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

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Can Trade Integration Reduce Emissions from Production? The Product Composition Channel*

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Abstract

In a trade model incorporating within-firm productivity differences in intermediate products, we show that specialization in the production of intermediate products enabled by decreased trade costs can reduce firm-level emissions. Using firm-level data from China (1998-2012), we provide supporting evidence in the context of domestic trade. Increased domestic trade integration, associated with the expansion of China's railway network, reduces emissions of sulfur dioxide, carbon dioxide, and other pollutants. Counterfactual analysis indicates that without the 1.88% (1,203-kilometer) railway expansion in 2005—the year in the middle of our sample period, as an example—national SO_2 emissions would have been 0.43% higher.

JEL classification: Q5, F1, R4
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1 Introduction

Concerned individuals and economists are interested in the environmental consequences of economic activities, including those related to trade. One key area of debate is whether policies——such as the Carbon Border Adjustment Mechanism adopted by the European Union——should be used to alter trade flows based on emissions of the underlying products. Economic theory suggests that 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 for 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". Industry-level empirical tests of the pollution haven hypothesis (PHH) have yielded mixed results in general (Antweiler et al., 2001; Cole and Elliott, 2003; Levinson, 2009). More recently, firm-level studies suggest three reasons why 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, whether and how trade-induced within-firm adjustments affect pollution remains largely unexplored.

In this paper, we propose that within-firm product composition is a channel through which trade can reduce emissions in production.[1] In the stylized model we develop, to satisfy local demand for a non-tradable final good, firms in each of the two locations produce the final product from intermediate products using Leontief technology. They can

[1]Because our empirical work focuses on emissions, an important form of pollution, we will use the term 'emission' in the remainder of the paper to maintain consistency in the discussion, even though our theory applies to pollution in general.

produce intermediate products by combining an emission-intensive input (dirty input) and an emission-light input (clean input), or purchase it from firms in the other location. Crucially, there exist productivity differences in the production of intermediate products both within firms and across locations. A firm will choose to source intermediate products externally if purchased intermediate products are cheaper than those produced in-house. As is typical in Ricardian models, when trade costs drop, multi-product firms concentrate their production on intermediate products in which they have a greater productivity advantage.

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

Second, the within-firm productivity gap between discontinued and retained products must be sufficiently large. This large difference in productivity ensures that for a firm, the reduction in emissions associated with outsourcing the least efficient intermediate products outweighs the increase in emissions from processing the most efficient intermediate products for firms in other locations. In contrast to the pollution haven hypothesis, our model suggests that when both conditions are satisfied in both locations, emissions can drop in both locations.

Using detailed firm-level data from China, we test the theory in the context of domestic trade. Following the approach of 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 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 the instrumental variables for the actual MA index in two-stage least-squares (2SLS) regressions.

We obtain three main empirical results. First, an increase in MA leads to significant reduction in firm-level emissions of sulfur dioxide (SO_2), carbon dioxide (CO_2), dust, and chemical oxygen demand (COD). Most of the drop in emissions can be attributed to a decrease in emission intensity. In terms of explanatory power, after controlling for firm fixed effects, year fixed effects, and city characteristics, 46.92% and 39.10% 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 decrease following an increase in MA. We carry out a simple counterfactual calculation and find that 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——national emissions of SO_2 would have been 0.43% higher that year.

Second, consistent with our model, an increase in MA prompts firms to drop intermediate products with low productivity and increase the output of remaining intermediate products. Such a reduction in product scope is accompanied by a reduction in emissions, which supports the mechanism of emission reduction in our theory.

Third, we find no evidence that firm-level emissions rise in cities with lax environmental regulations or ample local coal supplies, providing no support for the PHH. Our results remain robust when accounting for other emission-related or infrastructure-related policies, such as the four-trillion yuan stimulus in 2009 and trade liberalization associated with China's admission to the World Trade Organization (WTO) in 2001.

The current study proposes that trade-induced adjustments in within-firm product composition could reduce overall emissions from firms, thus enriching the literature on trade and pollution.[2] Existing studies largely focus on two types of adjustments: industry-level and firm-level. Examining industry-level adjustments in production, a large branch of literature yields mixed evidence on the PHH (Antweiler et al., 2001; Cole and Elliott, 2003; Levinson, 2009; Managi et al., 2009; Brunel, 2017).[3] The relationship between trade and the environment varies with the pollutants studied and the countries examined.[4] A second branch of literature, which emphasizes heterogeneity in firm-level adjustments to trade-often in the spirit of Melitz (2003)-offers additional insights about the complex relationship between trade and pollution. Trade can reduce emissions by reallocating production towards firms with high productivity (Martin, 2012; Kreickemeier and Richter, 2014; Holladay, 2016),[5] by inducing firms to invest in abatement technology or adopt cleaner technologies (Cui et al., 2016; Shapiro and Walker, 2018; Forslid et al., 2018; Gutiérrez and Teshima, 2018),[6], and by enabling firms to import dirty inputs (Cherniwchan et al., 2017; Cherniwchan, 2017). Relative to these studies that examine industry-level and firm-level adjustments, we focus on within-firm adjustments in product composition.

We are particularly related to Cherniwchan et al. (2017) and Barrows and Ollivier

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

[3]Levinson (2009) finds that the composition effect explained only 12 percent of the decline in pollution in the US manufacturing sector from 1987 to 2001, and trade liberalization accounted for only 4 percent of this compositional change. In Antweiler et al. (2001) and Cole and Elliott (2003), the trade-driven composition effect is even found to increase pollution in rich countries with stringent environmental policies and decrease it in poor countries with weaker environmental policies.

[4]For example, Cole and Elliott (2003) use cross-country data and find that trade increases the emissions of nitrogen oxides and carbon dioxide, but reduces the chemical oxygen demand. Frankel and Rose (2005) find that, after addressing endogeneity issues, trade can reduce countries' sulfur dioxide emissions. Bombardini and Li (2020) find that increased exposure to trade results in increased levels of Chinese sulfur dioxide pollution in regions with a comparative advantage in the polluting manufacturing industry.

[5]Only productive firms can survive and further export (selection effect), and exporting firms expand in scale relative to domestic firms due to increased external demand and fiercer import competition (reallocation effect). These effects will lead to a decrease in industry-level emissions if efficient firms are also cleaner.

[6]This channel is consistent with Bustos (2011), who find that exporters are more likely to adopt new technologies. However, according to Cherniwchan et al. (2017), it could be offset by reduced incentives for abatement investment in shrinking non-exporting firms. Rodrigue et al. (2022) quantify the impact of endogenous export and abatement decisions and find the latter has a much smaller impact on firm-level emissions.

(2018). Our production setup follows Cherniwchan et al. (2017) in that firms can source intermediate products or produce them in-house. However, in our model, a firm's product scope and trade pattern are determined by location-specific productivity, as standard in the Ricardian framework, whereas in Cherniwchan et al. (2017), the trade pattern is driven by heterogeneity in firm-level productivity along the lines of Melitz (2003). Our focus on product composition is similar to Barrows and Ollivier (2018), who investigate the role of product mix in determining firm-level emission intensity. When facing more competition, a firm's product scope shrinks to its "core competency" in their model; hence, emissions will decrease only if the core products are cleaner. In comparison, the reduction in emissions in our model is driven by specialization according to productivity advantage, and does not depend on the cleanliness of the firm's core product.

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). Relative to this branch of literature that examines emissions generated during transportation, we focus on how transportation infrastructure can reduce emissions at production sites.[7]

The rest of this paper proceeds as follows. In section 2, we develop the model to explain the role of within-firm difference in the productivity in the production of intermediate inputs. We then present the empirical design and data description in section 3, and report the empirical results regarding the effects of market access on emission in section 4. In section 5, we conclude the paper.

[7]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.

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. Each city demands one unit of 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). The relative productivity A_j/A_j^* varies across products, which is a crucial and new 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 outside 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 outside 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. Combining 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 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 outside city dominates the trade cost. By symmetry, the representative firm in the outside city source product j from the home city if $T_j > 1 + \tau$.

In the trading equilibrium, outsourcing by the home firm creates external demand for the firm in the outside city to produce intermediate products, and vice versa. The trade cost τ affects the range of intermediate products subject to trade 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. *Firms in the city where the relative price of emission-intensive input is cheaper (more expensive, respectively) also have higher productivity in producing intermediate products using the input more (less, respectively) intensively. Without loss of generality, let the foreign 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 with j and there is a monotone 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. 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.[8]

Because Assumption 1 implies that T_j is decreasing 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 outside city. The production pattern for the firm in the outside 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. [9]

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.

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:

[8] Assumption 1 can be generalized by allowing $\frac{\partial}{\partial j}(\frac{A_j}{A_j^*}) = 0$ for some j, meaning that A_j/A_j^* is weakly monotonically decreasing.

[9] 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 outside city.

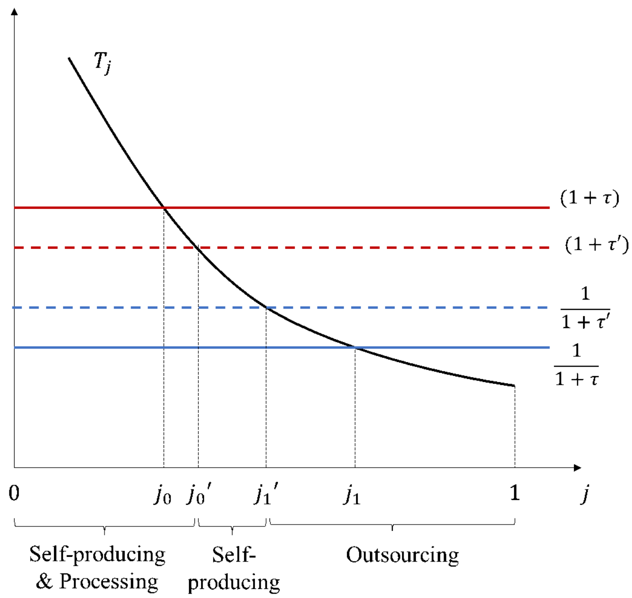

Figure 1: Effects of Trade Costs on the Production Pattern of the Home Firm

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 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[10] of the 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:

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

[10]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.

By symmetry, the total intermediate output and average output of intermediate products in the outside 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 location 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:

Because the 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. The home firm's total emission 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 home firm (z) with respect to trade cost τ is:

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

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

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

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 location that hosts more production of emission-intensive goods. Whether emission rises or drop, depends on whether firms in the location hold sufficient productivity advantage over firms in other locations. 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, both the home firm and foreign firm 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.

In the context of the model, an emission-based policy can be represented by a change in t, the emission tax. When t is increased in one location, say due to the implementation of the Carbon Border Adjustment Mechanism, the model predicts that the production of some products (and the associated emissions) will relocate to the other location. However, the direction of change in global emissions is ambiguous. A more detailed discussion can be found in 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:

$$ln(SO2_{ict}) = \beta_0 + \beta_1 \cdot ln(MA_{ct}) + \beta_2 \cdot X_{ct} + \beta_3 \cdot Z_{ict} + \psi_i + \omega_t + \mu_{ict} \tag{7}$$

where $SO2_{ict}$ is the kilograms of sulfur dioxide emitted by firm i in city c in year t. We choose Sulfur dioxide 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 kilograms 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 (MA) 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. The vector X_{ct} contains other city-level variables. Our theory suggested that location-specific price of dirty input and emission cost associated with regulation are important for choice of production location. Because there is no data on coal price at city or province level, we include in the regression the province-level production of coal (in log, denoted as *lncoal*) which it is likely to be negatively correlated with local price of coal.

We construct the measure of city-level emission regulation by following the method of Chen et al. (2018) which exploits the pollution-reduction targets set by the 11th 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 11th 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. city-level SO_2 emission and emission intensity obtained from the *China City Statistical Yearbook*. 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 emission in 2006.[11] This variable is denoted as *envir. regulation* in the regression tables.

To capture the effects of other city-specific factors beyond the fixed effects, we include in all regressions the following variables: highway density measured as kilometers of

[11]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.

highway per square kilometer (denoted as *road density*),[12] log of GDP (denoted as *lngdp*), log of GDP per capita (denoted as *lngdppc*), and applications for invention patents related to environmental protection (denoted as *envir. patents*).

The vector of firm-level control variables, Z_{ict}, include measures of firm size (log of output value, denoted *firm size*), firm age (log of years since establishment, denoted *firm age*), ownership type (an indicator variable for state-owned enterprises obtained from the dataset, denoted *SOE*) and capital intensity (fixed assets per worker, denoted *firm lnkl*). The variables ψ_i, ω_t, and μ_{ict} represent firm fixed effects, year fixed effects, and the error term, respectively.

3.2 Construction of the Market Access Index

Using data from the *China Railway Yearbook*, Chinese Research Data Services Platform (CNRDS), and *China City Statistical Yearbook*, we construct a market access index based on connectivity to freight railway for 291 cities in China from 1998 to 2016 by applying the method of Donaldson and Hornbeck (2016). The cities have different administrative ranks: four are municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing), fifteen hold the rank of vice-provincial cities, and the rest 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 market access. 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 market access in China.

The national railway network vector maps we use are constructed by Gao and Tang

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

(2024). In Gao and Tang (2024), the authors draw annual vector maps of railway network for freight transportation from 1998 to 2021. Using geographic information software (ArcGIS), the printed maps from the *China Railway Yearbook* published by Ministry of Railways of China or China State Railway Group Co., Ltd. are digitalized. The authors then locate railway stations on the digital maps by using geographic coordinates published by the CNRDS in 2016. Subsequently, city-level cities are matched to the railway station (if present) in the city that is the closet to the city administrative center. The shortest route between each pair of cities is obtained by applying the algorithm of Dijkstra et al. (1959) to the railway network vector maps.[13] For details about the construction of the maps, please see the Appendix section of Gao and Tang (2024).

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

$$MA_{jt} = \sum_{j' \neq j} \tau_{jj',t}^{-\theta} Y_{j',t} \tag{8}$$

where j and t are the indices of city and time, respectively. In the formula, we use $Y_{j',t}$, the GDP of destination city j', 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

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

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 $d_{jj',t}$ is the shortest railway distance between two

[13] The benchmark railway network does not include high-speed railway lines, as their presence was minimal in the the sample period of 1998 to 2012. For robustness checks, we also make annual maps of high-speed railways network and construct market access index based on high-speed railways.

cities calculated based on Dijkstra et al. (1959). ρ is a parameter that captures the concave relationship between shipping cost and railway distance, which is set to 0.8 (Baum-Snow et al., 2016).

3.3 Firm-level Data

Firm-level information in our sample 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 who collectively account for 85% of emissions of key pollutants in their respective counties. Thus, the CESD provides high-quality and comprehensive information on emission of large industrial firms in China. The merged data is an unbalanced panel of 305,459 firm-year observations, and the sample period is 1998-2012.[14] 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 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

[14] 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).

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.

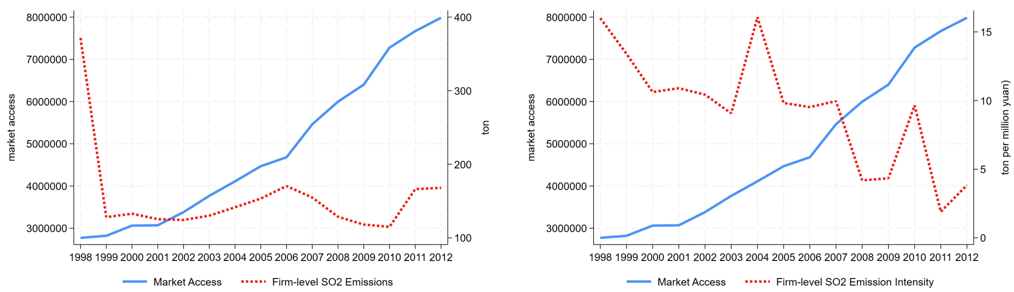

Figure 2: Trends in Market Access and the Mean of Firm-level SO_2 Emissions
Source: authors' calculations.

We plot the prefecture-level emissions, emission intensity, and MA in Figure 3. Note that the availability of emission data determines that the time series starts in 2003. The left panel shows that the total emissions at the prefecture level initially rose during the economic boom between 2003 and 2005, before experiencing fluctuations in subsequent years. The right panel shows that as MA rises, there is a sustained reduction in emission intensity.

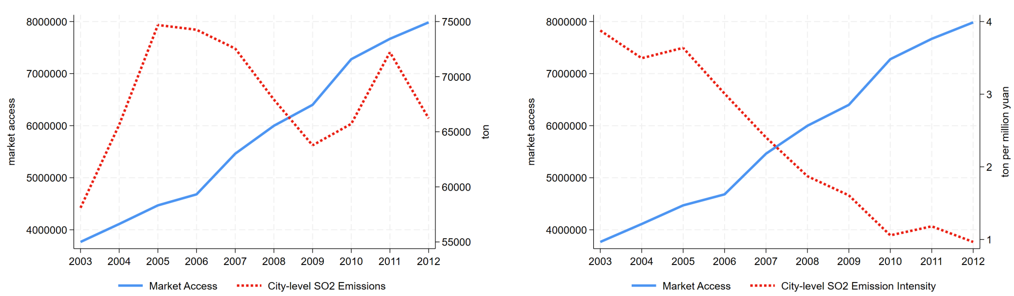

Figure 3: Trends in Market Access and the Mean of Prefecture-level SO_2 Emissions
Source: authors' calculations.

Figure 4 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 5. 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.

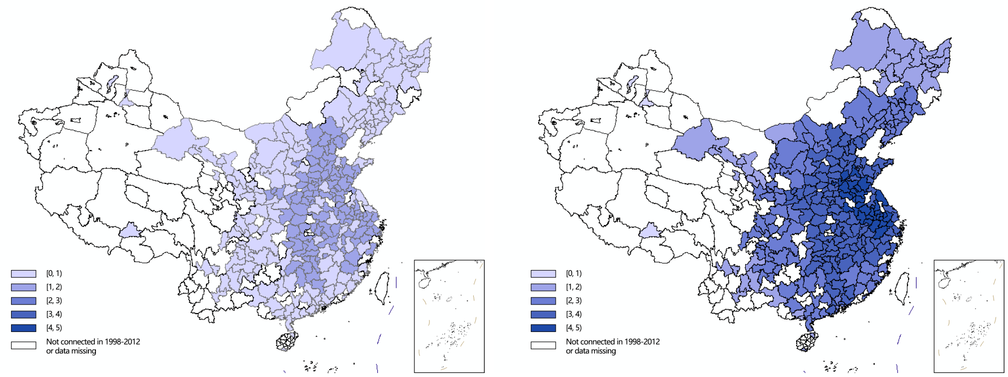

Figure 4: The Spatial Distribution of MA in 1998 and 2012

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.

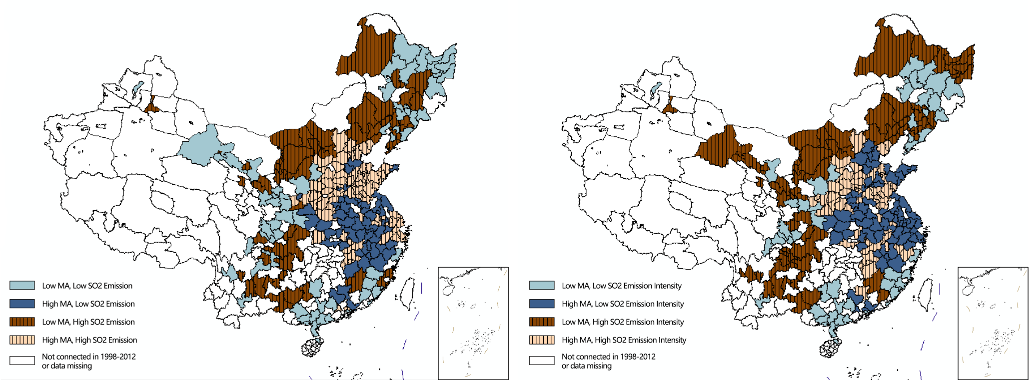

Figure 5: The Spatial Distribution of MA and SO_2 Emissions in 2012

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.

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 market access and SO_2 emission at the firm level. A 1% change in market access is associated with 2.062% decrease in SO_2 emission, which significant in both statistical and practical sense. When we add city-level controls and firm-level controls in Column (2), the estimate remains statistically significant. In the third column, we replace year fixed effects with industry-year fixed effects to account for potential effect 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 market access are -1.721 and -2.251 which are similar to Column (1).

The bin scatter plots in Figure 6 demonstrates visually the correlation between residualized emission and MA in the panel that give rise to the estimates in the OLS regression. 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.[15]

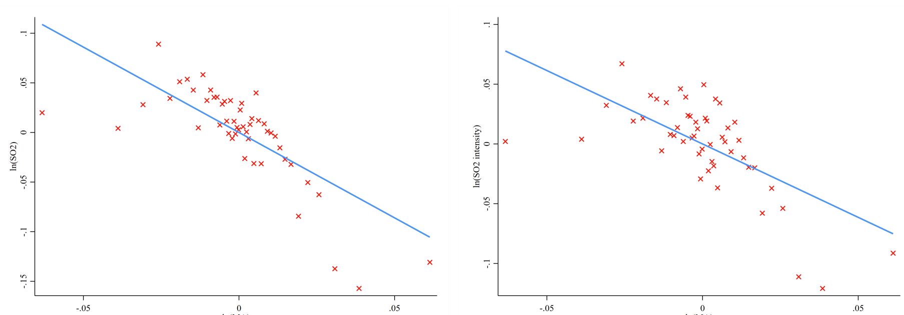

Figure 6: Scatter Plot of Market Access and Firm-level SO_2 Emissions
Source: authors' calculations.

[15] There are 50 bins the scatter plots.

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. As discussed in the literature on trade and pollution (Grossman and Krueger 1993; Copeland and Taylor 1995, etc.), the relationship between emissions and economic activities is complex and non-monotonic because the scale effect, composition effect, and technique effect of trade work in different directions. On the other hand, it is known that the Chinese government has purposely used railway lines as 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 issues, we use the instrumental variable (IV) method to identify exogenous variation in railway construction and the corresponding exogenous change in market access. Our strategy is to construct 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.[16]

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

[16]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.

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 7 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 market access measures and use them as the IVs for the actual market access index.

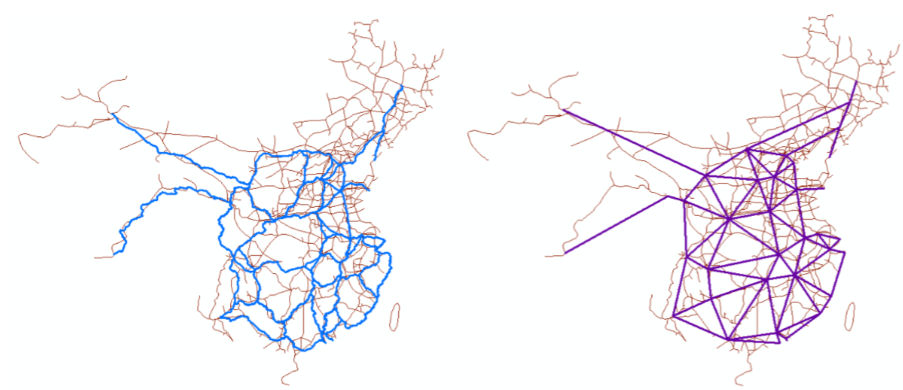

Figure 7: Artificial Transportation Networks Predicted by Exogenous Factors
Source: authors' calculations. Note: The blue network in the left panel and the purple network in the right panel are the artificial transportation newtorks.

The IV regression results in Table 3 confirm the findings from the OLS regressions, and the estimated effect of market access is slightly larger than the OLS estimate in Column (2) 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 market access is estimated to lower SO_2 emissions by 2.412%, 1.873%, and 2.339%, respectively. In Column (4), we use the SO_2 emission intensity as dependent variable and employ the first IV in estimation. Because the coefficient on market access

(-1.781) in Column (4) is equal to 0.74 times the coefficient (-2.412) in Column (1) where total emission is the dependent variable, the decrease in emissions is largely explained by the drop in emission intensity. In Columns (5) and (6), we repeat the IV regressions with the second IV and both IVs, respectively. The results are similar.

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. 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 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 market access is estimated to reduce the emission of dust by 2.774% and the emission intensity by 1.818%. The estimated effects of MA on emission of COD are also negative and significant, while in the gas 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 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 market access reduces the emission of CO_2 by 2.710% and the emission intensity by 1.465%. Therefore, market access 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:

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

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 market access 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 market access difference between the 25th and 75th centiles. Based on results in Columns (1) and (4) of Table 3, we obtain that $\Delta SO2\ explained = 46.92\%$ and $\Delta SO2\ intensity\ explained = 30.10\%$. Details about the calculation can be found in Table C1 in Appendix C. Therefore, after controlling for firm-level and city-level factors, market access 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 total emission of cities, 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 0.954% and the emission intensity drops by 0.946% 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.[17] The estimated coefficient on market access is

[17]The SO_2 concentration data comes from the NASA satellite M2TMNXAER V5.12.4 and are

also negative and significant. Note that because the unit of dependent variable in the third column (microgram of SO_2 per cubic meter) is not the same as the second column (tons of SO_2 per 10,000 yuan of GDP), sizes of the two coefficients are not comparable. Nevertheless, the marginal effects in all three columns are practically large relative to means of the respective dependent variables. Overall, improvement in market access is associated with both reduction of emission at firm level and general reduction in emission at the city level.

Based on the regression results, we carry out a counterfactual analysis to obtain a simple quantification of the aggregate effect of MA improvement. The analysis is based on the 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.[18] 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:

$$\sum_c \sum_i \hat{MA}_{c,2005} \cdot (-2.412) \cdot SO2_{ic,2005}$$

where -2.412 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 would have been 108,825 tons higher. The difference is equivalent to 0.43% of China's

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 indicator at the city level.

[18]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.

total emission of SO_2 in 2005, which was 25.49 million tons.[19]

4.3 Further Analysis: Conditions and Mechanism for Emission Reduction

After establishing the emission-reducing effects of market access in the previous two subsections, we now present evidence in support of Assumption 1 and the mechanism of emission reduction outlined in Proposition 1 and Proposition 2. Assumption 1, which posits a positive correlation between the cost advantage of the dirty input and the productivity advantage over intermediate products using the dirty input intensively, is crucial for our theoretical prediction about emission reduction. To verify whether the assumption is supported by evidence, we run the following regression

$$\begin{aligned} TFP_{jct} =& \gamma_0 + \gamma_1 \cdot coal\ per\ capita_{pt} + \gamma_2 \cdot emission\ intensity_{jct} \\ &+ \gamma_3 \cdot coal\ per\ capita_{pt} \cdot emission\ intensity_{jct} + \theta_{jc} + \theta_t + \nu_{jct} \end{aligned}$$

where TFP_{jct} is the productivity of product j in city c in year t, $coal\ per\ capita_{pt}$ the log of tons of coal production per capita in province p (in which city c is located) in year t, and $emission\ intensity_{jct}$ the emission intensity of product j in city c in year t.

To run 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 1.83, with a maximum

[19] Alternatively, we can use the prefecture-level data to compute the counterfactual aggregate difference in SO_2 emissions calculated as $\sum_c \widehat{MA_{c,2005}} \cdot (-0.954) \cdot SO2_{c,2005}$, where -0.954 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 0.43% 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.

of 6.

In the firm level data available to us, 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 compute the mean of 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. Subsequently, we use the city-product-year level 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 computed 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.

After verifying the viability 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 market access. Because values of product scope are positive integers, in Column (1) of Table 7, we use a two-step IV-Poisson procedure to estimate the effects of market access on product scope. To be specific, following Angrist (2001), in the first stage we regress $ln(MA)$ on the artificial $ln(MA)$ and obtain the predicted values which are then used in the Poisson regression the second stage. In the second stage, the standard errors are obtained from bootstrapping to correct for the bias in the variance-covariance estimator caused by the generated regressor. The results indicate that market access significantly lowers the product scope. Because the mean of product scope is 1.83, the coefficient of -0.215 is large in practical sense too. When we regress output per product at the firm-level on market access in Column (2), we find that market access significantly increases the average product.[20] Thus, both predictions in Proposition 1-namely the reduction in product scope and increase in output of remaining products following an increase in market access-are supported by the data.

As our sample is reduced to 122,314 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 7, the effects of market access on emission and emission intensity remain negative and significant, and the coefficients of -3.298 and -2.957 are larger in magnitude than the benchmark 2SLS results of -2.412 and -1.781 in Columns (1) and (4) of Table 3, respectively.

Second, we examine the key emission-reducing mechanism outlined in Proposition 2 that an increase in market access induces firms to specialize in products with high productivity. To verify whether this mechanism is present in the data, we introduce product-level TFP and interaction between TFP and market access in regressions in Table 8. In the first column of Table 8, 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 market access 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 market access improves. The second column employs output per product as the dependent variable. The results there indicate that as market access improves, output per product increases and the increase is larger for high-productivity products. Therefore, the results provide evidence for the mechanism for emission reduction in Proposition 2, namely firms specialize in high-productivity products after an improvement in market access.

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

[20] Because the quantities of products vary in their units, we use a standardized measure of average 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 output measure is calculated as $(x_{jict} - \mu_{jt})/\sigma_{jt}$

two columns of Table 9, we regress emission and emission intensity on product scope, using the counterfactual market access as the instrumental variable.[21] Clearly, product scope is positively related with emission and emission intensity.

In completing the third step, we test the threshold result in Proposition 2 that above a threshold, a large dispersion in within-firm productivity is necessary for trade-induced reduction in product scope to cause reduction in total emission. To do so, we include in the regression an indicator for firms which report a reduction in product scope between period $t-1$ and t (denoted $\mathbb{1}(\textit{scope reduction})$), an indicator for large within-firm productivity dispersion in period $t-1$ (denoted $\mathbb{1}(\textit{productivity dispersion})$), and their interaction term. Because the theory focuses on the gap between productivity of the product produced by the home firm and productivity of the product outsourced, we measure the within-firm productivity dispersion as the log ratio of the highest productivity among products of a firm and the lowest productivity. To search for the threshold for large productivity dispersion, we follow the procedure of Hansen (2000). To be specific, we set the threshold to each of the integer centiles of the log productivity difference, and run regressions iteratively. Judging by the R^2 in the threshold regressions, the most likely threshold value identified by the procedure corresponds the 66th centile. In the 2SLS regression of emission and emission intensity, as reported in Columns (3) to (4) or Table 9, the coefficients on the interaction terms between the indicator of product scope reduction and the indicator of large productivity dispersion are both negative and significant. Therefore, for firms exhibiting large within-firm productivity dispersion, discontinuing products with inferior productivity leads to a reduction in emissions.

Based on the test of mechanisms in three steps, reported in Table 7 through Table 9, the empirical evidence supports the premise of the theory that an increase in market access reduces emission by inducing firms to specialize in high-productivity products in their product range.

[21] In the first stage, we perform a Poisson regression of product scope on the log of counterfactural MA.

4.4 Testing the Pollution Haven Hypothesis

In our framework, if the productivity difference between the products kept and discontinued by a firm following an increase in market access is small, the PHH effect may be present. Intuitively, if the reduction in emissions associated with the change in product composition is smaller than the increase in emissions associated with market expansion, then total emissions can go up in one or more locations. In this case, our model suggests that locations with lower emission costs or a lower price for the dirty input attract production of products that use the dirty input more intensively. In China, there exists substantial variation in environmental regulation and coal endowment, the biggest source of primary energy in China. When market access improves, these two factors can lead to the reallocation of the production of dirty products and a rise in emissions, as suggested by the PHH.

While an index of city-level environmental regulation and province-level production of coal are included in all previous regressions as control variables, we now interact them with market access to test the PHH. In all regressions in Table 10, the interaction terms are always insignificant. Therefore, there is no evidence that following an increase in market access, locations with lax environmental regulation or access to cheap coal experience an increase in firm-level emissions.

4.5 Robustness Results

In this subsection, we show the results remain robust when we control for other policy changes, include market access 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 11. 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 do not find evidence that abatement equipment has an independent effect on emissions.[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 spending and real estate in 2009 which might have led to 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 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). In all columns, the coefficients on market access 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 market access 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 market access

[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 market access. The coefficients are highly insignificant, indicating that an increase in market access does not cause firms to increase installment of abatement equipment.

[23]These cities are known as "double-control areas".

variable and include only the market access 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 market access indices. We report the regressions with alternative market access indices in Table C3 in Appendix C. The estimated effects of all alternative measures of market access on emission are always negative and significant. Overall, the large number of checks in this subsection provide strong evidence of the robustness of the results.

5 Conclusion

To study the effects of trade on emissions, we develop a Ricardian model of trade and emission that incorporates productivity differences in the production of intermediate products. As trade costs decrease, the market for intermediate products becomes more integrated, and firms further specialize in intermediate products in which they have a cost advantage. We show that firm-level emission levels can drop with this specialization. This possibility arises when trade reallocates within-firm production to intermediate products in which they have higher productivity and when the within-firm productivity dispersion is large. In contrast with the pollution haven hypothesis, in our model, when firms in both cities discontinue production of low-productivity intermediates to concentrate on those in which they enjoy a superior productivity advantage, it is possible for emissions to drop everywhere.

In our empirical work, we examine the effects of market integration, associated with the expansion of China's railway network, on emissions in a large sample of Chinese manufacturing firms from 1998 to 2012. To address the endogeneity issues of market access, our measure of market integration, we use the potential market access predicted by geographic and historical variables as an instrumental variable. Based on two-stage

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

least-squares regressions, we find that an increase in domestic trade integration reduces the emission level and intensity of sulfur dioxide, carbon dioxide, dust, and chemical oxygen demand at the firm-level. In terms of explanatory power, after controlling for firm fixed effects, year fixed effects, and city characteristics, 46.92% and 39.10% of interquartile range of firm-level SO_2 emissions and emission intensity can be explained by the interquartile range of MA. At the city level, we also find that trade integration reduces both the level and intensity of emissions of sulfur dioxide. We use the data from 2005 as an example to carry out a counterfactual analysis and find that if there had been no expansion of the railway network in that year, national emissions of sulfur dioxide would have been 0.43% higher.

Consistent with the predictions of our model, domestic trade integration induces firms to specialize according to productivity advantage. Namely, they discontinue low-productivity products and increase output per product of the remaining products. We show this change in product composition is responsible for the observed reduction in emission. Meanwhile, after an increase in trade integration, there is no evidence that emission rises in cities with lax environmental regulation or with abundant local supply of coal. Therefore, we find no evidence of pollution haven.

The product composition channel of emission reduction that we propose also applies to international trade. Because an empirical evaluation of the product composition effect in international trade is beyond the scope of the current study, we defer it to future work.

Declaration of generative AI and AI-assisted 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.
SO_2 emissions	ton	305459	148.75	0.00	2180000.00	4121.99
SO_2 emission intensity	ton per million yuan	297252	9.15	0.00	45690.00	182.85
market access (MA) index	\	3342	4957648.30	1456604.80	12175258.00	2171515.60
ln(MA)	\	3342	15.33	14.19	16.32	0.42
ln(MA)_geocost	\	3342	15.09	14.09	16.07	0.38
ln(MA)_straight	\	3342	15.31	14.24	16.29	0.40
environmental regulation	\	3342	0.49	0.00	13.30	1.16
raw coal output	million ton	425	76.03	0.00	1061.94	138.84
highway density	km per km2	425	0.63	0.02	2.39	0.47
GDP	billion yuan	3342	97.85	1.61	2018.17	158.60
GDP per capita	yuan per capita	3342	22716.87	1349.46	450280.25	30642.94
green patent applications	count	3342	92.67	0	8232	368.35
total output	billion yuan	305459	316.92	0.01	192674.44	1947.97
age	year	305459	14.69	1	64	12.81
state-owned enterprises (SOE)	binary	305459	0.11	0	1	0.32
capital intensity (K/L)	thousand yuan per capita	305459	209.86	0.00	1989131.10	5522.29
product scope	number of varieties	122314	1.83	1	6	1.20
average output index	\	232373	0.01	-0.21	18.17	1.02

Note: ln(MA)_geocost is the log of counterfactural MA that is constructed by the artifitial transportation network connected by the least costly paths, and ln(MA)_straight is the log of counterfactural MA that is constructed by the artifitial transportation network connected by straight lines. Environmental regulation is an index of city's emission regulation as described in Section 3. Product scope measured by the number of product varieties. 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)
$ln(MA)$	-2.062***	-1.721**	-2.251***
	(0.774)	(0.731)	(0.744)
envir. regulation		-0.005	-0.015
		(0.013)	(0.014)
lncoal		0.029	0.041
		(0.033)	(0.033)
road density		-0.032	0.058
		(0.158)	(0.152)
lngdp		-1.393***	-1.340***
		(0.498)	(0.464)
lngdppc		0.615	0.609
		(0.423)	(0.398)
envir. patents		-0.017	-0.021
		(0.041)	(0.036)
$firm\ size$		0.220***	0.216***
		(0.015)	(0.014)
$firm\ age$		0.090***	0.071***
		(0.019)	(0.018)
SOE		0.182***	0.151***
		(0.055)	(0.051)
$firm\ lnkl$		-0.015	-0.011
		(0.010)	(0.010)
Dependent Variable's Mean	8.624	8.624	8.624
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No
Industry-year fixed effects	No	No	Yes
Observations	305,459	305,459	305,459
Adjusted R^2	0.788	0.789	0.794

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable is the log of sulfur dioxide emission level. $ln(MA)$ is the log of market access index. *envi regulation* is an index of city's emission regulation as described in Section 3, *lncoal* is the log of province-level production of coal, *roaddensity* is province-level highway density measured by highway length per area, *lngdp* is the log of city's GDP and *lngdppc* is the log of GDP per capita, *envir.patents* represents the number of patent applications related to environmental protection within each city. $firmsize$ is the firm size measured by the log of output value, $firmage$ is the firm age measured by the log of one plus years since establishment, SOE is an indicator variable for state-owned enterprises, $firmlnkl$ is the firm's capital intensity measured by the log of fixed assets per worker.

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)
$ln(MA)$	-2.412***	-1.873**	-2.339***	-1.781**	-1.415*	-1.732**
	(0.798)	(0.810)	(0.789)	(0.755)	(0.781)	(0.747)
envir. regulation	-0.005	-0.005	-0.005	0.001	0.001	0.001
	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
lncoal	0.028	0.029	0.028	0.048	0.049	0.048
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)
Dependent Variable's Mean	8.624	8.624	8.624	-1.075	-1.075	-1.075
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	305,459	305,459	305,459	297,252	297,252	297,252
	Panel B. First stage					
Dependent Variable:	$ln(MA)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$IV1$	0.766***		0.665***	0.767***		0.666***
	(0.035)		(0.082)	(0.034)		(0.083)
$IV2$		0.898***	0.136		0.900***	0.136
		(0.052)	(0.102)		(0.051)	(0.102)
Dependent Variable's Mean	15.410	15.410	15.410	15.402	15.402	15.402
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	47.383	51.099	51.152	47.387	51.421	51.534
K-P rk Wald F statistic	486.07	301.94	252.83	496.06	306.87	258.78
Hansen J statistic	\	\	2.431	\	\	1.082
Observations	305,459	305,459	305,459	297,252	297,252	297,252

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) 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. *envi regulation* is an index of city's emission regulation as described in Section 3, *lncoal* is the log of province-level production of coal.
3) The dependent variable in Panel B is the market access (MA) index. $IV1$ 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.

Table 4: Market Access and Emission of Other Pollutants

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)
$ln(MA)$	-2.774***	-1.818**	-4.340***	-3.620***	-2.122	-1.381	-2.710***	-1.465*
	(0.912)	(0.909)	(1.414)	(1.367)	(1.358)	(1.285)	(0.783)	(0.870)
Dependent Variable's Mean	7.316	-2.202	6.370	-3.363	15.328	5.717	5.533	-3.841
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	49.428	50.008	39.847	39.846	44.002	44.076	60.330	60.291
K-P rk Wald F statistic	507.63	511.19	438.00	449.03	496.92	505.07	539.66	535.87
Observations	250,983	244,992	319,191	310,614	281,515	274,150	170,412	169,191

Note: 1) *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variables in odd columns are the logs of emission level of dust, chemical oxygen demand (COD), gas, and carbon dioxide, respectively. The dependent variables in even columns are the logs of emission intensity of pollutants corresponding to the odd columns.

Table 5: Market Access and City-level Emissions

Dependent Variables:	$ln(SO_2)$	$ln(SO_2\ intensity)$	$ln(SO_2\ density)$
	(1)	(2)	(3)
$ln(MA)$	-0.954**	-0.946**	-0.246**
	(0.470)	(0.473)	(0.115)
Dependent Variable's Mean	10.719	-4.272	2.731
Year fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes
K-P rk LM statistic	62.475	62.501	59.400
K-P rk Wald F statistic	822.89	826.10	749.73
Observations	2,371	2,370	3,344

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) 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.

Table 6: Test of Assumption 1

Dependent Variable:	*productivity*	
	(1)	(2)
coal per capita	0.026***	0.024***
	(0.005)	(0.004)
coal per capita × *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) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the provincial level and shown in parenthesis.
2) The dependent variable is the product-level productivity as described in Section 4.3. *coal_person* is the log of raw coal output per capita at the provincial level. *intensity_p* 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.

Table 7: Market Access and Specialization

Dependent Variables:	Product scope	Output/product	$ln(SO_2)$	$ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)
$ln(MA)$	-0.215***	0.563***	-3.298***	-2.957***
	(0.054)	(0.209)	(0.972)	(0.944)
Dependent Variable's Mean	1.830	0.010	9.202	-0.576
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Product fixed effects	No	Yes	No	No
Time-varying firm controls	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes
K-P rk LM statistic	/	39.209	46.576	47.262
K-P rk Wald F statistic	/	552.55	548.61	553.14
Wald statistic	178.56	/	/	/
Observations	122,314	232,373	122,314	119,730

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable in Column (1) is firm's product scope measured by 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. 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) The coefficients in the first column are estimated by a two-step IV-Poisson procedure that reports Wald statistic in the first stage as product scope is a positive integer. The coefficients in Columns (2)-(4) are estimated by the 2SLS method that reports K-P rk LM statistic and K-P rk Wald F statistic.

Table 8: Specialization in Efficient Products

Dependent Variables:	Product exit	Output/product	$ln(SO_2)$	$ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)
$ln(MA)$	0.219	0.650*	-3.118***	-2.265**
	(0.141)	(0.364)	(1.051)	(1.030)
$ln(MA) \times productivity$	-0.031**	0.181**		
	(0.015)	(0.074)		
productivity	-0.010**	0.016		
	(0.005)	(0.018)		
Dependent Variable's Mean	0.075	0.063	8.150	-1.894
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Product fixed effects	Yes	Yes	No	No
Time-varying firm controls	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes
K-P rk LM statistic	43.375	43.046	31.928	32.040
K-P rk Wald F statistic	214.16	223.87	271.33	280.87
Observations	87,589	102,224	55,933	54,901

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) 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.
3) *productivity* is product-level productivity. A firm's productivity on a certain product is measured by the mean of TFP of all firms in sample in the same city that produce this product only. $ln(MA)\times$ *productivity* is the interation term between $ln(MA)$ and *productivity*.
4) Columns (3) and (4) perform the benchmark regressions in Table 3 by using sample of firms that can be continuously observed throughout the sample period.

Table 9: Product Scope, Productivity Dispersion and SO_2 Emissions

Dependent Variables:	$ln(SO_2)$	$ln(SO_2$ $intensity)$	$\Delta ln(SO_2)$	$\Delta ln(SO_2$ $intensity)$
	(1)	(2)	(3)	(4)
product scope	15.344***	13.464**		
	(4.124)	(5.948)		
$\mathbb{1}(scope\ reduction)$			3.363*	4.860**
			(2.02)	(2.476)
$\mathbb{1}(scope\ reduction) \times \mathbb{1}(productivity\ dispersion)$			-3.096*	-4.487**
			(1.852)	(2.271)
Dependent Variable's Mean	9.202	-0.576	-0.06	-0.154
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes
Wald statistic	111.67	284.22	\	\
K-P rk LM statistic	\	\	20.59	20.56
K-P rk Wald F statistic	\	\	10.26	10.25
Observations	122314	119730	16228	15,897

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variables in Column (1) and (2) are firm's emission level and emission intensity of sulfur dioxide. The dependent variables in Column (3) and (4) are changes in firm's emission level and emission intensity from period $t-1$ to t.
3) *product scope* is firm's product scope measured by the number of product varieties. $\mathbb{1}(scope\ reduction)$ is an indicator for firms which report a reduction in product scope between period $t-1$ and t. In the interaction term $\mathbb{1}(scope\ reduction) \times \mathbb{1}(productivity\ dispersion)$, $\mathbb{1}(productivity\ dispersion)$ is an indicator for firms with large within-firm productivity dispersion in period $t-1$. productivity dispersion is measured as the log ratio of the highest productivity among products of a firm and the lowest productivity. The optimal threshold of productivity dispersion, as indicated by $R2$, is the 66th centile.
4) All regressions are estimated by the 2SLS method. The first stages of Columns (1) and (2) are Poisson regressions that report Wald statistic. Columns (3) and (4) follow standard 2SLS procedure that reports K-P rk LM statistic and K-P rk Wald F statistic.

Table 10: Testing the Pollution Heaven Hypothesis

Dependent Variable:		$ln(SO_2)$	
	(1)	(2)	(3)
$ln(MA)$	-2.222***	-2.558***	-2.322***
	(0.790)	(0.832)	(0.815)
$ln(MA) \times envir.\ regulation$	-0.037		-0.050
	(0.053)		(0.055)
envir. regulation	0.003	-0.011	-0.001
	(0.014)	(0.016)	(0.015)
$ln(MA) \times lncoal$		-0.026	-0.030
		(0.029)	(0.030)
lncoal	0.029	0.034	0.036
	(0.033)	(0.036)	(0.036)
Dependent Variable's Mean	8.624	8.624	8.624
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes
K-P rk LM statistic	60.789	52.651	63.448
K-P rk Wald F statistic	237.00	262.21	169.53
Observations	305,459	305,459	305,459

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable is the log of sulfur dioxide emission level. *envir.regulation* is an index of city's emission regulation as described in Section 3, *lncoal* is the log of province-level production of coal. $ln(MA) \times envir.regulation$ and $ln(MA) \times lncoal$ are the interaction term between $ln(MA)$ and *envir.regulation* and that between $ln(MA)$ and *lncoal*, respectively.

Table 11: Robustness Checks

Dependent Variable:	$ln(SO_2)$				
	(1)	(2)	(3)	(4)	(5)
$ln(MA)$	-2.830***	-2.244***	-2.739***	-2.423***	-2.406***
	(0.828)	(0.848)	(1.018)	(0.805)	(0.807)
$facility\ per\ worker$	0.005				
	(0.005)				
Dependent Variable's Mean	8.559	8.459	8.988	8.624	8.624
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes	Yes
double-control × year dummies	No	No	No	Yes	No
Tariff reductions × year dummies	No	No	No	No	Yes
K-P rk LM statistic	50.42	51.892	68.47	46.579	47.370
K-P rk Wald F statistic	469.26	544.66	261.67	430.94	488.49
Observations	249839	218008	213385	305459	305,452

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable is the log of sulfur dioxide emission level. $facility\ per\ worker$ in Column (1) is the number of emission abatement equipment per worker. Column (2) excludes observations from 2009. 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.

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:

$$z = g((1+\tau)y^*\int_0^{j_0}\frac{h_j}{A_j}dj + y\int_0^{j_1}\frac{h_j}{A_j}dj). \tag{10}$$

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

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

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

$$\frac{\partial j_1}{\partial\tau}\frac{yh_{j_1}}{A_{j_1}} + y^*\int_0^{j_0}\frac{h_j}{A_j}dj > -\frac{\partial j_0}{\partial\tau}\frac{y^*h_{j_0}}{A_{j_0}}. \tag{11}$$

As in the condition (5) in Section 2, the first item on the left side of inequality (11) 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:

$$\frac{-y^* \frac{\partial j_0}{\partial \tau}}{y \frac{\partial j_1}{\partial \tau}} < \frac{\tilde{A_{j_0}}}{\tilde{A_{j_1}}}. \tag{12}$$

Similarly, we can write the condition as in (12) for the foreign firm, that is:

$$\frac{y \frac{\partial j_1}{\partial \tau}}{-y^* \frac{\partial j_0}{\partial \tau}} < \frac{\tilde{A^*_{j_1}}}{\tilde{A^*_{j_0}}}. \tag{13}$$

Combining (6) and (13), we obtain the condition for both firms to reduce emissions after the drop in trade costs:

$$\underbrace{\frac{\tilde{A_{j_1}}}{\tilde{A_{j_0}}}}_{\mathbb{L}} < \underbrace{\frac{y \frac{\partial j_1}{\partial \tau}}{-y^* \frac{\partial j_0}{\partial \tau}}}_{\mathbb{M}} < \underbrace{\frac{\tilde{A^*_{j_1}}}{\tilde{A^*_{j_0}}}}_{\mathbb{R}}. \tag{14}$$

The part $\mathbb{M}$ in (14) 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

[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.

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 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.

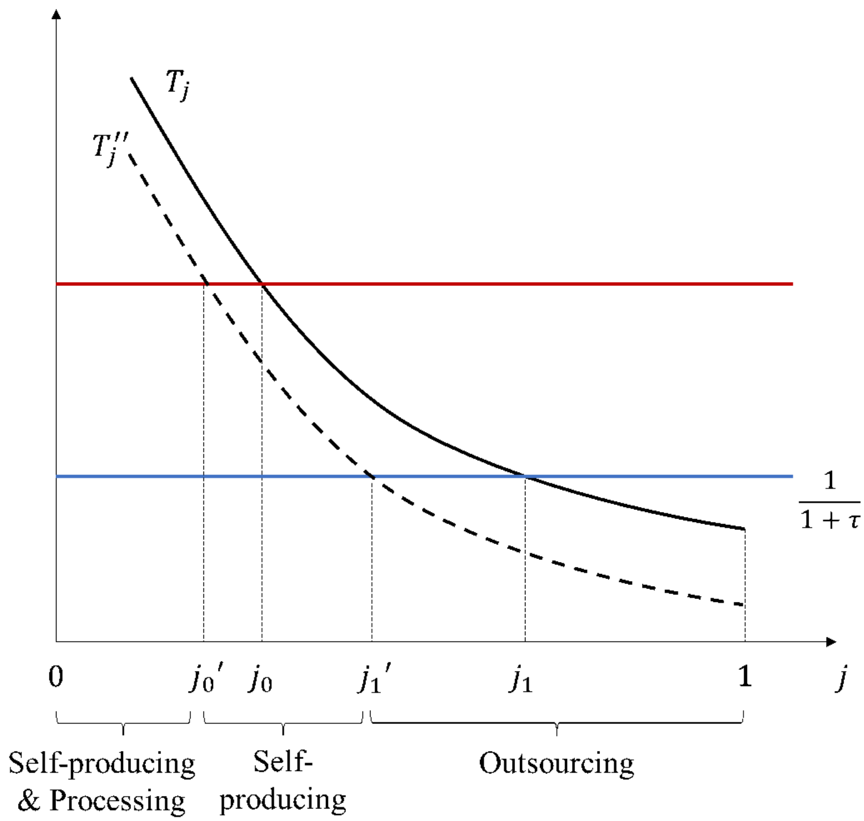

Figure B1: Effects of An Increase in Emission Tax in the Home City

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		
$ln(MA)$	15.087	15.714	0.627	-2.412	46.92%
$ln(SO_2)$	7.784	11.007	3.223		
			B. Emission intensity		
$ln(MA)$	15.078	15.700	0.622	-1.781	30.10%
$ln(SO_2\ intensity)$	-2.169	1.511	3.680		

Note: The explanatory power statistic in the last column is calculated as explained in subsection 4.1. 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

Dependent Variable:	$ln(SO_2)$	
	(1)	(2)
$ln(MA)$	-2.385***	
	(0.796)	
$ln(MAHSR)$	-0.001	-0.002
	(0.004)	(0.004)
Dependent Variable's Mean	8.624	9.155
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Time-varying firm controls	Yes	Yes
Time-varying city controls	Yes	Yes
Time-varying province controls	Yes	Yes
K-P rk LM statistic	49.580	46.032
K-P rk Wald F statistic	231.86	11505
Observations	305,459	98,528

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable is the log of sulfur dioxide emission level. $ln(MAHSR)$ is a market access index that is constructed based on high-speed railway network. 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.

Table C3: Robustness Checks: Alternative Parameters of MA

Dependent Variable:				$ln(SO_2)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(MA)$	-2.412***						
	(0.798)						
$ln(MA)\_t2$		-2.227***					
		(0.733)					
$ln(MA)\_t3$			-1.515***				
			(0.466)				
$ln(MA)\_t4$				-1.636***			
				(0.520)			
$ln(MA)\_s2$					-6.747***		
					(2.304)		
$ln(MA)\_s3$						-1.470***	
						(0.458)	
$ln(MA)\_ppi$							-3.087***
							(1.051)
Dependent Variable's Mean	8.624	8.624	8.624	8.624	8.624	8.624	8.624
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying city controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying province controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P rk LM statistic	47.383	47.149	40.035	44.707	49.047	42.490	49.191
K-P rk Wald F statistic	486.07	526.89	308.03	599.60	266.12	411.13	283.18
Observations	305,459	305,459	305,459	305,459	305,459	305,459	305,459

Note: 1) *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at the city level and shown in parenthesis.
2) The dependent variable is the log of sulfur dioxide emission level. $ln(MA)$ 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 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 $ln(MA)\_s3(\sigma = 1; \theta = 3.8)$. $ln(MA)\_ppi$ has the same parameter values as $ln(MA)$ but replace nominal freight rate with freight price after PPI adjustment.