market access constructed with alternative parameters of the price elasticity of trade, θ, and the parameter governing the concavity of shipping cost to railway distance, σ. These variables include $ln(MA)\_t2(\sigma = 0.8; \theta = 4.1)$, $ln(MA)\_t3(\sigma = 0.8; \theta = 8.3)$, $ln(MA)\_t4(\sigma = 0.8; \theta = 6)$, $ln(MA)\_s2(\sigma = 0.6; \theta = 3.8)$, and $ln(MA)\_s3(\sigma = 1; \theta = 3.8)$. [3] The variable $ln(MA)\_ppi$ has the same parameter values as $ln(MA)$ but replace nominal freight rate with freight price after PPI adjustment. [4] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the city level and shown in parenthesis.