ABSTRACT

Title of Dissertation: ESSAYS ON INTERNATIONAL TRADE AND THE ENVIRONMENT
Heehyun Rosa Lim
Doctor of Philosophy, 2022

Dissertation Directed by: Professor Nuno Limão
Professor Eunhee Lee
Department of Economics

This dissertation examines the relationship between international trade and environmental outcomes. In particular, I study the impact of international trade on airborne pollutants, including the change in emissions and concentration as well as their welfare consequences.

In the first chapter, I suggest the intermediate import channel as a new perspective to understand the linkage between international trade and air pollutant emissions. I first review the existing literature's understanding of the impact of trade on emissions. The review shows that the literature mostly focuses on the increased market access but overlooks the increased access to imported inputs. Using the data on the US manufacturing industries, I then document a few stylized facts that are suggestive of the linkage between intermediate imports, input usage, and emissions. I show that in the US, the import penetration among inputs used has increased while the energy intensity of US manufacturing has declined, the latter of which explains a third of the within-industry reduction in NO_x emission intensity. To analyze the channels by which trade in intermediate inputs affects emission intensity, I build a model of heterogeneous

firms, intermediate trade, and inputs with different emission profiles. By focusing primarily on the emissions linked with input usage, my model examines the effect of improved access to foreign intermediates on firms' input choices and emission outcomes. The model shows that with lower intermediate import costs, firms become less energy-intensive by either increasing their intermediate intensity, using energy-saving technology, or both. Moreover, the general equilibrium force, as well as amplification through the input-output linkage, bring a further decrease in emission intensity in all firms. The model also presents the selection and reallocation effect which further amplifies the within-firm improvements.

In the second chapter, I run empirical and quantitative analyses to test the theoretical model from the first chapter against the US manufacturing data. In the empirical analysis, I estimate the model prediction, which states that industry-level emission intensity can be expressed in the producer price index when the cost of energy and market access are controlled, using the industry-level panel data between 1998 and 2014. By using the import price of intermediates as an instrumental variable for the producer price index, I find evidence that a lower producer price, driven by a lower intermediate import price, leads to lower NO_x emission intensity. The reduced-form evidence supports the model mechanism that states that a lower import price of intermediates decreases emission intensity. I then calibrate the model to 1998 aggregate US manufacturing and quantify the change in emission intensity driven by the change in intermediate import cost. The quantification shows that the fall in intermediate import cost between 1998 and 2014 explains about 8-10% of the observed technique effect in NO_x emissions. 68% of the decrease comes from the within-firm changes via firms' substituting away from energy inputs, global sourcing, and adopting energy-saving technology, which highlights the importance of taking within-firm channels into account to understand the effects of trade policies on emissions.

The third chapter (co-authored) re-examines the welfare gains from international trade by incorporating the transboundary nature of air pollutants.[1] We run country-level panel regressions and find that concentration is correlated with transboundary pollution, constructed as the weighted sum of other countries' emissions. We then build a general equilibrium model of international trade and environmental externality from local pollutants of transboundary nature, in which the concentration of a country is affected by both its own and other countries' emissions. The model shows that the change in welfare can be decomposed into the change in real income and the change in air pollutant concentration, the latter of which can further be decomposed into that driven by own emissions and by other countries' emissions. We use this model to quantify the welfare implications of two trade shocks – China shock and the EU 2004 enlargement. The results show multiple channels that shape heterogeneous welfare consequences across countries. First, liberalizing countries experience an increase in emissions due to an increase in production. Second, the emissions of other countries move in either direction, depending on the effects of pollution relocation and increased production due to cheaper inputs. Third, the levels of concentration increase in liberalized countries and some other countries due to the increase in own emissions or transboundary pollution, or both. We run additional counterfactual exercises with stricter environmental regulations imposed on liberalized countries and show that there can be welfare gains in many countries by lowering emissions and transboundary pollution, suggesting the potential effects of combining trade and environmental policies.

[1] This chapter is from a joint work with Eunhee Lee.

ESSAYS ON INTERNATIONAL TRADE AND THE ENVIRONMENT

by

Heehyun Rosa Lim

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2022

Advisory Committee:
Professor Nuno Limão, Co-Chair
Professor Eunhee Lee, Co-Chair
Professor Maureen Cropper
Professor Thomas Drechsel
Professor Joshua Linn

Acknowledgments

I am extremely grateful to Nuno Limão and Eunhee Lee for their invaluable guidance and continuous support throughout all stages of my Ph.D. study. They have been immensely and patiently supportive, which helped me stay strong despite daily stress and struggles.

I would also like to thank Maureen Cropper for her encouragement throughout the program and insights on the research, and I am thankful to Thomas Drechsel and Joshua Linn for sharing comments and serving on the dissertation committee. I thank Guido Kuersteiner, John Shea, Luminita Stevens, and Pierre De Leo for their comments and discussions on the project.

I benefited much from comments and discussions from the Brown Bag Seminar at the University of Maryland. I am especially grateful to participants at UMD Trade Group for providing helpful comments and encouragement. I also would like to thank Frank (Shihangyin) Zhang for being an amazing colleague and discussion partner. And I very much appreciate my dear friends, Rachel Liu and John Soriano, who have always shared unconditional support and endless fun throughout the entire time.

Finally, I would like to express my gratitude to my parents, Haenghwan Lim and Kyungsook Kim, and my brother, Taewook Lim, and Kang-e for their tremendous love. Last but never the least, from the bottom of my heart, I would like to say a big thank you and love you to Hyunseok An who has always been there with me, no matter what.

Table of Contents

List of Tables

List of Figures

Chapter 1: A theory of intermediate trade and emissions

1.1 Introduction

Between 1990 and 2017, US manufacturing nitrogen oxides (NO_x) emissions decreased by 62%. Likewise, other pollutant emissions declined significantly during this period.[1] As emissions cause multiple types of damage, these declines are significant. For example, NO_x is a major contributor to the formation of acid rain, along with sulfur dioxide (SO_2). It also damages the human respiratory system, potentially leading to premature death or other health costs (Dockery et al., 1993).[2]

It is widely documented that the change in emissions is driven by within-industry reduction in emissions per unit of output, henceforth emission intensity (Levinson, 2009, 2015; Shapiro and Walker, 2018). The literature suggests international trade as one explanation, along with changes in regulation stringency and technological development in the country. In particular, a key mechanism in the literature is how increased market access generates within-industry effect via two channels. First, increased market access increases profits and, thus, induces firms to adopt emission-intensity reducing technology (Batrakova and Davies, 2012; Forslid et al., 2018). Second, selection and reallocation effects shift market share to cleaner and more productive firms

[1] For instance, sulfur dioxide (SO_2) decreased by 84%, and particulate matters and fine particulate matters (PM_{10} and $PM_{2.5}$) by 81% and 77%.

[2] In addition, NO_X is a major precursor of particulate matter, of which the health effects are documented in Chay and Greenstone (2003).

(Forslid et al., 2018; Kreickemeier and Richter, 2014; Shapiro and Walker, 2018).

The focus on market access overlooks another important feature of the development of international trade – increased access to imported inputs. Consideration of input usage in production is crucial as inputs have different emission profiles. For example, 60% of NO_x emissions are generated from burning fuel. When the costs of various imports change, so change their relative prices and the input usage decisions of firms. In turn, firms' emission intensity changes as well.

Using the US manufacturing data, I show a few stylized facts that suggest the linkage between intermediate trade and emission. The data shows that US manufacturing industries have been increasingly importing their intermediate inputs. At the same time, they have been decreasing their reliance on energy inputs compared to intermediate inputs. The second trend also indicates that the US manufacturing has been becoming cleaner, as energy is the input with highest emissions. Indeed, the decomposition of the change in emission intensity shows that between 1998 and 2014, a third of within-industry reduction in NO_x emission intensity can be explained by the fall in energy usage. These findings are suggestive of the potential role of firms' substituting energy inputs with intermediates on the observed clean-up among the US manufacturing.

To study the role of trade on within-industry effect by affecting firms' input choices, I present a quantitative model that incorporates intermediate trade, inputs with various emission profiles, and energy-efficiency technology adoption. The model demonstrates the mechanism that drives both within-firm and across-firm forces affecting the aggregate emission intensity. Firms have heterogeneous productivity and produce output using three types of inputs: labor, energy, and manufactures. Energy generates emissions; thus, emission intensity is directly linked to energy intensity. Manufacturing inputs are traded, and firms use domestic manufacturing inputs and can also choose to use foreign ones by paying fixed costs. Additionally, firms may pay a fixed cost to adopt energy efficiency technology. Since firms' decisions regarding sourcing and technology adoption change the relative input costs they face, their energy intensity, and thus emission intensity, changes in response to these decisions.

The novelty of this model is that it provides a channel through which trade directly affects firms' emission intensity, i.e., by lowering the price of cleaner inputs and, thus, changing input mix. In contrast, in a setting without intermediate factors in production, trade affects firms' emission intensity by inducing technology adoption (Batrakova and Davies, 2012; Forslid et al., 2018) or indirectly via general equilibrium forces (Shapiro and Walker, 2018). My model shows that lower intermediate import costs decrease aggregate emission intensity through within-firm reduction of energy intensity, and through across-firm improvements including selection and reallocation effects.

The rest of the chapter proceeds as follows. First, I review the existing related literature in Section 1.2. Then I present the stylized facts on US manufacturing input usage and emissions in Section 1.3, which motivate this research. I develop a quantitative model of intermediate trade and emissions in Section 1.4 and present model results in Section 1.5. I conclude in Section 1.6 by summarizing the findings and future extensions.

1.2 Literature Review

This project is related to several strands of literature. First, this project builds on a large body of literature on trade and the environment. Much of the literature follows Copeland and Taylor (2003) and assumes that emissions are generated as byproduct of production (Forslid et al., 2018; Shapiro and Walker, 2018). While this provides a simpler structure and tractability, the degree of emission intensity across firms or industries heavily depends on the pollution elasticity, on which little research has been conducted.[3] In contrast, this project explicitly links emissions with energy usage, allowing us to understand the heterogeneity in emission intensity in relation to the heterogeneity in energy intensity, which is easily observed from the data. Moreover, by linking emissions to a specific input, my model can capture the effect of shocks that affect inputs in multiple ways, one of which is the focus of this study: the import liberalization of non-energy inputs.

In addition, this project builds on the model of trade-induced technology upgrading (Bustos, 2011). A few studies adopt and apply this idea in the context of environmental technology adoption (Batrakova and Davies, 2012; Cui et al., 2016; Forslid et al., 2018). They show that exporters are cleaner than non-exporters because exporters have more profitable incentives from installing technology and cutting the marginal costs of production. In this setting, increased market access is what brings about the upgrade in technology. My work contributes to this body of literature by suggesting an additional channel of trade-induced technology adoption: improved access to foreign inputs.

A few papers investigate the underlying drivers of the decline in US manufacturing emissions (Levinson, 2009, 2015; Shapiro and Walker, 2018). The closest work to this project is Shapiro and Walker (2018), which uses a quantitative model of trade and environment, combining Melitz (2003) and Copeland and Taylor (2003) to decompose the change in emissions between 1990 and 2008 into the effect of regulation and the effect of the change in US and foreign "competitiveness." Their US competitiveness shock captures the change in US productivity and exporting trade

[3] Shapiro and Walker (2018) recently estimated the pollution elasticity using the US manufacturing data.

costs, while foreign competitiveness shock captures the change in foreign productivity, foreign exporting trade costs, and foreign regulation stringency. For all six pollutants in their study, the change in foreign competitiveness does little to explain the change in total emissions, which they interpret as evidence that trade has little to do with emissions reductions. My project is distinct from and complements their work in two ways. First, it isolates the shock in trade costs in contrast to using the change in competitiveness, which combines the change in productivity, regulation, and trade costs. By explicitly using the change in trade costs as a shock, I identify the impact of trade without other concurrent forces combined. Second, I introduce an aspect of trade that is omitted in their analysis: enhanced access to foreign inputs. Their findings show that the change in US competitiveness explains about half of the observed change in emissions, but they fail to link this with trade. My model illustrates a mechanism in which trade in intermediates affects US competitiveness – as lower cost of using foreign inputs brings production cost advantage and higher effective productivity – and quantifies this impact on emissions.

Lastly, I build on the existing studies that explore the impact of imports on emissions. A few empirical works explore the role of input tariffs on emissions. Cherniwchan (2017), for example, finds that firm-level total emissions and emission intensity decreased in response to the change in input tariffs after NAFTA. Martin (2011) shows that the reductions in intermediate input tariffs decreased firms' fuel intensity in India. The closest to this project is Akerman et al. (2021), which use Swedish firm-level data to show that the increase in intermediate imports brings a decrease in energy and CO2 emission intensity. Using mediation analysis, they show that the improvement in firm TFP is the main channel (so-called "productivity-enhancing effect") as opposed to the offshoring of pollution-intensive activities or the change in product mix.

My project makes a few contributions relative to Akerman et al. (2021). First of all, this project suggests more concrete and specific ways by which firms' effective productivity (in terms of emission) can improve: by substituting energy with intermediate inputs or adopting energy-saving technology. Indeed, the latter is isomorphic to adopting TFP-enhancing technology in my model setting. Second, this project discusses not only those firms that participate in trade but also those firms that do not use foreign intermediates. These domestically-sourcing firms are also affected by the change in input import cost from the general equilibrium force in which all input costs, including domestic intermediate input cost, adjust. Thus, the project captures a broader picture of the impact on firm- and aggregate-level emission intensity.

1.3 Stylized facts

This section introduces a set of stylized facts regarding US manufacturing. They motivate the focus of this project: intermediate trade, the usage of energy and non-energy inputs, and the adoption of emission-reducing technologies.

Fact 1. *The import penetration in manufacturing intermediates has been rising, and it is highly correlated with the rising ratio of intermediates to energy usage.*

Figure 1.1 shows two key summary statistics. One is the foreign share in manufacturing inputs used by the US manufacturing industries on the left axis. I use the US Bureau of Economic Analysis (BEA)'s Supply-Use Table (SUT) and Import Matrix (IM) dataset to calculate the share. Specifically, I aggregate the industry-level usage of inputs to the US aggregate and divide the total expenditures on foreign manufacturing inputs by the total expenditures on manufacturing inputs. The share of foreign inputs increased from 17% in 1997 to 23.5% in 2017.

It is also notable that although the long-run trend is increasing, there were short-run variations during the period. There were two notable events in international trade: China's WTO accession in 2002 and the Great Trade Collapse (GTC) in 2008, which are marked by a dotted line. After China's accession, the increasing trend accelerated until import penetration dropped during the GTC. The share, however, picked up again after one year and has continued until the end of the data set.

The other is the ratio of non-energy intermediate usage to energy input usage, as shown in a dashed line. The ratio is the relative expenditures on non-energy intermediates to energy inputs used by US manufacturing. I deflate the expenditures on intermediates and energy inputs to obtain the real expenditures, which are intended to capture the input quantities used. I use the expenditures and deflators from the NBER-CES Manufacturing Database, which provides such information at NAICS-6 level.[4] The graph shows that the ratio has increased by nearly 60% during this period.[5] The correlation between the two is 0.83. In the Appendix, I also present the first-difference regression showing that the change in the ratio of intermediate to energy is positively correlated with the change in import penetration even after the yearly trend and industry (NAICS 6-digit) characteristics are controlled.[6]

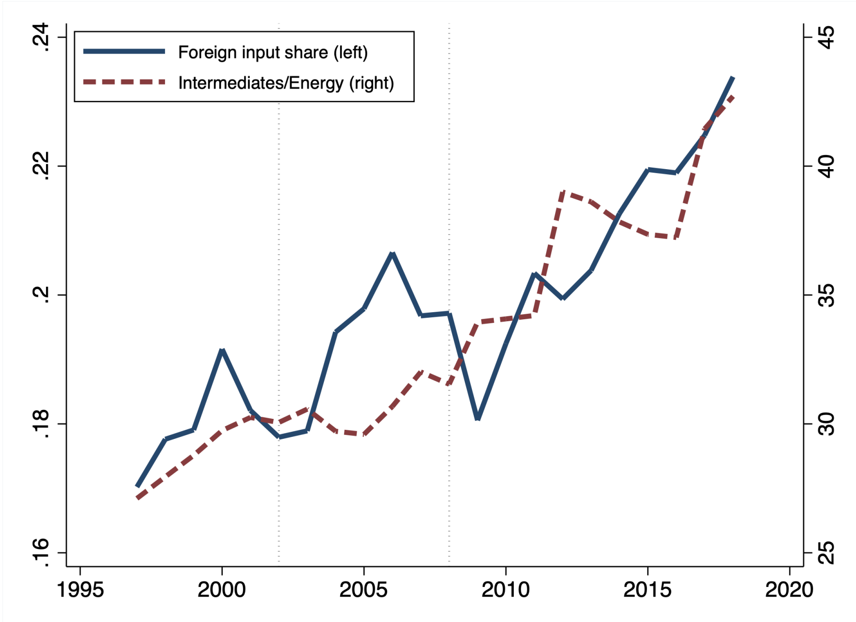
While the graph and regression results are silent on the causal linkage, they provide suggestive evidence of the linkage between the two. For example, with increased access to cheaper foreign

[4] NBER-CES database provides the total expenditures on materials and energy inputs. The former includes the latter, so I obtain the expenditures on non-energy intermediates by subtracting energy inputs from the materials. Also, the database has price indices specific to materials and energy expenditures, so I can calculate the price index for non-energy intermediates and use it to deflate the expenditures on non-energy intermediates.

[5] During the same period (1997-2017), the ratio of the real expenditures on non-energy intermediates to the employment of production workers almost doubled, which indicates that non-energy intermediate inputs not only substituted energy but also labor as well. However, when I look at the ratio of the real expenditures on non-energy intermediates to the real expenditures on production workers' pay (i.e., total wage bill to production workers), the ratio decreased by 28%. But this does not necessarily contradict the previous result. I use the price deflator for the value of shipment to deflate the wage bill, so this finding can result from the increase in wage level being larger than the increase in the produced goods. Note that there is no separate price deflator for a wage from the NBER-CES.

[6] See Table A.1.

Figure 1.1: Foreign share in intermediate expenditures



Note: The left is the ratio of the expenditures on imported manufacturing inputs to the total expenditures on manufacturing inputs. The right is the ratio of non-energy intermediates to energy input in real expenditures. *Source*: Author's calculation from using BEA Supply-Use Table, BEA Import Matrix, and NBER-CES Manufacturing Database.

intermediate inputs, followed by higher import penetration, firms incline toward using more intermediates and less energy.[7] This project investigates the possibility and role of this channel in the observed reduction in emissions.

Fact 2. *The decrease in energy consumption per unit output in the US manufacturing explains a third of the observed decline in emission intensity.*

Over 60% of NO_x emissions are generated from fuel combustion.[8] To see the relative importance of this part of the emissions in the observed change in aggregate emission intensity, I

[7]The rise in import penetration among manufacturing inputs can be driven by different factors, such as cheaper foreign prices, or reduced trade barriers and uncertainties. If the import penetration increases due to the fall in the US intermediates' productivity or the rise in their prices for other reason, however, the price of an intermediate bundle would not necessarily decrease.

[8]According to the NEI, 60% of NO_x emission was from fuel combustion in 2014. The share was 71% in 2002. Other emission sources include but are not limited to industrial processes, processing materials, and transportation within facilities.

decompose the change in emission intensity into the change in energy-related emission intensity and the change in other components. First, I re-write the total amount of emissions as the multiplication of total energy usage and the average emission generated from unit energy usage. The amount of emission from unit usage of energy can again be decomposed into the original emissions generated from energy usage (henceforth, emission factor) and the share of residuals after abatement.

$$\begin{aligned}\text{Emission} &= \text{Energy} \times \frac{\text{Emission}}{\text{Energy}} \\ &= \text{Energy} \times \text{Emission factor} \times (1 - \text{Abatement})\end{aligned}$$

Dividing both sides by gross output value (Y) and expressing them as log-differences, I obtain the following decomposition of the change in emission per gross output value.[9]

$$\Delta \ln \frac{\text{Emission}}{Y} = \Delta \ln \frac{\text{Energy}}{Y} + \Delta \ln(\text{Emission factor}) + \Delta \ln(1 - \text{Abatement})$$

I obtain the the real gross output value (Y) from NBER-CES Manufacturing Databse by using the value of shipments and the industry-level price deflator. To most accurately capture the energy consumption that is related to combustion emission, I only include the non-electricity energy consumption that is used for fuel-purpose in *Energy*. Other types of energy consumption include fossil fuel materials used as intermediate materials for production (henceforth, feedstocks).[10] The US Energy Information Agency (EIA)'s Manufacturing Energy Consumption Survey (MECS)

[9] In the Appendix, I further decompose $\frac{\text{Energy}}{Y}$ into the change driven by the TFP growth and the rest of the change in energy intensity. $\bar{Y}$ denotes the change in the real gross output after subtracting the change of TFP (i.e., $\Delta \ln \bar{Y} = \Delta \ln Y - \Delta \ln TFP$). See Table A.2.

[10] This is common in plastics and chemicals manufacturing, for example.

provides the quantity of energy (in Btu) used by each manufacturing industry, separately for fuel and non-fuel purposes. *Emission factor* is measured as a weighted average of emission factor of different fuel types, obtained from the US Environmental Protection Agency (EPA)'s WebFire, using the unit of consumption as weights.[11] In essence, the change in *Emission factor* captures the change in emissions resulting from the change in fuel composition — for example, if an industry increases its dependence on renewable energy, the *Emission factor* would go down.

I present the change between 1998 and 2014, which are the earliest and latest years where all the necessary data are available. In addition, to make the decomposition comparable to the discussion centered on the technique effect, I calculate the aggregate change in each of these components by calculating the average of the industry-level change with their 1998 output shares.

Table 1.1: Change in the US NO_x emission intensity (1998-2014)

(1) Emission/Y	(2) Energy/Y	(3) Emission factor	(4) Residual
-0.63	-0.21	-0.05	-0.37

Notes: The numbers are the change from 1998 to 2014 in log-points. Emission is total emission, Y is real gross output value, and Energy measures the non-electricity consumption used for fuel purpose. *Sources:* MECS, NBER-CES, and NEI.

Table 1.1 presents the decomposition of the change in emission per real gross output in the US manufacturing into three components: the change in energy consumption per real gross output, the change in emission factor, and the remainder. The table shows that about a third of the decline in the emission intensity (21 log-points out of 63 log-points) comes from the fall in energy intensity.[12]

[11] Specifically, I use the emission factor for burning each fuel type.

[12] Figure A.1 in the Appendix shows the non-electricity energy consumption used for fuel-purpose per unit of real gross output, corresponding to the time series of $\frac{\text{Energy}}{Y}$ from the above decomposition. Compared to the 1994 level,

Fact 3. *The share of establishments that choose to adopt emission-reducing activities has been increasing.*

Figure 1.2 plots the share of establishments that installed equipment or retrofitted equipment improve energy efficiency for 1998 and 2014. 'Any energy-mgmt' measures the share of establishments that participates in one or more of the energy-management activities, which not only include equipment installation or retrofits for improving energy efficiency, but also include more general activities such as technical assistance, energy audits or assessments, or financial assistance related to energy-management. The other bars, from 'cooling' to 'steam production', measure the share of establishments that installed equipment or retrofitted equipment for the primary purpose of improving energy efficiency.

Compared to 1998, a larger share of establishments responded that they installed or retrofitted energy-saving equipment.[13] By definition, these energy-efficiency technologies reduce the required energy consumption compared to before installation. Although this is only a part of the comprehensive set of emission-reducing technologies or activities, it serves as a proxy for firms' extra expenditures on emission-reducing investments. The observed increase in emission-reducing equipment motivates my investigation of the role of technological upgrades in the observed improvement in emission intensity in overall US manufacturing.

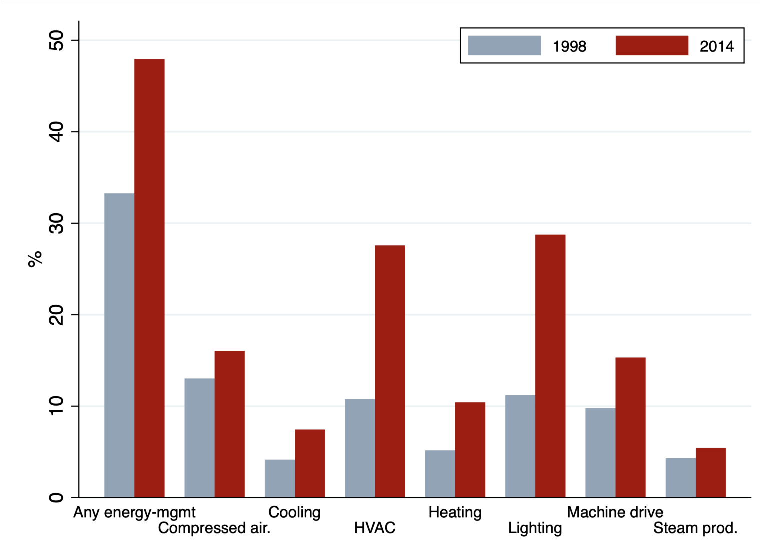
Figure 1.3 shows the change in energy-saving equipment installation in relation to the change in input imports at industry level.[14] It presents the log difference in the share of establishments

energy intensity decreased by over 20% in 2014 for fuel purpose energy. This pattern may indicate that there was some substitution from fuel to non-fuel inputs in US manufacturing although it is only suggestive and does not tell anything about the driving force. Nonetheless, this is motivation to dig deeper to understand the sources of such change. This project aims to understand whether the change in intermediate import cost has played a role in such changes in the demand of different inputs, which eventually induces the change in emission intensity.

[13] Appendix Figure A.2 shows the same graph using the 1994 and 2014 data, which shows even larger growth in installations starting from 1994.

[14] The list of industries used in the figure is presented in the Appendix Table A.3.

Figure 1.2: Share of establishments that installed energy-efficiency equipment



Note: The bars present the ratio of the establishments that installed or retrofitted equipment for the primary purpose of improving energy efficiency among the total number of establishments participating the MECS survey. *Source*: Author's calculation from using the MECS.

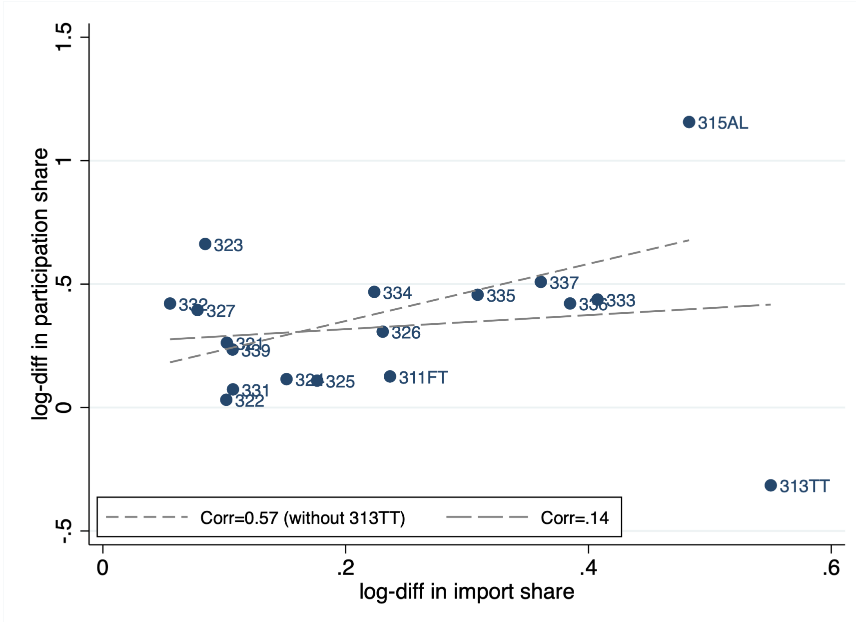
participating in any energy-management activities on the vertical axis. The horizontal axis shows the log difference in the ratio of expenditures on imported inputs to total input expenditures. This is the same measure that was used in Fact 1. The scatter plot shows a positive relationship between the two differences with unconditional correlation at 0.14.[15] Appendix Figure A.3 uses all available observations from 1998 to 2014 (long-difference compared to the 1994 value) and shows that the positive correlation between the growth in foreign inputs and the growth in energy-saving equipment installation is observed in other years as well.

1.4 Model of intermediate trade and emissions

I introduce a two-country model that captures the effect of intermediate input trade costs on firm-level and aggregate-level emissions. The model has a home and a foreign country. I

[15] The correlation increases by much to 0.57 if I exclude the textile mills and textile production mills industry (313TT).

Figure 1.3: Change between 1998 and 2014



Note: The vertical axis represents the log-difference of the share of establishments that installed energy-management equipment. The horizontal axis represents the log-difference of the share of expenditures on foreign inputs in the total input expenditures. *Source*: Author's calculation from using the MECS, BEA Supply-Use Tables, and BEA Import Matrix.

illustrate the case for consumers and firms in home country, but those in foreign country have the same structure and decisions. I denote the variable of a foreign country with superscript '*'.

1.4.1 Environment

1.4.1.1 Preferences

A representative agent gains utility from consumption and disutility from pollution.

$$U = \prod_{s} \left(\left[\int_{\nu} q_s(\nu)^{\frac{\sigma_s - 1}{\sigma_s}} d\nu \right]^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\mu_s} f(Z) \tag{1.1}$$

Specifically, consumers have Cobb-Douglas preferences across sectors (s) and constant elasticity of substitution (CES) preferences across varieties (ν) within each sector with the elasticity of substitution $\sigma_s > 1$. Consumers spend μ_s share of their expenditures on industry s, so $\sum_s \mu_s = 1$. I assume that utility decreases with total emission – thus, $f'(Z) < 0$. I specify the functional form of $f(Z)$ in the quantitative analysis in Section 2.3. I assume there is no transport of local pollutants, so a country's pollution is only due to its own production.

The CES demand of a variety ν is given by

$$q_s(\nu) = I_s P_s^{C\sigma_s - 1} p_s(\nu)^{-\sigma_s} \tag{1.2}$$

where I_s is consumers' aggregate expenditures spent in sector s, and P_s^C is the CES price index faced by consumers, defined as

$$P_s^C \equiv \left[\int_{\nu \in \Omega_s} p_s(\nu)^{1-\sigma_s} d\nu \right]^{\frac{1}{1-\sigma_s}} \tag{1.3}$$

I assume that consumers purchase goods from both the home and foreign country, so the set of varieties available to consumers (Ω_s) includes the varieties from both.

1.4.1.2 Technology

Since all decisions are similar for different sectors, I illustrate the case only for generic industries and omit the sector notation s. I assume that a competitive fringe of entrepreneurs obtains their productivity φ after paying a fixed cost f_e in terms of labor. After observing the φ draw, an entrepreneur who decides to operate a business pays a fixed cost f_o in terms of labor to start production.

Firms produce differentiated varieties, combining three types of inputs, labor (l), energy

(e), and a manufacturing bundle (m). With the core productivity level at φ, a firm's production function is given by

$$q(\nu;\varphi) = \varphi \times l(\nu;\varphi)^{\eta_l} e(\nu;\varphi)^{\eta_e} m(\nu;\varphi)^{\eta_m} \times \Xi$$

where $\eta_l + \eta_e + \eta_m = 1$ and $\Xi \equiv \eta_l^{-\eta_l} \eta_e^{-\eta_e} \eta_m^{-\eta_m}$ is a constant term.

The optimal cost of unit input bundle (before taking firm-level heterogeneity into account) is

$$c = w^{\eta_l} \Big(r(1 + t\epsilon) \Big)^{\eta_e} P^{\eta_m}$$

where w is the wage, e is the energy cost, and P is the manufacturing material bundle cost. Manufacturing input varieties are aggregated into a bundle, using the CES aggregator. I assume a roundabout structure, in which the same manufacturing material bundle is used as both final goods for consumption and as intermediate inputs for production. Lastly, firms need to pay *ad-valorem* environmental tax (t), which is levied on the pollutant content of energy (ϵ).[16]

1.4.2 Trade and technology adoption decisions

The entrepreneurs need to make two additional decisions regarding production regarding the sourcing of manufacturing bundles and adoption of energy-saving technology. Domestically-sourcing firms use a bundle of domestic varieties. A firm may decide to source from both domestic and foreign suppliers, after paying a fixed cost f_g in terms of labor. I define P^* as the price of manufacturing bundle sourced from a foreign. The price of the globally-sourced

[16] An alternative way to model an environmental tax is to levy tax on emissions, making the cost of using energy inputs as $e + t\epsilon$. For modeling simplicity, I choose to use a tax structure that is ad-valorem and levied on the pollutant content of energy.

bundle, P^G, is

$$P^G = \Big[\int_{\nu \in \Omega} p(\nu)^{1-\sigma} d\nu + \int_{\nu \in \Omega^*} \Big(\tau p(\nu)\Big)^{1-\sigma} d\nu \Big]^{\frac{1}{1-\sigma}}$$
$$= \Big[P^{1-\sigma} + (\tau P^*)^{1-\sigma} \Big]^{\frac{1}{1-\sigma}} < P$$

where $\tau \geq 1$ is the ad-valorem trade cost that occurs when a foreign good is imported. Note that P^G is always smaller than P under the assumption of CES aggregation ("love of variety"), so a firm pays the lower cost for manufacturing inputs when it globally sources them.[17]

In addition, a firm may choose to install energy-saving technology, which improves energy efficiency, after paying a fixed cost f_a in terms of labor. This adoption lowers the effective cost of using energy for production from r to r/β with β being larger than 1.[18] Throughout the rest of the chapter, I use g as an indicator of global sourcing and a as an indicator of technology adoption.

Lastly, firms may choose to sell to other markets than their domestic ones. To focus on the mechanism related to importing intermediates – among trade's effects – I assume that exporting does not incur a fixed cost. So in this model, all firms decide to export.

The price of a good produced by a firm with productivity φ and decisions (g, a) when it is sold to a domestic market can be written as

$$p_{\mathrm{d}}(\varphi; g, a) = \frac{\sigma}{\sigma - 1} \varphi^{-1} w^{\eta_l} \left\{ r(1 + t\epsilon) B(a) \right\}^{\eta_e} P(g)^{\eta_m} \tag{1.4}$$

[17]The price index that a consumer faces (P^C) and that a globally-sourcing firm faces (P^G) are not necessarily the same, as I do not assume the same import cost for final consumption and intermediate consumption.

[18]Alternative form of relevant technology is abatement technology, which lowers the emission content of using energy from ϵ to $\alpha\epsilon$ ($0 < \alpha < 1$). I choose the energy-efficiency technology since it applies to a wider range of pollutants, such as carbon dioxide, for which there lacks notable abatement technology.

where $P(g)$ and $B(a)$ are given by

$$P(g) = \begin{cases} P & \text{if } g = 0 \\ P^G & \text{if } g = 1 \end{cases}$$

$$B(a) = \begin{cases} 1 & \text{if } a = 0 \\ \beta^{-1} & \text{if } a = 1 \end{cases}$$

Selling a good to a foreign market incurs an ad-valorem iceberg cost $\tau_x > 1$. In summary, the price of the good of a firm with productivity φ and (g, a) decisions for selling to a market $i \in \{d \text{ (domestic)}, x \text{ (foreign)}\}$ is

$$p_i(\varphi; g, a) = \frac{\sigma}{\sigma - 1}\varphi^{-1} w^{\eta_l} \left\{r(1 + t\epsilon)B(a)\right\}^{\eta_e} P(g)^{\eta_m}\tau_i \tag{1.5}$$

where $\tau_d = 1$.

Before proceeding further, it is useful to define a few terms that capture the marginal benefit of these decisions for simpler notation.

Definition 1. *s_g and s_a are the premium of global sourcing and technology adoption decisions, given by*

$$s_g \equiv \left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)} > 1 \tag{1.6}$$

$$s_a \equiv \beta^{-\eta_e(1-\sigma)} > 1 \tag{1.7}$$

Note that both s_g and s_a are larger than 1. *Either decision lowers the cost of production and,* *thus, increases a firm's revenue and profits – to the power of $\eta_m(1-\sigma)$ and $\eta_e(1-\sigma)$. The total profit of a firm with productivity φ and sourcing and adoption decisions (g, a) can be written as*

$$\begin{aligned}\pi(\varphi; g, a) &= \frac{1}{\sigma} \sum_{i=d,x} X_i p_i(\varphi; g, a)^{1-\sigma} - (f_o + g f_g + a f_a) w \\ &= \tilde{\sigma} c^{1-\sigma} \underbrace{\varphi^{\sigma-1}}_{productivity} \underbrace{\Big[(1-g) + g s_g\Big]}_{global\ sourcing} \underbrace{\Big[(1-a) + a s_a\Big]}_{technology} \sum_{i=d,x} X_i \tau_i^{1-\sigma} - (f_o + g f_g + a f_a) w\end{aligned} \tag{1.8}$$

where $\tilde{\sigma} \equiv \frac{1}{\sigma}(\frac{\sigma}{\sigma-1})^{1-\sigma}$, and X_i is the size of market demand from destination i.[19]

A firm's total profit increases with productivity, all else equal. In addition, the marginal benefit of global sourcing and energy efficiency technology increases with the firm's productivity, while the marginal cost of either decision is constant. These features result in productivity cutoffs that determine a firm's entry and sourcing and technology adoption decisions, (g, a).

Proposition 1. *There exist cutoffs, $\varphi_o, \varphi_g, \varphi_a$, such that firms with $\varphi < \varphi_o$ exit, firms with $\varphi \geq \varphi_g$ choose to globally source, and firms with $\varphi \geq \varphi_a$ choose to adopt energy-saving technology. The order of these cutoffs is either $\varphi_o \leq \varphi_g \leq \varphi_a$ (case 1) or $\varphi_o \leq \varphi_a \leq \varphi_g$ (case 2). If the fixed costs f_g and f_a are sufficiently large, the cutoffs for entry, global sourcing, and technology adoption are given by*

$$\varphi_o = \Big[\frac{f_o w}{\sum_{i=\{d,x\}} X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma}}\Big]^{\frac{1}{\sigma-1}} \textit{ for both cases}$$

[19]For example, $X_d = A_d P_d^{\sigma-1}$, where A_d is the total expenditure spent by domestic consumers or firms on domestically-produced goods, and P_d is the aggregate price index of domestic firms.

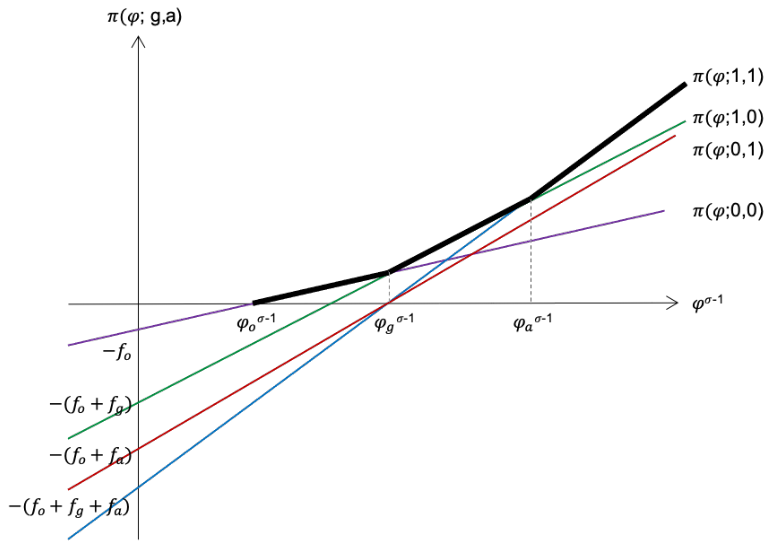
	case 1 $(\varphi_o \leq \varphi_g \leq \varphi_a)$	*case 2* $(\varphi_o \leq \varphi_a \leq \varphi_g)$
$\varphi_g =$	$\left[\frac{f_g w}{\sum_{i=\{d,x\}} X_i \tilde{\sigma}\left(c/\tau_i^x\right)^{1-\sigma}(s_g-1)}\right]^{\frac{1}{\sigma-1}}$	$\left[\frac{f_g w}{\sum_{i=\{d,x\}} X_i \tilde{\sigma}\left(c/\tau_i^x\right)^{1-\sigma} s_a(s_g-1)}\right]^{\frac{1}{\sigma-1}}$
$\varphi_a =$	$\left[\frac{f_a w}{\sum_{i=\{d,x\}} X_i \tilde{\sigma}\left(c/\tau_i^x\right)^{1-\sigma} s_g(s_a-1)}\right]^{\frac{1}{\sigma-1}}$	$\left[\frac{f_a w}{\sum_{i=\{d,x\}} X_i \tilde{\sigma}\left(c/\tau_i^x\right)^{1-\sigma}(s_a-1)}\right]^{\frac{1}{\sigma-1}}$

Proof. In Appendix A.2.1. □

There are two key points regarding Proposition 1. First, there is no case in which all four potential combinations of the (g, a) decision occur across firms. If there is a productivity cutoff, φ_g, at which a firm with $\varphi < \varphi_g$ optimally chooses $(g, a) = (0, 0)$, and a firm with $\varphi \geq \varphi_g$ chooses $(1, 0)$, then there is no productivity higher than φ_g at which a firm decides do domestically source. In other words, all firms with productivity higher than φ_g globally source regardless of their technology-upgrading decisions. The intuition is based on the two features of the model: a) productivity and input costs complementarily determine the cost of production, and b) fixed costs are constant. If the marginal benefit of global sourcing is higher than the marginal cost at some productivity level (φ_1), then the same always holds for any higher productivity level ($\varphi_2 > \varphi_1$) regardless of its technology-adoption decision. If a firm with φ_2 is not using an energy-efficiency technology, the marginal benefit of global sourcing is larger than the marginal cost, as higher productivity amplifies the marginal benefit while the marginal cost is constant. If φ_2 is using the technology, then the lower cost of using energy also amplifies the marginal benefit. Figure 1.4 provides a visual illustration. The black, bold line is the maximum profit across four choices, demonstrating that the total profit of $(0, 1)$ is always under the maximum.

Second, if the benefit of global sourcing is sufficiently large or the fixed cost of global sourcing is sufficiently small, all firms choose to source globally. This occurs, for example, when the import cost or price of foreign inputs is sufficiently low. Similarly, all firms choose to adopt an energy-efficiency technology if the benefit exceeds the cost at all productivity levels – e.g., if the technology is highly effective (large β).

Figure 1.4: Productivity cutoff (*case 1* as an illustration)



Since a firm's (g, a) decision is directly linked to its productivity φ, I omit (g, a) and use only φ to denote each firm through the rest of the chapter.

1.4.3 Firm emissions

Using a unit of energy generates ϵ emissions. The total emissions (z) and total quantity of output (q) of a firm with φ are as follows. $z(\varphi)$ is obtained from the Cobb-Douglas feature such that the energy cost take η_e share of the variable production cost.

$$z(\varphi) = \epsilon \times \underbrace{\frac{\sigma-1}{\sigma}\eta_e \frac{\sum_{i=\{d,x\}} X_i p_i(\varphi)^{1-\sigma}}{r(1+t\epsilon)}}_{\text{energy used by a firm with } \varphi}$$

$$q(\varphi) = \sum_{i=\{d,x\}} X_i p_i(\varphi)^{-\sigma}$$

I define emission intensity as the amount of emission made from producing a unit of output. By dividing $z(\varphi)$ by $q(\varphi)$, I obtain the expression of emission intensity as given by

$$z_q(\varphi) \equiv \frac{z(\varphi)}{q(\varphi)} = \epsilon \frac{\sigma - 1}{\sigma} \frac{\eta_e}{r(1+t\epsilon)} \frac{\sum_{i=\{d,x\}} X_i p_i(\varphi)^{1-\sigma}}{\sum_{i=\{d,x\}} X_i p_i(\varphi)^{-\sigma}}$$

Since the price of a good sold to a foreign market equals to the price of a good sold to a domestic market multiplied by export cost – that is, $p_x(\varphi) = p_d(\varphi)\tau_x$ – I can rewrite firm-level emission intensity as

$$z_q(\varphi) = \epsilon \frac{\sigma - 1}{\sigma} \frac{\eta_e p(\varphi)}{r(1+t\epsilon)} \times MAcost \tag{1.9}$$

where I changed the notation of the domestically-selling price from $p_d(\varphi)$ to $p(\varphi)$, and $MAcost = \frac{X_d + X_f \tau_x^{1-\sigma}}{X_d + X_f \tau_x^{-\sigma}}$.[20] Note that $MAcost$ is the average cost of accessing domestic market ($\tau_d = 1$) and foreign market ($\tau_x > 1$) calculated using the quantities sold in each market as weights.

If I insert the expression for the price of a good sold to a domestic market (in Equation 1.5) to the above expression, the firm's emission intensity becomes

$$z_q(\varphi) = \epsilon\eta_e \times \underbrace{\varphi^{-1}}_{\text{productivity}} \times \underbrace{B(\varphi)^{\eta_e}}_{\text{energy efficiency tech}} \times \underbrace{\frac{w^{\eta_l} P(\varphi)^{\eta_m}}{\{r(1+t\epsilon)\}^{1-\eta_e}}}_{\text{relative cost of non-energy}} \times \underbrace{MAcost}_{\text{market access cost}} \tag{1.10}$$

[20] $MAcost = \sum_{i=\{d,x\}} \frac{X_i p(\varphi)\tau_i^{-\sigma}}{\sum_{j=\{d,x\}} X_j p(\varphi)\tau_j^{-\sigma}} \times \tau_i$.

where

$$P(\varphi) = \begin{cases} P & \text{if } \varphi < \varphi_g \\ \\ P^G & \text{if } \varphi \geq \varphi_g \end{cases}$$

$$B(\varphi) = \begin{cases} 1 & \text{if } \varphi < \varphi_a \\ \\ \beta^{-1} & \text{if } \varphi \geq \varphi_a \end{cases}$$

Equation 1.10 describes the determinants of firm-level emission intensity, which include productivity, use of energy-efficiency technology, the relative cost of inputs, and average market access cost. Firm-level emission intensity varies according to a firm's productivity, global-sourcing decision, and technology-adoption decision. Proposition 2 summarizes how firm-level emission intensity depends on these factors, and Figure 1.5 shows firm-level emission intensity for *case 1* as an illustration.

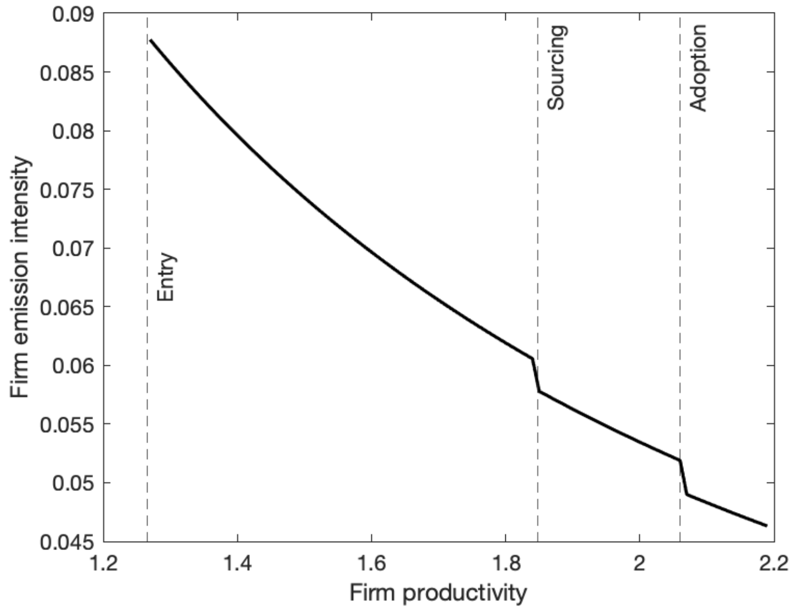
Proposition 2. *All else equal, a firm's emission intensity is lower with higher productivity, global sourcing, and technology adoption.*

Proof. A few simple algebra steps show that

$$\frac{\partial \ln z_q}{\partial \ln \varphi} = -1$$
$$\frac{z_q(\varphi; g=1, a)}{z_q(\varphi; g=0, a)} = \left(\frac{P^G}{P}\right)^{\eta_m} < 1 \text{ for all } \varphi, a$$
$$\frac{z_q(\varphi; g, a=1)}{z_q(\varphi; g, a=0)} = \beta^{-\eta_e} < 1 \text{ for all } \varphi, g$$

□

Figure 1.5: Firm-level emission intensity (*case 1* as an illustration)



1.4.4 Aggregate emission intensity

The aggregate emission intensity ($Z_Q \equiv \frac{Z}{Q}$) is a weighted average of firm-level emission intensity, using firms' output share as weights.

$$Z_Q = \int_{\varphi} z_q(\varphi)\omega_q(\varphi)dG(\varphi)$$

The output share is $\omega_q(\varphi) = \frac{Mp(\varphi)^{-\sigma}}{P^{-\sigma}}$, in which M is the mass of operating firms and P is the CES price index defined as $P = \left(M \int_{\varphi} p(\varphi)^{1-\sigma}dG(\varphi)\right)^{\frac{1}{1-\sigma}}$. Note that the expression $\frac{Mp(\varphi)^{-\sigma}}{P^{-\sigma}}$ is composed of a firm's price when it sells a good to a domestic market, $p(\varphi)$, and the aggregate price index of the good, P. Since all firms export to a foreign market and face the same exporting cost, the output share in a domestic market among domestic firms is equivalent to the output share in terms of the total output sold in both domestic and foreign market.[21]

I insert the expression of $\omega_q(\varphi)$ and $z_q(\varphi)$ from Equation 1.9 into the above expression, and use the expression of P to obtain Equation 1.11. This expression shows that the aggregate emission intensity can be summarized as the ratio of producer price index (P) to the cost of using energy $(r(1+t\epsilon))$ and the average market access cost ($MAcost$) and the parameters (ϵ, η_e, σ).

$$\begin{aligned} Z_Q &= \epsilon\eta_e \frac{\sigma-1}{\sigma}\frac{1}{r(1+t\epsilon)} \times MAcost \times \frac{M}{P^{-\sigma}} \int_{\varphi} p(\varphi)^{1-\sigma} dG(\varphi) \\ &= \epsilon \times \eta_e \frac{\sigma-1}{\sigma}\frac{P}{r(1+t\epsilon)} \times MAcost \end{aligned} \tag{1.11}$$

The expression can be easily understood by examining firm-level outcomes such that more productive firms have both lower prices and lower emission intensity. Similarly, firms with lower cost structures – either from global sourcing or technology adoption or both – have lower prices and a lower emission intensity than those without such cost advantages. In other words, the factors that result in a lower price are also the factors that bring about cleaner production. This is the reason why P captures part of the change in Z_Q. The average cost of market access, $MAcost$, increases emission intensity because it increases the amount of a good that needs to be produced in excess, as iceberg costs.

[21] See Appendix A.2.2 for detailed exposition.

The producer price index, P, can be expanded as

$$
\begin{aligned}
P &= \left[M \int_{\varphi} p(\varphi)^{1-\sigma} dG(\varphi)\right]^{\frac{1}{1-\sigma}} \\
&= \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} \times \left[\int_{\varphi} \varphi^{\sigma-1} B(\varphi)^{\eta_e(1-\sigma)} P(\varphi)^{\eta_m(1-\sigma)} dG(\varphi)\right]^{\frac{1}{1-\sigma}} \\
&= \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} \times \Upsilon \qquad (1.12)
\end{aligned}
$$

where

$$
\Upsilon = \begin{cases}
\left[\int_{\varphi_o}^{\varphi_g} \left(\frac{\varphi}{P^{\eta_m}}\right)^{\sigma-1} dG_o(\varphi) + \int_{\varphi_g}^{\varphi_a} \left(\frac{\varphi}{P^{G\eta_m}}\right)^{\sigma-1} dG_o(\varphi) + \int_{\varphi_a}^{\infty} \beta^{-\eta_e(1-\sigma)} \left(\frac{\varphi}{P^{G\eta_m}}\right)^{\sigma-1} dG_o(\varphi)\right]^{\frac{1}{1-\sigma}} \\
\text{if } \varphi_o \leq \varphi_g \leq \varphi_a \\
\left[\int_{\varphi_o}^{\varphi_a} \left(\frac{\varphi}{P^{\eta_m}}\right)^{\sigma-1} dG_o(\varphi) + \int_{\varphi_a}^{\varphi_g} \beta^{-\eta_e(1-\sigma)} \left(\frac{\varphi}{P^{\eta_m}}\right)^{\sigma-1} dG_o(\varphi) + \int_{\varphi_g}^{\infty} \beta^{-\eta_e(1-\sigma)} \left(\frac{\varphi}{P^{G\eta_m}}\right)^{\sigma-1} dG_o(\varphi)\right]^{\frac{1}{1-\sigma}} \\
\text{if } \varphi_o \leq \varphi_a \leq \varphi_g
\end{cases}
$$

with $G_o(\varphi)$ being the cumulative distribution of φ conditional on $\varphi \geq \varphi_o$. The term Υ measures the effective aggregate productivity, consisting of firms' core productivity (φ), intermediate input price they face (P or P^G), and the level of technology (β) for those that adopted the technology.

In order to further expand P, I assume Pareto distribution for firms' productivity. The cumulative distribution of firms' productivity is given by

$$
G(\varphi) = 1 - \left(\frac{\varphi}{b}\right)^{-\theta}
$$

where b is the location parameter, and θ is the shape parameter. Using the Pareto distribution, Υ can be simplified as

$$\Upsilon = P^{\eta_m} \left(\frac{\theta}{\theta - \sigma + 1} \right)^{\frac{1}{1-\sigma}} \varphi_o^{-1} \left[1 + \left(\frac{\varphi_g}{\varphi_o} \right)^{-\theta} \frac{f_g}{f_o} + \left(\frac{\varphi_a}{\varphi_o} \right)^{-\theta} \frac{f_a}{f_o} \right]^{\frac{1}{1-\sigma}} \tag{1.13}$$

for either case of cutoff distribution. The intermediate steps for the derivation are in Appendix A.2.3.

As a result, the aggregate emission intensity can be written as

$$\begin{aligned} Z_Q =& \epsilon \eta_e \left(\frac{\theta}{\theta - \sigma + 1} \right)^{\frac{1}{1-\sigma}} \times \frac{w^{\eta_l} P^{\eta_m}}{\{r(1+t\epsilon)\}^{1-\eta_e}} \times M^{\frac{1}{1-\sigma}} \\ & \times \varphi_o^{-1} \left[1 + \left(\frac{\varphi_g}{\varphi_o} \right)^{-\theta} \frac{f_g}{f_o} + \left(\frac{\varphi_a}{\varphi_o} \right)^{-\theta} \frac{f_a}{f_o} \right]^{\frac{1}{1-\sigma}} \times MAcost \end{aligned} \tag{1.14}$$

This expression leads to the following proposition on the determinants of the aggregate emission.

Proposition 3. *All else equal, the aggregate emission intensity decreases when the cost of using non-energy inputs relative to the cost of using energy decreases. Specifically, this cost decreases with a lower wage, lower intermediate price, higher energy price, or higher regulation cost. Moreover, the aggregate emission intensity decreases when the entry cutoff increases, a larger share of firms choose to source globally, or a larger share of firms choose to adopt energy efficiency technology.*

Proof. Under the Pareto assumption, $\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}$ is the share of globally-sourcing firms (in number), and $\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}$ is the share of firms that adopt energy-efficiency technology. The rest of the proposition directly follows from Equation 1.14. □

Aside from input costs and cutoffs, other factors determine the aggregate emission intensity. For example, the emission intensity is lower when using energy generates less emission (smaller ϵ), energy share in production is lower (smaller η_e), there are more varieties (larger M), or average market access cost is lower (smaller $MAcost$). The relationship between the mass of varieties and the aggregate emission intensity can be understood if we think of Z_Q as the emission per unit of the aggregate bundle of products, in which the aggregate bundle portrays the love-of-variety feature.

1.4.5 Competitive equilibrium

I briefly discuss a few assumptions and conditions to close the model. First, I assume a fixed value for final consumption on the goods ($\bar{I}$). Also, I assume a fixed country-level labor supply ($\bar{L}$) and global energy supply ($\bar{E}^{global}$), and that labor is immobile, whereas energy is mobile and freely traded across countries. Lastly, I assume that trade costs are entirely iceberg costs and tax revenues are lost.[22]

Moreover, I introduce additional variables that appear in the competitive equilibrium conditions. First, define τ^F as the import cost on final consumption goods.[23] In addition, μ is the share of foreign intermediates in a global bundle in the home country, and the analogous import share for final good bundle in the home country is μ^F. The revenue share of globally-sourcing firms in the home country is denoted as $\tilde{\lambda_g}$.[24] The variables with '*' denote the values of a foreign country. Lastly, M^e is the mass of entrepreneurs drawing productivity.

[22] Some papers assume that tax revenues are lost to rent-seeking, thus not collectible (Shapiro and Walker, 2018).

[23] For example, the share of foreign inputs in the home country is $\mu = \frac{(P^*\tau)^{1-\sigma}}{P^{1-\sigma}+(P^*\tau)^{1-\sigma}}$.

[24] For example, $\tilde{\lambda_g} = 1 - \frac{1-\left(\frac{\varphi_g}{\varphi_o}\right)^{\sigma-\theta-1}}{1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}}$ for case 1 and $\frac{\left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)}\beta^{-\eta_e(1-\sigma)}\left(\frac{\varphi_a}{\varphi_o}\right)^{\sigma-\theta-1}}{1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}}$ for case 2 in the home country.

In a competitive equilibrium, the following equations hold.

$$f_e w = \int_{\varphi_o}^{\infty} \pi(\varphi)\, dG(\varphi) \tag{1.15}$$

$$R = \bar{I}(1-\mu^F) + \frac{\bar{I}^* \mu^{F*}}{\tau^{F*}} + \eta_m \frac{\sigma-1}{\sigma}\left[R(1-\tilde{\lambda_g}) + R\tilde{\lambda}_g(1-\mu) + \frac{R^* \tilde{\lambda}_g^* \mu^*}{\tau^*}\right] \tag{1.16}$$

$$\bar{L} = \frac{\sigma-1}{\sigma}\eta_l \frac{R}{w} + M^e\left[f_e + f_o(1-G(\varphi_o)) + f_g(1-G(\varphi_g)) + f_a(1-G(\varphi_a))\right] \tag{1.17}$$

$$\bar{E}^{global} = \frac{\sigma-1}{\sigma}\eta_e \frac{1}{r}\left(\frac{R}{(1+t\epsilon)} + \frac{R^*}{(1+t^*\epsilon^*)}\right) \tag{1.18}$$

Equation 1.15 describes the free-entry condition, which assures that the aggregate profits are zero. Equation 1.16 and 1.17 describe the goods market clearing and labor market clearing conditions. These three conditions hold for each country. The last condition, Equation 1.18, describes the energy market clearing condition, which holds at the global level.

1.5 Model results: effect of intermediate import cost

1.5.1 Effect on firm decisions

In this section, I show how the change in intermediate import cost affects firms' decisions regarding entry, sourcing, and technology adoption. First of all, intermediate import costs affect the operating firms' decision about sourcing and technology. Specifically, the productivity cutoffs for either decision increase with higher import costs, decreasing the share of firms participating in global sourcing or technology adoption.

Proposition 4. *Holding the relative price $\frac{P^*}{P}$ fixed, higher τ increases the ratio of global sourcing cutoff, φ_g, and technology adoption cutoff, φ_a, to entry cutoff, φ_o. The partial elasticity is as* *follows.*

$$\frac{\partial \ln}{\partial \ln \tau}\left(\frac{\varphi_g}{\varphi_o}\right) = \begin{cases} \frac{s_g}{s_g - 1}\eta_m \mu & \textit{if } \varphi_o \leq \varphi_g \leq \varphi_a \\ \\ \eta_m \mu & \textit{if } \varphi_o \leq \varphi_a \leq \varphi_g \end{cases}$$

$$\frac{\partial \ln}{\partial \ln \tau}\left(\frac{\varphi_a}{\varphi_o}\right) = \begin{cases} \eta_m \mu & \textit{if } \varphi_o \leq \varphi_g \leq \varphi_a \\ \\ \frac{s_a}{s_a - 1}\eta_m \mu & \textit{if } \varphi_o \leq \varphi_a \leq \varphi_g \end{cases}$$

where $\mu \equiv \frac{\tau^{1-\sigma} P^{*1-\sigma}}{P^{1-\sigma} + \tau^{1-\sigma} P^{*1-\sigma}}$ *is the foreign share in the home country's global intermediate bundle.*

Proof. I show the proof for case 1, which orders the cutoffs as $\varphi_o \leq \varphi_g \leq \varphi_a$. The expressions for the relative location of global sourcing and technology adoption cutoffs compared to the operation cutoff are

$$\frac{\varphi_g}{\varphi_o} = \left(\frac{f_g/f_o}{s_g - 1}\right)^{\frac{1}{\sigma-1}}, \ \frac{\varphi_a}{\varphi_o} = \left(\frac{f_a/f_o}{s_g(s_a - 1)}\right)^{\frac{1}{\sigma-1}}$$

Combining $\frac{\partial \ln s_g}{\partial \ln \tau} = \mu$ and the definition of s_g as in Equation 1.6 with $\frac{\partial \ln}{\partial \ln \tau}\left(\frac{\varphi_g}{\varphi_o}\right) = \frac{\partial \ln}{\partial \ln s_g}\left(\frac{\varphi_g}{\varphi_o}\right) \times \frac{\partial \ln s_g}{\partial \ln \tau}$ and $\frac{\partial \ln}{\partial \ln \tau}\left(\frac{\varphi_a}{\varphi_o}\right) = \frac{\partial \ln}{\partial \ln s_g}\left(\frac{\varphi_a}{\varphi_o}\right) \times \frac{\partial \ln s_g}{\partial \ln \tau}$, I can obtain the expressions of partial elasticity as the proposition. The proof for case 2 ($\varphi_o \leq \varphi_a \leq \varphi_g$) is analogous. □

Proposition 4 states that higher (lower) τ brings higher (lower) cutoffs for global sourcing and technology adoption. Let me consider the consequences of lower τ. The decrease in global sourcing and adoption cutoffs increases the expected profit of operation, inducing additional entry. But with additional entry and a larger share of firms engaged in a more efficient way of production – global sourcing or technology adoption or both – the survival of the least productive firms becomes harder, inducing them to eventually exit the market. In the end, a lower intermediate import cost increases the entry cutoff and generates this selection effect, analogous to the selection effect that arises from market expansion in Melitz (2003). Thus, Proposition 5 follows.

Proposition 5. *Holding the relative price $\frac{P^*}{P}$ fixed, higher τ decreases the entry cutoff, φ_o.*

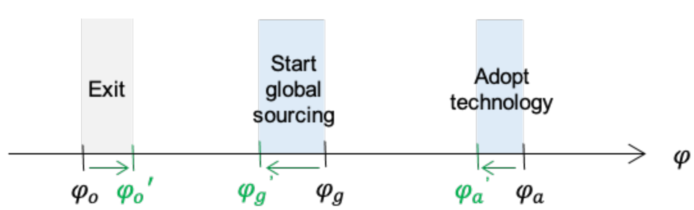
$$\frac{\partial \ln \varphi_o}{\partial \ln \tau} < 0$$

Proof. In Appendix A.2.4. $\square$

In summary, when the intermediate import cost increases, the entry cutoff decreases, inducing more least productive firms to enter, the relative location of global sourcing cutoff increases, reducing the share of globally-sourcing firms, and the relative location of adoption cutoff weakly increases, reducing the share of firms that have adopted technology.[25] The opposite occurs when the intermediate import cost decreases.

Figure 1.6 illustrates the changes in cutoffs when τ *falls* in *case 1* as an example. The firms with $\varphi \in [\varphi_o, \varphi_o')$ exit the market, those with $\varphi \in [\varphi_g', \varphi_g)$ switch from domestic to global sourcing, and firms with $\varphi \in [\varphi_a', \varphi_a)$ adopt energy-saving technology.

Figure 1.6: Effect of lower τ on the cutoffs (*case 1* as an illustration)



[25]In case 2, τ does not affect $\frac{\varphi_a}{\varphi_o}$ in a partial effect.

1.5.2 Effect on aggregate emission intensity

If I assume that wage, energy price, aggregate manufacturing price, and the mass of potential entrepreneurs in both countries are fixed, the partial derivative of $\ln Z_Q$ with respect to $\ln \tau$ is given by

$$\frac{\partial \ln Z_Q}{\partial \ln \tau} = \underbrace{\frac{\theta}{\sigma - 1}\frac{\partial \ln \varphi_o}{\partial \ln \tau}}_{\text{mass of varieties}} - \underbrace{\frac{\partial \ln \varphi_o}{\partial \ln \tau}}_{\text{selection}} - \underbrace{\frac{1}{\sigma - 1}\frac{\partial \ln}{\partial \ln \tau}\left[1 + \left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o} + \left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}\right]}_{\text{intensive \& change in } (g,a) \text{decisions \& reallocation}} \tag{1.19}$$

The expression shows three channels whereby τ affects the Z_Q in the partial equilibrium effect. Proposition 5 shows that a higher τ decreases φ_o, inducing more firms to enter. Due to imperfect substitution between goods, the larger mass of varieties leads to a disproportionately larger quantity of aggregate output compared to emissions, which is described in the first term of Equation 1.19. Lower φ_o, however, suggests a higher share of firms with low productivity in the market. As firm-level emission intensity decreases with productivity, the entrance of the least productive firms increases the aggregate emission intensity, captured by the second term.

The third term in the partial derivative captures several forces. First, firms that are already globally sourcing face higher prices for the intermediate bundle with higher τ, thus choosing to substitute intermediates with other inputs including energy. As a result, their emission intensity is increased. I have defined an 'intensive' channel as this change in emission intensity with fixed cutoffs. By rewriting the bracketed terms as follows, the intensive channel is readily apparent. With higher τ, the global intermediate bundle price P^G increases – even when both countries' manufacturing prices (P and P^*) are fixed – so the intermediate intensity of globally-sourcing firms decreases, which increases the energy intensity (that is, again, when wage and energy prices are fixed).

$$
\begin{aligned}
&1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}\\
&=\begin{cases}
1+\left\{\left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)}-1\right\}\left(\frac{\varphi_g}{\varphi_o}\right)^{\sigma-\theta-1}+\left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)}\left\{\beta^{-\eta(1-\sigma)}-1\right\}\left(\frac{\varphi_a}{\varphi_o}\right)^{\sigma-\theta-1} & \text{if } \varphi_o\le\varphi_g\le\varphi_a\\
1+\left\{\beta^{-\eta(1-\sigma)}-1\right\}\left(\frac{\varphi_a}{\varphi_o}\right)^{\sigma-\theta-1}+\beta^{-\eta(1-\sigma)}\left\{\left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)}-1\right\}\left(\frac{\varphi_g}{\varphi_o}\right)^{\sigma-\theta-1} & \text{if } \varphi_o\le\varphi_a\le\varphi_g
\end{cases}
\end{aligned}
$$

At the same time, global sourcing and technology adoption cutoffs change with τ. With a higher τ, $\frac{\varphi_g}{\varphi_o}$ increases, inducing some firms to cease using global sourcing in favor of domestic intermediates. Since domestically-sourced production is dirtier than globally-sourced, this change in $\frac{\varphi_g}{\varphi_o}$ increases the aggregate emission intensity. In case 1 ($\varphi_o \le \varphi_g \le \varphi_a$), $\frac{\varphi_a}{\varphi_o}$ also becomes larger, increasing the aggregate emission intensity. Lastly, higher τ decreases the premium of global sourcing, which reduces the market share of globally-sourcing firms. As globally-sourcing firms have lower emission intensities than their domestically-sourcing counterparts, this increases the aggregate emission intensity.

The following proposition summarizes the aforementioned forces and shows the net effect of the intermediate import cost on the aggregate emission intensity.

Proposition 6. *Holding wage, energy price, aggregate price, and the mass of potential entrepreneurs of both countries fixed, the aggregate emission intensity is locally increasing in manufacturing input import costs.*

$$\frac{\partial \ln Z_Q}{\partial \ln \tau} > 0$$

Proof. In Appendix A.2.5. □

In the general equilibrium, prices and the mass of potential entrepreneurs adjust, which induces a further change in firm-level and aggregate-level emission intensity. The general equilibrium results are discussed in Section 2.3.

1.5.3 Discussion of the model assumptions

In this sub-section, I briefly discuss two assumptions I made in the model framework. First, the environmental regulation in my model takes the form of an energy tax weighted by the emission content of energy.[26] In the US, there is no NO_x tax or energy tax levied on the fuel's content of NO_x, and the pollutant has been regulated with a mix of different policy instruments including, but not limited to, tradable permits (equivalently, cap-and-trade) and command and control. For simplicity, in this model I use an energy tax in order to capture the burdens faced by firms resulting from their emission-generating activities. The model mechanisms remain the same with different regulation types, as the mechanisms themselves do not depend on how or whether emission is regulated. The intermediate import cost affects emission intensity by changing energy intensity, and in turn, energy intensity changes from the two channels: a) the relative cost of energy to other inputs and b) the adoption of technology. Lower import costs lower the intermediate input bundle price, regardless of whether emissions or energy is regulated (channel a). Also, lower import costs induce firms to adopt energy-saving technology (channel b). The adoption of this technology reduces firms' overall production costs even in the absence of any environmental regulation. Appendix A.3 has more detailed discussion.

Second, I choose to use the Cobb-Douglas production function, based on the observation that the long-run share of energy is close to constant (Hassler et al., 2012). But this assumes

[26]This is how some countries price carbon. For example, France levies a tax on energy products based on the content of CO_2 in the fossil fuels used in production.

unit elasticity between inputs. In the short run, the elasticity is usually lower. Allowing a smaller elasticity of substitution would affect two key mechanisms differently. On one hand, with lower elasticity, the strength of the input substitution channel (substituting energy with non-energy inputs) would be reduced. On the other hand, the impact of technology adoption would be larger, since the energy-saving technology, which was factor-neutral in the Cobb-Douglas setting, becomes energy-augmenting technology. Thus, the decrease in energy intensity resulting from installing this technology would be larger. The net implication of using CES (with lower elasticity between energy and non-energy) is not straightforward and would depend on the size of each of the two effects.

1.6 Conclusion

In this chapter, I propose a new perspective to understand the linkage between international trade and air pollutant emissions. In particular, I suggest the intermediate input import channel, which affects emission intensity via input substitution, technology adoption, and across-firm reallocations. This adds to the existing literature's understanding, which focuses on the role of trade through the increased market access but overlooks the increased access to imported inputs.

Specifically, I review a few stylized facts that motivate this study's focus, including the decline in energy intensity and the rise in import penetration among inputs used by US manufacturing. In addition, I show that the reduction in energy intensity explains a third of the within-industry reduction in NO_x emission intensity, highlighting the importance of understanding the change in energy usage.

I then build a model of heterogeneous firms, intermediate trade, and inputs with different emission profiles to analyze the channels by which trade in intermediate inputs affects emission intensity. By focusing primarily on the emissions linked with input usage, my model can examine the effect of improved access to foreign intermediates on firms' input choices and emission outcomes. The model shows that with lower intermediate import costs, firms become less energy-intensive by either increasing their intermediate intensity, using energy-saving technology or both. Moreover, the general equilibrium force as well as amplification through the input-output linkage bring a further decrease in emission intensity in all firms. The model presents the selection and reallocation effect which further amplifies the within-firm improvements.

The model has the potential to be extended in multiple ways to study the intersection of trade and the environment. First, one could nest the selection into exporting so that the model can analyze the impact of input import and market access in a comparable setting and study potential interactions between the two. In addition, by extending this framework to a multi-country, multi-sector version, in which the trade pattern matches with the data at a more disaggregate level, one could analyze the potential concern over the pollution haven hypothesis or pollution relocation.

Chapter 2: Effect of intermediate import on the US manufacturing emissions

2.1 Introduction

The theoretical model of intermediate trade and emission in the previous chapter showed how the change in intermediate import cost can affect aggregate emission intensity by bringing both within-firm and across-firm changes. In this chapter, I explore the relevance and importance of the role of intermediate import in aggregate emission intensity by bringing the model to the data. Specifically, I estimate the determinants of aggregate emission intensity, based on the model expression, using panel data of US manufacturing industries. I then quantify the magnitude of the role of intermediate import cost changes in the observed reduction of US manufacturing emission intensity.

In the model, a reduction in non-energy intermediate prices lowers firm emission intensity conditional on the cost of energy. And this relationship is reinforced by selection and reallocation toward larger and cleaner firms when aggregated up to the industry level. This effect of intermediate prices translates into a lower price of the output for this industry. Other characteristics such as higher average industry productivity also translate into a lower output price and more adoption. Thus, when I aggregate emission intensity to the industry level, I find it is increasing in output price after energy cost and market access cost are controlled. I test the determinants of aggregate emission intensity using US manufacturing panel data for 1996–2014. I use the intermediate import price as an instrumental variable for the aggregate producer price, as guided by the model, to control for endogeneity as well as to identify the impact of intermediate trade on emission intensity. I find that a 1% increase in the producer price – driven by higher import price of intermediate inputs – brings a 1.5% increase in aggregate emission intensity, conditional on energy price and market access cost.

Then I quantify the effect of the fall in intermediate import costs on US manufacturing emission intensity. I calibrate the model to 1998 US manufacturing data and show the mechanisms through which intermediate import cost affects emission intensity. I isolate the effects of three types of shocks that occurred between 1998 and 2014 – the change in the cost of importing manufacturing inputs, regulation stringency, and the emission factor of energy usage.[1] By comparing the equilibrium between the scenario with all three shocks and the scenario without a change in intermediate import cost, I show that the implied size of the effect of intermediate import cost change is approximately 8-10% of the within effect driven by energy usage change. The decomposition shows that 68% of the effect comes from within-firm improvement (including the change in input mix, sourcing, and technology adoption), 30% from the selection effect, and only 2% from the reallocation effect.

The finding that the intensive margin plays the largest role is worth noting since this margin is less discussed in the model without input-output linkage and, thus, intermediate trade. For example, in a few papers investigate the underlying drivers of the decline in US manufacturing emissions, the main channel is across-firm effects (Levinson, 2009, 2015; Shapiro and Walker, 2018). This chapter complements their works by introducing an omitted driver of the clean-up of

[1] The emission factor is the quantity of pollutant emissions from an emission-generating activity, including, but not limited to, fuel combustion.

US manufacturing firms – improved access to cheaper, imported inputs – which brings within-firm adjustments.

The rest of the chapter proceeds as follows. Section 2.2 presents the empirical analysis of the model prediction, and Section 2.3 discusses the quantitative analysis and results. Section 2.4 concludes.

2.2 Empirical analysis

In the model developed in Chapter 1, the aggregate emission intensity depends on the aggregate producer price index, energy price, and the average market access cost including access to domestic markets. Intermediate import costs affect the aggregate producer price by changing not only the intermediate bundle price that firms face, but the overall distribution of firms and their sourcing and technology decisions. This section empirically tests the model prediction regarding the determinants of the aggregate emission intensity and the role of intermediate import cost, using the US manufacturing panel data.

2.2.1 Specification

2.2.1.1 OLS specification

Equation 1.11 provides a set of determinants of the aggregate emission intensity, which includes the aggregate producer price index (P), energy price (r), regulation (t), emission factor (ϵ), and average market access cost ($MAcost$), along with the energy cost share (η_e) and the elasticity of substitution (σ).

$$Z_Q = \epsilon \times \eta_e \frac{\sigma - 1}{\sigma} \frac{P}{r(1 + t\epsilon)} \times MAcost$$

This shows that the emission intensity increases with the producer price, decreases with the (tax-inclusive) cost of energy usage, and increases with the average market access cost. The relationship between emission intensity and the two prices arises since the factors that decrease the aggregate price index, except for energy cost, also push down the energy intensity and, thus, emission intensity. For example, higher aggregate productivity means lower input intensity overall in the economy. Taking logs of Equation 1.11 and approximating it around some initial point (t_0, ϵ_0) and free trade on exporting $(\bar{\tau_f} = 1)$ gives

$$\ln Z_Q \approx \ln \eta_e \frac{\sigma - 1}{\sigma} + \frac{1}{1 + t_0\epsilon_0} \ln \epsilon + \ln P - \ln r - \frac{t_0\epsilon_0}{1 + t_0\epsilon_0} \ln t + \ln MA \tag{2.1}$$

where MA is the product of export intensity and the average export cost. See Appendix B.2.1 for the derivations.

$$MA = \text{Export Intensity} \times \ln \tau_f$$

Assuming that input cost shares ($\eta' s$) and the elasticity of substitution (σ) are time-invariant, I obtain the following OLS specification, with j and t denoting industry and year.

$$\ln(Z_Q)_{jt} = \beta_\epsilon \ln \epsilon_{jt} + \beta_p \ln P_{jt} + \beta_r \ln r_{jt} + \beta_t \ln t_{jt} + \beta_{ma} \ln MA_{jt} + \delta_j + \delta_t + \xi_{jt} \tag{2.2}$$

2.2.1.2 2SLS specification

Producer price (P) and energy price (r) are determined simultaneously in the model. In addition, some variables can be omitted from the scope of this model. To address potential endogeneity concerns, I use the two-stage least squares (2SLS) approach, instrumenting P and r.

The model provides an expression of P that guides the choice of instrumental variables for it. Putting Equation 1.13 into 1.12 gives the following expression of P.

$$P = \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} P^{\eta_m} \left(\frac{\theta}{\theta-\sigma+1}\right)^{\frac{1}{1-\sigma}} \underbrace{\varphi_o^{-1}\left[1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}\right]^{\frac{1}{1-\sigma}}}_{\text{intensive, selection, and reallocation effect}} \tag{2.3}$$

As discussed in Section 1.5, holding wage, energy price, and the number of varieties fixed, the intermediate import cost affects the aggregate emission intensity by making the global intermediate bundle cheaper (thus decreasing energy intensity) and inducing selection and reallocation effects toward less emission-intensive firms. The last two terms capture the net effect of these forces that appear as the change in P and in Z_Q accordingly.[2]

Taking logs of Equation 2.3, approximating $\ln\left[\varphi_o^{-1}\left\{1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}\right\}^{\frac{1}{1-\sigma}}\right]$ around (τ_0, P_0^*, P_0), and approximating $\ln(1+t\epsilon)$ around (t_0, ϵ_0), I obtain

$$\begin{aligned}\ln P \approx& \Psi + \eta_l \ln w + \eta_e \ln r + \eta_e \frac{t_0\epsilon_0}{1+t_0\epsilon_0}\ln t + \eta_e \frac{t_0\epsilon_0}{1+t_0\epsilon_0}\ln \epsilon + \frac{1}{1-\sigma}\ln M \\ &+ \eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)\ln P + \frac{\theta+\sigma-1}{(\sigma-1)}\eta_m\mu_0 \ln(P^*\tau)\end{aligned}$$

[2] The model portrays only a stylized version of firms' decisions, so there can be other channels by which intermediate prices affect emission intensity than the ones from the current model. For example, the change in intermediate prices may induce firms to increase their investment in abatement technology, which would also affect emission intensity. But as long as the change in abatement technology is captured by the change in output price, the relevance condition holds.

where μ_0 is an import penetration of intermediate inputs – that is, the product of the share of globally sourcing firms and foreign share in global intermediate bundle – at some initial level (denoted by the subscript 0).[3] I combine P^* and τ to capture the price of foreign intermediates that are faced by firms.[4]

Moving $\eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)\ln P$ from the right-hand side to the left-hand side and dividing both sides by $1-\eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)$ gives the following expression.

$$\ln P \approx \left(1-\eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)\right)^{-1}\times\Bigg[\Psi+\eta_l\ln w+\eta_e\ln r + \eta_e\frac{t_0\epsilon_0}{1+t_0\epsilon_0}\ln t+\eta_e\frac{t_0\epsilon_0}{1+t_0\epsilon_0}\ln\epsilon+\frac{1}{1-\sigma}\ln M+\frac{\theta+\sigma-1}{(\sigma-1)}\eta_m\mu_0\ln(P^*\tau)\Bigg] \quad (2.4)$$

The term $\left(1-\eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)\right)^{-1}$ captures the multiplier effect coming from having input-output linkage with the roundabout structure.[5] For example, the import cost's effect on the intermediate bundle price affects the producer price, which again affects the intermediate price.

To match with the data, I convert the expression into a multi-sector version by assuming that the manufacturing intermediate bundle is composed of multiple manufacturing goods in Cobb-Douglas with $\sum_k \gamma_k^i = 1$. Note that I add the price of intermediates excluding the own industry

[3] $\Psi = -\frac{1}{\theta}\ln\left(\frac{\sigma-1}{\theta-\sigma+1}\frac{b^\theta f_o}{f_e}\right)-\frac{\theta+\sigma-1}{\theta(\sigma-1)}\times\ln\left[1+\left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta}\frac{f_g}{f_o}+\left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta}\frac{f_a}{f_o}\right]_{\tau_0,P_0,P_0^*}-\frac{\theta+\sigma-1}{(\sigma-1)}\eta_m\mu_0\ln(P_0^*\tau_0)+\frac{\theta+\sigma-1}{(\sigma-1)}\eta_m\mu_0\ln P_0$.

[4] Based on the model definition, P^* should be the price of foreign goods sold to foreign consumers or firms, and τ includes not only the observed import costs (e.g., tariffs, freight, and insurance costs) but also iceberg costs. Due to the latter, it is hard to separate P^* and τ, thus I use $P^*\tau$ which captures the price of imported goods faced by domestic firms or consumers.

[5] $\left(1-\eta_m\left(1-\frac{\theta+\sigma-1}{(\sigma-1)}\mu_0\right)\right)^{-1}$ is >1 with σ and θ in the range of values that are commonly used in the literature with $\eta_m\approx 0.6$ and $\mu_0=0.16$ for the US 1998 data, which is the initial year of my sample.

on the right-hand side $\left(\prod_{k\neq i}(P^k)^{\gamma_k^i}\right)$.

$$
\begin{aligned}
\ln P^i \approx & \left(1-\eta_m^i\gamma_i^i\left(1-\frac{\theta^i+\sigma^i-1}{(\sigma^i-1)}\mu_0^i\right)\right)^{-1}\times \\
& \Bigg[\Psi^i+\eta_l^i\ln w^i+\eta_e^i\ln r^i+\eta_e^i\frac{t_0^i\epsilon_0^i}{1+t_0^i\epsilon_0^i}\ln t^i+\eta_e^i\frac{t_0^i\epsilon_0^i}{1+t_0^i\epsilon_0^i}\ln\epsilon^i+\frac{1}{1-\sigma^i}\ln M^i \\
& +\eta_m^i\left(1-\frac{\theta^i+\sigma^i-1}{\sigma^i-1}\mu_0^i\right)\ln\prod_{k\neq i}(P^k)^{\gamma_k^i}+\frac{\theta^i+\sigma^i-1}{(\sigma^i-1)}\eta_m^i\mu_0^i\ln(P^{*i}\tau^i)\Bigg] \qquad (2.5)
\end{aligned}
$$

The model does not have an analytic closed-form expression for the energy price. I use the lagged value as an instrument for it. The identifying assumption is that the lagged energy price is not correlated with the unobserved confounders affecting the emission intensity.

Using Equation 2.5 as a basis for the first stage on P, I get the following 2SLS specification, with j and t denoting industry and year.

$$
\text{2nd-stage: } \ln(Z_Q)_{jt} = \beta_\epsilon\ln\epsilon_{jt}+\beta_p\ln\hat{P}_{jt}+\beta_r\ln\hat{r}_{jt}+\beta_t\ln t_{jt}+\beta_{ma}\ln MA_{jt}+\delta_j+\delta_t+\xi_{jt} \qquad (2.6)
$$

$$
\text{1st-stage: } \ln P_{jt} = \alpha\ln IV_{jt}+FE+\chi_{p,jt} \qquad (2.7)
$$

$$
\ln r_{jt} = \gamma\ln r_{jt-2}+FE+\chi_{r,jt} \qquad (2.8)
$$

IV_{jt} is a vector of instrumental variables for $\ln P_{jt}$. In obtaining the above specification, I assume the model parameters on input cost share ($\eta's$ and $\gamma's$), the elasticity of substitution (σ), and Pareto shape (θ) are time-invariant. Among $IV_{jt}=\left\{\ln w_{jt},\ln M_{jt},\ln P_{jt}^m,\ln(P^{m*}\tau)_{jt}\right\}$, I first use the import price of intermediates $\ln(P^{m*}\tau)_{jt}$ as the instrument, for this captures the main mechanism that my model focuses on. Then I add the rest of the variables as instruments for overidentification tests.

Some questions of identifying assumptions are worth clarifying. The exclusion restriction holds when the impact of intermediate prices on emission intensity shows up as in output price changes. In other words, it would not hold if there was an unobserved change in intermediate prices that affects emission intensity but did not show up in output prices. One possible example is abatement technology, which is not included in the current model specification. For example, if the change in intermediate prices induced firms to invest more in abatement technology, emission intensity would decrease. But if firms did not adjust their output prices (i.e., low pass-through), the exclusion restriction would be violated as the effect of intermediate price changes did not show up in output price. This concern is addressed since I control for emission factors. Likewise, controlling for regulation, emission factors, and exporting captures many channels that are relevant to emission intensity.

But, nonetheless, it still warrants caution that there can be other unobserved forces that would bring similar concerns. To minimize such threats, I exclude own industries when I calculate the price of intermediates, which eliminates the unobserved forces that connect emission intensity and intermediate prices through channels that are separate from output prices. Moreover, import prices of intermediates are less vulnerable to these threats than domestic prices, as they are more driven by foreign-origin forces.

The model predicts that $\beta_\epsilon, \beta_p, \beta_{ma}$ are positive and $\beta_{r,}\beta_t$ are negative. In the first stage, $\ln(P^{m*}\tau)_{jt}$ is expected to increase $\ln P_{jt}$. As I do not allow for heterogeneous $\beta's$ across industries or time, the estimated coefficients capture the average effect of each variable.

2.2.2 Data

I combine multiple data sources on trade, emissions, regulations, and output and input to have a panel data on US manufacturing industries. The unit of the regression dataset is the NAICS 6-digit, and there are 322 NAICS-6 industries in the sample. The sample includes nonconsecutive 11 years from 1996 to 2014 – 1996-2002, 2005, 2008, 2011, and 2014. The sample is not annual due to the limited years available for emissions data.

2.2.2.1 Trade

US import trade data are from the US Census Bureau. The dataset on import includes customs import value, import charges, import duties, and the quantities of import at HS-10 level. By providing the information on both value and quantity, the dataset allows me to calculate the average value of each imported HS-10 product, which I use as the import price in the analysis. I aggregate the data to NAICS 6-digit level and concord them with 2012 NAICS classifications.

The information on US trade cost on exporting is from the World Integrated Trade Solution (WITS) by the World Bank, which records the tariff rates and trade value between countries. I obtain the weighted average of the effectively applied tariff rates imposed on US goods, using the exports value to each country as weights. I obtain the data in 1987 SIC 4-digit and concord them into 2012 NAICS 6-digit to match with the other data.

Lastly, I use the World Input-Output Database (WIOD) to obtain the value of export intensity. This database records trade between country-industry pairs as well as trades made for final consumption. I combine two versions of the data: the 2013 release (covering 1995-2011) and the 2016 release (covering 2000-2014).[6] I use the earlier version for the years before 2000 and the later version for 2000-2014. This data provides information on US manufacturing sales made in domestic and foreign markets, which are used to calculate the relative ratio of foreign to total sales.

2.2.2.2 Emissions

The US Environmental Protection Agency (EPA)'s National Emissions Inventory (NEI) is the source of data on the amount of NOx emissions. I use the facility-level dataset which includes the information on each facility's industry classification, location, and emissions of different pollutants. While the data begins in 1990, subsequent publications have been irregular – for example, it was published almost annually during the mid-1990s and early 2000s, but it has been published every 3 years since 2002. Thus, the years covered in this dataset determine the sample years of my analysis.

To calculate the average emission factor of fuel combustion at each level, I combine two sources of information. The EPA's WebFire provides data on the emissions generated burning each fuel type (e.g., coal, natural gas). In addition, the US Energy Information Administration (EIA)'s Manufacturing Energy Consumption and Expenditures (MECS) provides information on energy usage by manufacturing industries, such as the amount of energy generated from each fuel and the expenditures spent on each fuel. The MECS is released every three years, thus I use the latest available year's information for the years that are not covered in the MECS.

[6] The 2013 release has 38 industries and 40 individual countries with the rest of the world (ROW) lumped together and reported as one. The 2016 release has 56 industries and 43 individual countries and the ROW.

2.2.2.3 Emissions regulations

I use attainment status for the measure of emissions regulations, obtained from the EPA's Green Book. If the air quality in a county (or equivalent geographic area) does not meet the national standard (National Ambient Air Quality Standard, NAAQS), the EPA designates the area to be out of attainment. If an area of a state is not in attainment, that state needs to develop a State Implementation Plan (SIP) to create a path to achieve attainment. SIPs may require facilities to increase monitoring and reporting, offset emissions from existing sources when building new sources of emissions, or install certain types of pollution control technologies. Restrictions on further construction or operation of existing construction may also be included.

Several aspects of attainment designations support their use as an exogenous measure of regulation stringency in this paper.[7] First, the NAAQSs are set federally and apply equally to all industries and counties, so the standard that determines attainment status can be considered exogenous to any one industry's conditions. In addition, other factors determine the overall air quality of an area, such as transportation, electric utilities, or meteorological conditions, so it is less likely that a single NAICS-6 manufacturing industry drives out-of-attainment designation.

2.2.2.4 Manufacturing output and input

One primary source for the information on manufacturing output and input usage is the NBER-CES Manufacturing Database. The data contains annual information on US manufacturing industries from 1958 to 2018, including but not limited to, measures of size (e.g., value of shipments, value-added), production factors (e.g., employment, capital, material, energy), and

[7] Attainment status has been widely used as a measure of stringency in the literature (Chay and Greenstone, 2003; Greenstone, 2004).

price indices (e.g., output and inputs). The data is provided at NAICS 2012 6-digit.

In addition, I use the US Bureau of Economic Analysis (BEA)'s Supply-Use Table (SUT) to obtain the information on input-output linkages. I use the detailed SUT for 1997, available at NACIS-6 $\times$ NAICS-6 level (for output $\times$ input industry), to construct domestic and imported intermediate bundle prices by using the expenditure share of each input industry in each output industry.

My model and analysis are relevant only with the fuel types that generate emissions upon their usage, but the energy price index from NBER-CES includes that of electricity. Thus, I construct non-electricity energy prices using fuel prices from EIA and industry-level fuel usage from MECS. Specifically, I use the price coal, oil, and gas.

Lastly, I use the County Business Patterns (CBP) from the US Census Bureau for industry-county-level employment, which is used to calculate the industry-level out-of-attainment measure.

2.2.3 Measurement

2.2.3.1 Emission intensity

Industry-level emission intensity is measured as the amount of emissions divided by real gross output. I deflate the value of shipments by NAICS 6-digit-level output deflator to obtain the real gross output.

2.2.3.2 Prices

The NBER-CES provides the price index for the value of shipment, which is used as the measure of producer price index at the industry level.[8] Wage is calculated by dividing the total payroll by total employment. To match with other input price indices, I normalize the wage to 1 for the year 2012.

Energy price is constructed by combining the national price of each fuel type and the industry's expenditure share of each fuel type. Specifically, I closely follow the price index of NBER-CES, except for the exclusion of the electricity price. Formally, I first construct the weighted mean of the annual growth (in log difference) in fuel prices, as

$$\Delta \ln r_{jt} = \sum_f \chi_{jt}^f \Delta \ln r_t^f \tag{2.9}$$

where r_t^f is the national price of fuel f, and χ_{jt}^f is the expenditure share of fuel f in industry j.[9] Then I calculate the price level by applying the annual growth to 1 in the year 2012. The expenditure share of fuel within each industry j, χ_{jt}^f, is only available at NAICS 3-digit in the MECS, thus the energy price measure is at NAICS 3-digit level.

The domestic intermediate is calculated as a weighted average as well. Specifically, I use the industry-level price index, which is the same measure I use for the producer price measure, as intermediate input price and calculate the weighted average using the cost share of each intermediate input of the year 1997.[10] Own industries are excluded from the calculation of

[8]NBER-CES uses the producer price index from the US Bureau of Labor Statistics.

[9]For the years that are not covered in the MECS, I use the latest available years' information on the expenditure share.

[10]1997 is the closest year that has the detailed-level SUT dataset.

the weighted average, which is consistent with the model-derived specification and captures the 'input' cost.

The import price of intermediates is calculated analogously. I first combine customs import value, CIF charges, and import duties to obtain the trade-cost-inclusive total import value. I only include HS-10 products that are classified as intermediate goods according to the Broad Economic Categories (BEC). I divide this total import value by quantity to obtain the average unit value and calculate the yearly log difference. Then I aggregate the annual growth of import price at HS-10 level up to NAICS 6-digit, using the import value as weights, and again aggregate them up to output industry level, using the 1997 cost share. Lastly, I apply the weighted mean of annual growth of import prices to $2012 = 1$ to obtain the import price index.

2.2.3.3 Regulation

Industry-level out-of-attainment status is calculated as the weighted average of an out-of-attainment indicator with the employment share as weights. I use the 3-year-lagged information on attainment status. Formally,

$$t_{it} = \sum_{c} \omega_{it}^{c} NA_{ct-3}$$

where ω_{it}^{c} is the share of employment in county c and industry i among the total employment of industry i. NA_{ct-3} is an out-of-attainment indicator that is 1 if a county is out of attainment for at least one pollutant among NO_x, PM_{10} and $PM_{2.5}$. I include the out-of-attainment status for PMs as well since NO_x is a precursor to PM formation, so the regulation on PMs is expected to indirectly restrict NO_x emissions. Lastly, note that this measure does not exactly match the regulation stringency from the model – which is the ad-valorem tax rate on emission content of fuel. As t_{it} ranges from 0 to 1, I do not put a log on it and use the level of it.

2.2.3.4 Other variables

The export intensity is calculated by dividing the sales purchased by foreign countries by the total sales.[11] Then I multiply the export intensity and the log of the average export tariff to obtain the market access measure. The number of establishments is obtained from aggregating the CBP's number of establishments from county-industry-level to industry-level. Lastly, the industry-level emission factor – emission created by a unit usage of energy – is calculated as the weighted average of fuel-specific emission factors, using the share of fuel usage as weights. Note that the share of fuel usage is different from the expenditure share since the former is in terms of the physical amount of energy generated from each fuel, measured in Btu, while the latter is in terms of expenditures. The information on fuel usage is also from MECS, which is at a 3-digit-level, thus the unit of emission factor is also at NAICS 3-digit level.

2.2.3.5 Descriptive statistics

Table 2.1 shows the 1996 and 2014 values of the variables used in the analysis. The table shows various degrees of price increases among inputs. While the price of all inputs increased, the increase in energy price is larger than wage or intermediate price (either domestic or imported), suggesting the decrease in the relative price of non-energy inputs. In addition, comparing the import price and domestic price of intermediates shows that the imported intermediates are cheaper in both years, although their price increased by a larger degree during this period.

[11] Specifically, the sales include the purchase for intermediate usage, capital formation and inventories, and final consumption.

The change in the out-of-attainment measure captures the increased stringency during the period. Employment in out-of-attainment counties more than doubled from 1996 to 2014. The emission factor decreased by 12 log points, which means that the composition of fuel moved toward a cleaner set.

Table 2.1: Descriptive statistics

	(1) 1996	(2) 2014	(3) =(2)-(1)
Emission per real gross output	-3.541	-4.679	-1.138
Producer price	-0.266	0.021	0.287
Energy price	-0.840	0.084	0.924
Regulation (out-of-attainment)	0.071	0.168	0.097
Emission factor	-2.093	-2.214	-0.121
Market access cost	0.010	0.005	-0.005
Instrumental variables			
Import price of intermediates	-0.396	-0.013	0.383
Domestic price of intermediates	-0.212	0.012	0.224
Wage	-0.472	0.065	0.537
Number of establishments	6.117	6.009	-0.108

Notes: All variables are in a natural log except for regulation and market access cost.

2.2.4 Results

2.2.4.1 Baseline

Table 2.2 reports the results from the OLS and 2SLS-IV estimations, and Appendix Table B.1 presents the summary statistics of the regression sample. All columns in Table 2.2 use NAICS-6 fixed effects and year fixed effects. In all IV columns, I use the import price of intermediates and the two-year-lagged energy price to instrument producer price and energy price. Column 3 presents the result obtained from adding the domestic price of intermediates as an instrument. Lastly, column 4 shows the results from using the full set of instruments as guided by the model expression of the producer price – that is, I add wage and the number of establishments.

Panel A presents the OLS results and the second-stage results from 2SLS specifications. Panel B presents the estimates from the first stage on producer price, which is the main method by which intermediate trade affects emission intensity in my model. Panel C presents evidence from reduced-form regressions of emission intensity on instrumental variables. In Panels B and C, I present the estimates of the import price and domestic price of intermediates, the variables of most interest. The comprehensive result of first-stage and reduced-form regressions can be found in Appendix Table B.2 and B.3.

The OLS estimate in column 1 shows that the emission intensity increases with producer price, all else equal, confirming the positive relationship between the two from the model. The coefficient on energy price is, however, positive, the opposite of the expected direction. The coefficients on regulation, emission factor, and market access are consistent with the model prediction, although they are not statistically significant at 10% level except for that on emission factor.

Column 2 shows the 2SLS results that I obtain by instrumenting the producer price and the energy price with the import price of intermediates and the two-year-lagged energy price as instruments. While the estimated coefficients are overall similar to those in the OLS column, the effect of the producer price on emission intensity decreases slightly, which suggests that the IV fixes the upward bias on this coefficient. One example of the source of this upward bias is the introduction of new production technology. It would raise production efficiency, decreasing emission intensity and producer prices at the same time. The estimate on energy price is still positive but not statistically different from zero. The second stage estimates do not

Table 2.2: Regression results

	(1)	(2)	(3)	(4)
	OLS		2SLS-IV	
Panel A. OLS and 2SLS second stage				
Producer price	1.542***	1.452***	1.475***	1.436***
	(0.088)	(0.284)	(0.176)	(0.174)
Energy price	0.234**	0.142	0.141	0.146
	(0.105)	(0.123)	(0.123)	(0.123)
Regulation	-0.803	-0.778	-0.782	-0.776
	(0.684)	(0.688)	(0.687)	(0.688)
Emission factor	0.766**	0.625*	0.621*	0.635*
	(0.361)	(0.374)	(0.372)	(0.371)
Market access cost	4.133	3.931	3.846	4.014
	(5.167)	(5.217)	(5.182)	(5.188)
Panel B. 2SLS first stage on producer price				
Import price of int.		0.537***	0.239***	0.227***
		(0.031)	(0.031)	(0.031)
Domestic price of int.			0.404***	0.410***
			(0.044)	(0.043)
Panel C. Reduced-form results				
Import price of int.		0.791***	0.341*	0.343*
		(0.161)	(0.182)	(0.181)
Domestic price of int.			0.611***	0.615***
			(0.113)	(0.113)
1st-stage F-statistic		151.438	124.509	77.147
Hansen J test p-value			0.906	0.651
Robust confidence interval set:				
Producer price		[1.011, 1.893]	[1.202, 1.748]	[1.166, 1.706]
Energy price		[-0.049, 0.332]	[-0.050, 0.332]	[-0.046, 0.337]
Number of observations	3373	3373	3373	
NAICS-6 fixed effects	O	O	O	
Year fixed effects	O	O	O	

Notes: The dependent variable is the natural log of emission per real gross output. All regressors are in a natural log except for regulation and market access cost. All IV columns use the two-year lag of energy price and the import price of intermediates as instruments. Column 3 adds the domestic price of intermediates, and column 4 adds wage and the number of establishments as instruments. I present Kleibergen-Paap F-statistics. Robust confidence interval set is the 95% two-step identification-robust confidence set, as introduced in Andrews et al. (2019). All columns use industry (NAICS 6-digit) fixed effects and year fixed effects. Robust standard errors are in brackets. $*, **, ***$ indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$.

much change when I add more instruments, as shown in column 3 and 4. For both columns, the overidentification test results from these columns show that I cannot reject that the instruments as a group are exogenous.

Panel B results show how producer price changes in response to the import and domestic prices of intermediates. Moving from column 2 to column 3, the estimate of the import price of intermediates decreases once I add the domestic price of intermediates. This indicates that the two are positively correlated, and the estimate in column 2 captures the combined effect of intermediate prices. However in column 4, where I add additional instruments, the estimates do not much change. It is not surprising to see the smaller coefficient on import price compared to domestic price, since the share of domestic intermediates is higher than that of foreign intermediates among the total usage of intermediates.[12] It is reassuring to see that the magnitude of coefficient on the import and domestic prices is in line with the model-predicted value (respectively, 0.28 and 0.39).[13]

Although the high values of F statistics suggest them to be most likely strong instruments, Kleibergen-Paap F-statistics (and other F-statistics) may not be sufficient in a nonhomoskedastic setting with multiple endogenous variables. Thus, I also present robust confidence intervals for the second-stage coefficients on the endogeneous variables – producer price and energy price. The last two rows of the table present 95% two-step identification-robust confidence set as recommended by Andrews et al. (2019). The estimated second-stage coefficients are included in the sets, suggesting that the coefficients are significant at the 5% level in the presence of weak instruments.

[12] The import penetration in the intermediates used by US manufacturing is about 22% in 2014.

[13] I use $\sigma = 4.5, \theta = 5.5$ and the average values of the US manufacturing for cost shares ($\eta_m = 0.6, \gamma_i^i = 0.27$) and intermediate import penetration for 1998 ($\mu_0 = 0.16$).

Panel C presents the reduced-form effect of the import and domestic price of intermediates. The regression estimates show that the lower import price of intermediates brings a reduction in emission intensity. The estimate of 0.341 in column 3 means that the decrease in import price by its within-industry standard deviation (20.9 log points) decreases the emission intensity by 7.1 log points.[14]

2.2.4.2 Robustness

The baseline results on the estimates of main interest are robust to controlling for trends and additional fixed effects. Column 1 and 2 in Table 2.3 show the 2SLS results obtained from adding NAICS-3-digit $\times$ year trend and NAICS-3-digit-year fixed effects to Table 2.2, column 3. Note that the variables that are measured at NAICS-3-year level are dropped in column 2.

The estimates on the producer price in the second stage and intermediate import and domestic prices in the first stage are similar to the baseline results in both columns, which is reassuring as these are the variables of most interest. A notable result is that the sign of the coefficient on energy price and emission factor changes when I add the aggregate trend, as represented in the first column. Although they are imprecisely estimated, this switch in the sign of the coefficients indicates that there is some unobserved trend at the aggregate level that affects energy price, emission factor, and emission intensity in the same direction.

In addition, the estimates of the effect of market access vary across columns and are imprecise with large standard errors. One reason can be the lack of variation in this measure. The measure of market access has a relatively smaller variation than other variables as it is constructed as the product of exporting cost and export intensity, which generally move in opposite directions.

[14] Appendix Table B.4 presents the summary statistics after industry effects are eliminated.

Table 2.3: Robustness results

	(1)	(2)	(3)
Panel A. OLS and 2SLS second stage			
Producer price	1.280***	1.420**	1.401***
	(0.460)	(0.621)	(0.176)
Energy price	-0.277		0.146
	(0.326)		(0.123)
Regulation	-0.284	-0.429	-0.771
	(0.684)	(0.735)	(0.689)
Emission factor	-0.771		0.642*
	(0.542)		(0.372)
Market access cost	2.444	-0.936	4.142
	(5.469)	(6.208)	(5.187)
Panel B. 2SLS first stage on producer price			
Import price of int.	0.258***	0.272***	0.179***
	(0.030)	(0.034)	(0.027)
Domestic price of int.	0.200***	0.062	0.417***
	(0.076)	(0.125)	(0.042)
1st-stage F-statistic	28.989	34.102	89.629
Hansen J test p-value		0.213	0.372
Robust confidence interval set:			
Producer price	[0.568, 1.992]	[-0.112, 2.498]	[1.167, 1.719]
Energy price	[-0.782, 0.228]		[-0.049, 0.332]
Number of observations	3373	3373	3373
Industry FEs, Year FEs	O	O	O
3-digit X Year trend	O		
3-digit-Year FEs		O	

Notes: The dependent variable is the natural log of emission per real gross output. All regressors are in a natural log except for regulation and market access cost. All columns use the two-year lag of energy price, the import price of intermediates, and the domestic price of intermediates as instruments. I present Kleibergen-Paap F-statistics. Robust confidence interval set is the 95% two-step identification-robust confidence set, as introduced in Andrews et al. (2019). All columns use industry (NAICS 6-digit) fixed effects and year fixed effects. The additional fixed effects used for each column are marked in the table. Robust standard errors are in brackets. $*, **, ***$ indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$.

Moreover, the variation within NAICS-3-Year becomes even smaller since the measure of export intensity is at the NAICS-3-digit level.

Lastly, to check that the results are not driven by the 1997 input-output structure, which is used for constructing intermediate prices, I construct the import and domestic prices using the 1992 input-output data. Using these measures does not change the results significantly, as shown in column 3.

2.3 Quantitative analysis

In the previous section, I tested the expression of aggregate emission intensity as suggested by the model in Chapter 1. One interpretation of the reduced-form results was that the fall in intermediate input import price lowers aggregate emission intensity. In this section, I quantify the role of intermediate imports on US manufacturing emissions by calibrating the model to the US data and running counterfactual exercises of the change in trade costs. I first calibrate the model to the 1998 US manufacturing data to solve for the baseline equilibrium in the following subsection. Then I calibrate three parameters – emission factor, environmental regulation, and intermediate import cost – using the new target moments based on the 2014 data and comparing them with the baseline values. By doing so, I calibrate three types of shocks that occurred between 1998 and 2014.

2.3.1 Calibration

The model is calibrated to the 1998 US manufacturing data. I assume a symmetric setting, in which the US is one of the four symmetric countries. In other words, 4 countries have the same parameter values in the baseline. In this section, I explain the calibration strategy, and additional details can be found in Appendix Table B.5.

Externally calibrated parameters

Table 2.4 shows the parameter values that are externally calibrated, either from the data or the literature. Three parameters determine the size of the economy: consumers' expenditures on manufacturing ($\bar{I}$), labor supply ($\bar{L}$), and global energy supply ($\bar{E}^G$). The final expenditures on manufacturing are from the WIOD, aggregating the US final consumption, change of inventory, and gross fixed capital formation. Labor supply is the total employment in manufacturing, obtained from the US Census Annual Survey of Manufacturers (ASM). For the global energy supply, I obtain the total physical amount of non-electricity energy (all sources converted into trillion Btu) used by US manufacturing from the MECS and multiply it by 4. I exclude electricity usage since it is not an emission-generating source from the manufacturer's perspective.[15]

I take the elasticity of substitution across varieties (σ) and the Pareto parameters (θ and b) from Shapiro and Walker (2018).[16] The Cobb-Douglas input cost shares (η_l, η_e, η_m) are calculated as the 1998-2014 average share of each input from the BEA's SUT.[17] Finally, I normalize the fixed cost for drawing productivity and operation (f_e and f_o) at 1.[18]

Two parameters govern the environmentally-related mechanisms: the effectiveness of energy-saving technology (β) and emission factor (ϵ). EPA (2011) states that the expected reduction in

[15] The electric utility sector makes emissions during their generation and provision of electricity to other sectors including manufacturing, but their production and emissions are beyond the scope of this paper.

[16] Section 2.3.5 and Appendix B.3.1 discuss the implications of using different σ and θ values.

[17] Specifically, I first deflate each year's expenditures on labor, the inputs from energy sectors, and the inputs from manufacturing sectors, using the price deflator from the NBER-CES Manufacturing Database. Then I aggregate the deflated expenditures over the years from 1998 to 2014 and calculate the relative size among them.

[18] The normalization only affects the overall magnitude of φ in the economy but not other calibrated parameters or outcomes.

energy bill savings from energy-efficient products is 5%-10%.[19] I use the value of β, matching the 5% reduction – that is, $\beta^{-\eta_e} = 0.95$. With $\eta_e = 0.13$, this results in $\beta = 1.5$.[20] The emission factor (ϵ) is calculated by dividing the US total manufacturing emissions by the US total non-electricity energy consumption, which are obtained from the NEI and MECS, respectively. This allows me to match the baseline total emissions to the data.[21]

Table 2.4: Externally calibrated parameters

Parameters		Value
σ	EOS across varieties	4.76
η_l	Labor cost share	0.27
η_e	Energy input cost share	0.13
η_m	Manufacturing input cost share	0.6
θ	Pareto shape parameter	5.14
b	Pareto location parameter	1
β	Energy-saving effectiveness	1.5
ϵ	Emission factor	1.23
f_e	Fixed cost for entry	1
f_o	Fixed cost for operation	1
$\bar{I}$	Consumption expenditure	1,753,741
$\bar{L}$	Labor supply	16,943
$\bar{E}^G$	Global energy supply	58,636

Notes: Consumption expenditure is in millions of 2000 US Dollars, labor supply is in 1000 persons, and energy supply is in trillion Btu. The emission factor is in 100 US tons per trillion Btu.

Internally calibrated parameters

Five parameters are jointly calibrated, using the relevant target moments.[22] The fixed cost

[19] EPA (2011) states that "Because energy-efficient products require less energy to operate than conventional products, purchasing these products can reduce facility energy loads and achieve energy bill savings on the order of 5–10 percent."

[20] I run the model with different β values in Section 2.3.5 and Appendix B.3.1 for a sensitivity analysis.

[21] To be accurate, not all emissions are generated from burning fuel, although fuel-combustion emission are the majority. By using total emission, which includes both fuel combustion and other emission sources, I make an implicit assumption that the emissions from other sources are generated in proportion to the emissions from burning fuel. This allows me to use my model, focused on fuel-combustion emissions, to understand changes in the aggregate emission from US manufacturing. An alternative is to analyze the model within fuel-combustion emission only.

[22] That is, although I have a target moment used for each parameter, the set of parameters jointly determine the

for global sourcing (f_g) is calibrated to match the ratio of importer manufacturing firms (among all manufacturing firms) for the year 1997, which Bernard et al. (2007) provides as 14%. I use the value for 1997, as the ratio is not available for 1998. The fixed cost for energy-saving technology adoption (f_a) is calibrated analogously, using the ratio of manufacturing establishments that install or retrofit energy-efficiency equipment. MECS provides the number of establishments that invest in different types of energy-efficiency equipment or activities. The ideal target for calibrating f_a would be the ratio of establishments that invest in at least one type of energy-efficiency equipment. But the dataset does not include this information, thus I instead use the highest ratio of adoption across equipment types, under the assumption that equipment installations are concentrated and the same set of firms install multiple types of equipment. This would result in high fixed cost of adoption in the calibration.[23] Appendix B.3.1 show the result obtained from calibrating f_a based on this assumption.

For the level of emission regulation, I target the ratio of air-pollution-related tax revenue to GDP for the 1998 US, provided in the OECD's Environmentally-related Tax Revenue dataset. It is likely that this calibrated level of the tax rate would be the lower bound of regulation stringency, for many types of non-tax regulation, such as cap-and-trade programs and command-and-control technology standards, are not captured in this data. Another caveat is that the available data is for the aggregate US, so it contains the regulation on other industries. Thus, if manufacturing is more strictly regulated than other industries, such as electricity, in the US, the calibrated tax rate underestimates the relevant stringency. Lastly, to calibrate the baseline intermediate trade

set of target moments. The model is exactly calibrated, matching 5 moments to obtain 5 parameter values in the baseline.

[23] The contrasting assumption would be that all establishments choose to adopt only one type of equipment, in which case I should sum up the ratio of adoption across equipment types, and the calibrated fixed cost would be lower.

cost (τ), I use the share of foreign manufacturing inputs within total manufacturing input used by the US manufacturing industries as a target. For the trade cost on final goods, I target the export intensity of US manufacturing, which is the ratio of sales made in the foreign final market to total final sales.

Table 2.5 summarizes the data moments and the model fit. The calibrated model closely matches the data except in the case of the emission tax rate. To match the tax revenue ratio of 0.8%, the emission tax rate (t) should be even lower, close to zero. In order to have some effect from regulation – and also considering that the calibration using the tax revenue moment provides a lower bound for the regulation stringency – I choose to use 0.02 as the baseline t. In a robustness analysis in Appendix B.3.1, I show how assuming different tax rates affects the analysis.

Table 2.5: Internally calibrated parameters

Parameters		Target	Data	Model	Value
f_g	Fixed cost for global sourcing	Ratio of importer firms	14%	14.3%	0.7
f_a	Fixed cost for technology adoption	Ratio of firms with energy-efficiency equipment installed	8.3%	8.2%	1.6
t	Emission tax rate	US air pollution tax revenue per GDP	0.8%	1.2%	0.02
τ	Intermediate trade cost	Foreign share in manufacturing input	15.4%	15.3%	1.85
τ_F	Final trade cost	Export intensity	15.6%	15.6%	2.21

Shocks

I calibrate the change in regulation stringency, emission factor, and intermediate import cost to use them to use them as shocks in counterfactual exercises. First, to calibrate the change in the regulation stringency (t'), I use the change in the share of manufacturing employment in out-of-attainment counties. This is the aggregate-level measure of regulation stringency analogous with the one used in the empirical analysis. I use this approach, instead of looking at the change in the air pollution tax revenue per GDP, because the latter suggests that there was no change in the regulation stringency between 1998 and 2014. However, with the introduction of various cap-and-trade programs, such as NOx Budget Program in 2003 and the initiation of $PM_{2.5}$ regulation in the late 1990s, it is hard to accept that the regulation stringency for NO_x has not changed. The share of manufacturing employment in out-of-attainment counties increased by 2.5 times, so I use 0.05 for the 2014 value of t.

For the emission factor (ϵ'), I use the change in the average emission factor of US manufacturing firms' energy usage, using the same measure I used in the empirical analysis. Specifically, I use the emission factors for each fuel type and the time-varying share of each fuel type among the total non-electricity energy consumption by US manufacturing. Then I calculate the ratio of the 2014 emission factor to the 1998 value and multiply the ratio by the baseline ϵ value. In a nutshell, it captures the change in the emission factor due to the change in fuel composition (e.g., switch from coal to natural gas). Recall that I use the 'backed-out' emission factor in the baseline to match the initial level of emissions exactly. But calibrating the 2014 value of ϵ using the actual change in emissions would attribute the change from other unobserved factors to emission factor.

Table 2.6: Calibration of the 'post' values

Parameters		**Value**	**Source**
τ'	Trade cost on int. goods	1.67	Match the 2014 foreign share in manufacturing input $= 23\%$
t'	Emission tax rate	0.05	Apply the change in the out-of-attainment counties' manufacturing share ($\times 2.5$) to the baseline $t = 0.02$
ϵ'	Emission factor	1.17	Use 2014 fuel consumption and fuel-level emission factor

Lastly, to calibrate the intermediate import cost, τ, for 2014, I target the foreign share in manufacturing input in the year 2014 (0.23). I use the newly calibrated values of environmental tax and emission factor, t' and ϵ', and the same values for the other parameters from the baseline.

I get $\tau' = \tau_{2014} = 1.67$, which is a 10% decrease from the 1998 import cost ($\tau = 1.85$).

External validity

I review if the calibration explains key untargeted statistics related to trade and technology adoption. Table 2.7 reports the review of external validity. First, I review the total import penetration in the US' manufacturing consumption, including both final goods and intermediate inputs.[24] The only trade-related parameter that is changed between 1998 and 2014 is τ. Without a change in other trade-related parameters – including sourcing fixed cost, export cost, or final import cost – this generates 24.8% increase in the total import penetration, which is close to the 25.1% growth observed from the data.[25]

I also check the share of globally-sourcing firms for the year 2014. The model implies that 23.5% of manufacturing firms (in terms of the number) source globally, which is a little higher than 19.3% from the data. This suggests that the model overestimates the increase in the share of importers among manufacturing firms and underestimates the share of imported inputs in input usage among importers – because the targeted import share of intermediates captures both the share of importers among all firms and the share of imported inputs among importers. In other words, global sourcing is more concentrated (among fewer firms) in the data. One possible reason is that while the model assumes homogeneous sourcing behavior among importers – in that, all importers source the same share of inputs globally – there can be importer size advantages, which

[24]This is calculated as the ratio of the expenditures on foreign manufacturing goods to the total expenditures on manufacturing consumption, including both final and intermediate consumption.

[25]It may be surprising to see that the change in the US intermediate import cost alone generates the change in total import penetration that is close to what is observed in the data. One possible explanation can be based on the decrease in import penetration among final goods, which implies the rise in costs of importing final goods (or analogously the rise in costs of exporting final goods from the foreign countries' sides). So it can be the case that my calibrated model does not capture some part of the growth in intermediate import penetration, but as it also does not capture the fall in final import penetration (since I hold the cost of importing final goods fixed), the change in total import penetration from the model becomes close to that in the data in net.

suggests a high concentration in input imports among large importers, as discussed in the recent literature (Antràs et al., 2017). Thus, in the data, the increase in input imports could have been driven less by the entry into global sourcing and more by the intensive increase among importers than the model suggests. This discrepancy, however, would not affect the model's counterfactual results much since, as Section 2.3.4 shows later, the entry into global sourcing explains a small portion of the change in aggregate emission intensity.

Lastly, the model generates 8.9% of firms with energy-efficiency equipment in the year 2014, which is lower than 16% observed in the data. The current calibration assumes that the level of technology (β) or the fixed cost of adopting technology (f_a) did not change between 1998 and 2014, both of which could have experienced meaningful improvements. This means that the model underestimates the decrease in emission intensity resulting from firms' adoption of energy-efficiency technology after the cut in input import costs.

Table 2.7: External validity

Untargeted moments	**Model**	**Data**
Change in total import penetration in manufacturing input and final consumption ('98-'14)	+24.8%	+25.1%
Share of global sourcing firms ('14)	23.5%	19.3%
Share of tech-adoption firms ('14)	8.9%	16.0%

2.3.2 GE effect of import costs

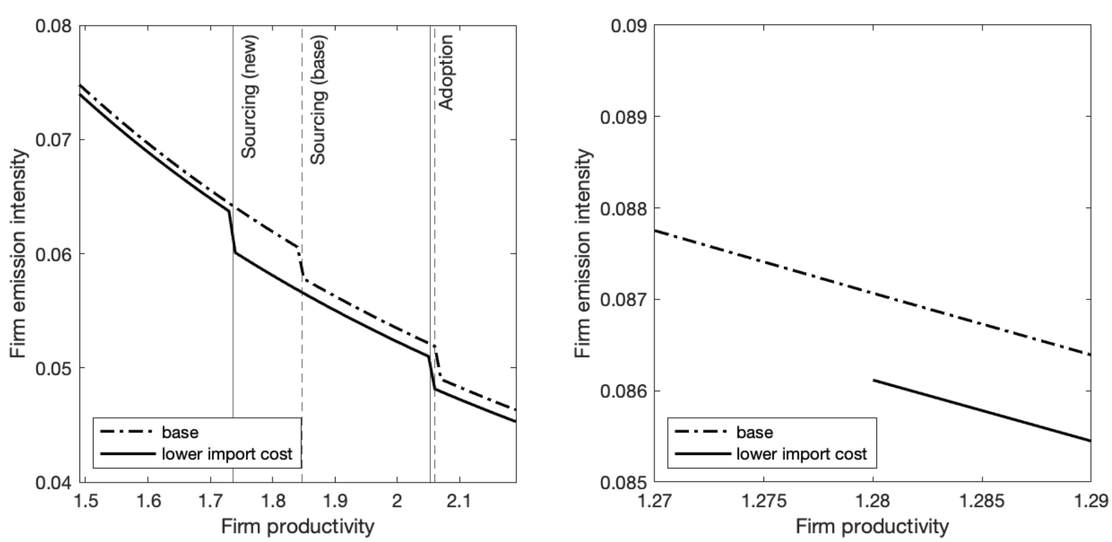
This section presents the effect of intermediate import costs in the general equilibrium (GE). Looking at GE effects is important since there will be changes in wages, energy price, and the aggregate price index for manufacturing products in both home and foreign countries, which affect the input decisions as well as firms' entry, sourcing, and technology adoption decisions.

For example, if energy price falls sufficiently in the GE so that the relative price of energy input compared to that of intermediate input decreases even with lower import costs, firms' energy intensity may increase.

By solving the model with market clearing conditions, as described in the previous chapter's theoretical model (Section 1.4.5), I analyze whether the partial effects presented in the model remain when aggregate prices and potential entrepreneur mass are allowed to adjust. The figures in this section present the results obtained from changing only the home (US) country's intermediate import cost from the baseline economy, unless stated otherwise. The previous sections' calibration of τ for 1998 and 2014 produces 10% decrease in τ (from $\tau_{1998} = 1.85$ to $\tau_{2014} = 1.67$).

Figure 2.1's left panel shows the change in firm-level emission intensity when intermediate import cost decreases from the baseline τ to the 2014 value. The dot-dash line indicates the baseline firm emission intensity, and the solid line indicates the emission intensity after the reduction in τ. The x-axis presents firm productivity, and for better visibility, I present the subset range of firm productivity.

Figure 2.1: Firm-level emission intensity



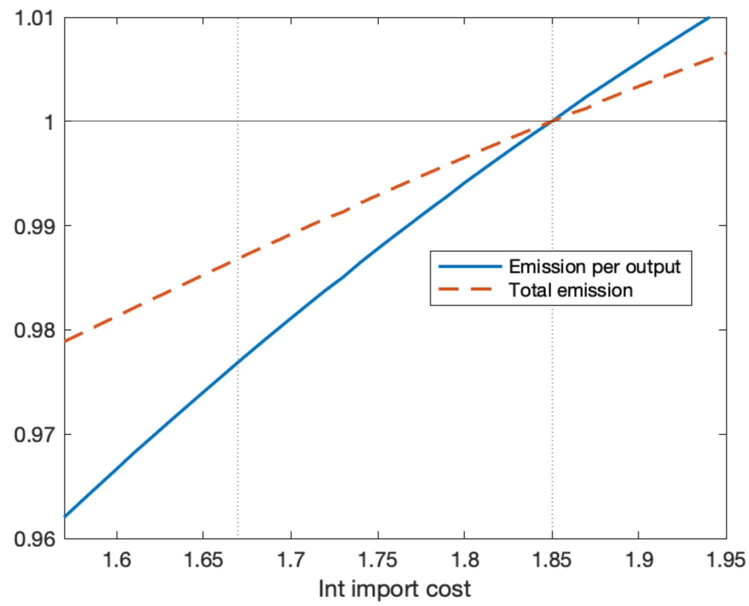
In the calibrated baseline, the share of globally sourcing firms is larger than the share of firms that adopt the technology. Under my model setting, this indicates that the global sourcing cutoff is lower than the technology adoption cutoff. With the lower intermediate import cost, the sourcing cutoff decreases, inducing more firms to use the global bundle of intermediates. This reduces their energy intensity and, thus, emission intensity. The adoption cutoff also changes since firms that lie just below the original adoption cutoff source globally and, thus, benefit from the lower import costs. The increased profitability induces some firms to invest in energy-saving technology. The change in this cutoff, however, is smaller than the one in the sourcing cutoff.

Figure 2.1's right panel presents the emission intensity of firms that are near the entry cutoff. The entry cutoff increases, and the least productive and the most emission-intensive firms exit – see those with productivity lower than 1.28 in the figure.

Both figures show evidence of within-firm improvement in emission intensity in all firms. Lower intermediate import cost means a lower cost of using the global intermediate bundle, so the globally-sourcing firms' intermediate intensity increases while energy intensity decreases. In addition, the selection and reallocation effects combined with the roundabout structure decrease the domestic intermediate price in the general equilibrium, so the emission intensity of the firms that use only domestic intermediates also decreases.

The change in aggregate emission intensity and total emissions are presented in Figure 2.2. The baseline τ and the 2014 τ are marked in the figure, and I normalize the emission intensity and total emissions by their baseline level. The reduction in emission intensity not only comes from within-firm improvement and cutoff changes as described above, but the reallocation of market share to cleaner firms further decreases aggregate emission intensity. The figure shows that combined effect. The total emissions decrease as well, but the magnitude of the change is smaller than that of the emission intensity, indicating the growth of the production in the home country.

Figure 2.2: Aggregate emission intensity



2.3.3 Quantifying the effect of intermediate import cost changes

To investigate the role of intermediate cost reduction in the observed decrease in the NOx emission intensity during 1998-2014, I conduct two counterfactual exercises. First, I solve for the equilibrium after applying two shocks – the change in emission tax rate and the change in emission factor. While multiple other shocks happened during this time, the rise of regulation stringency and the change in fuel composition are the most widely discussed drivers of the emission changes.[26] Then I solve for the equilibrium in the scenario that intermediate import cost also changes along with these two shocks. By comparing the two, I can obtain the implied

[26]It would be ideal to also have the information on firms' pollution control equipment installations. But the data on pollution abatement activities and expenditures is available only for a few years in the 1990s and only for 2005 afterward.

effect of the intermediate import cost shock during the period.

2.3.3.1 Assumption on welfare

To quantify the welfare implications, I assume the functional form of the (dis)utility from air pollutant emission which was previously introduced as $f(Z)$ in the model. Specifically, I follow Shapiro (2021) and define the (dis)utility from emissions as

$$f(Z) = [1 + \delta(Z - Z_0)]^{-1} \tag{2.10}$$

By inserting Equation 2.10 into the utility function defined in the model (Equation 1.1), I get the following full expression of aggregate utility (U) and indirect utility (V)

$$\begin{aligned} U &= \left[\int_{\nu} q(\nu)^{\frac{\sigma-1}{\sigma}} d\nu \right]^{\frac{\sigma}{\sigma-1}} f(Z) \\ &= \left[\int_{\nu} q(\nu)^{\frac{\sigma-1}{\sigma}} d\nu \right]^{\frac{\sigma}{\sigma-1}} [1 + \delta(Z - Z_0)]^{-1} \qquad (2.11) \\ V &= \left[\frac{I}{P^C} \right] [1 + \delta(Z - Z_0)]^{-1} \qquad (2.12) \end{aligned}$$

where P^C is the price index faced by consumers. The first term of V represents the utility from consumption, and the second term damage from emissions. By definition, my functional form of $f(Z)$ abstracts from any disutility from air emission in the baseline (when $Z = Z_0$).[27]

I calibrate the disutility parameter, δ, to match the social marginal cost of NO_x. For the social cost, I use $8,976$ USD per US ton, which is the simple average of the minimum and

[27]The alternative form is what is used in Shapiro (2016), which is $V = \left[\frac{I}{P}\right] \left[\frac{1}{1+(\gamma^{-1}Z)^2}\right]$. This can estimate the effect of emission on utility in the baseline year as well.

maximum values from Heo et al. (2016).[28] I interpret the marginal social cost as the marginal willingness to pay for reduced emissions, expressed as $\frac{dI}{dZ} = -\frac{\partial V/\partial Z}{\partial V/\partial I}$, following the literature (Bockstael and Freeman, 2005; Copeland and Taylor, 2003). Based on this definition and Equation 2.12, δ can be obtained by solving

$$\delta = \frac{\text{marginal social cost}}{I - \text{marginal social cost}}.$$

I use the calibrated $\bar{I}$ for I. The calculated value for δ is 4.6×10^{-7}. Unfortunately, there is no existing estimate of δ for comparison in the literature, as few papers use the current functional form of environmental disutility – which captures the disutility in a reduced-form way – and the existing ones examine environmental disutility in the context of CO_2.[29] As CO_2 is a global pollutant, its marginal social cost is estimated very differently – in terms of global, not local welfare.

It is useful to briefly discuss the standard approach of quantifying welfare implications of environmental damages in the environmental economics literature. One common way is to measure the total social costs – so-called gross external damages (GED) – by multiplying the marginal social cost of emission and total emissions, based on the assumption that the marginal cost is constant within the range of emission values studied. The GED is then compared with 'benefits' which are usually the value-added (VA) of some industry or the entire economy. For example, Muller et al. (2011) analyze the size of external environmental damages compared to each industry's economic value by looking at GED and VA. Another approach is to indirectly

[28] I convert the values from Heo et al. (2016), which are in 2005 USD per metric ton, to 2000 USD per US (short) ton. I use the US GDP deflator for the conversion of the US dollar. The ratio between metric ton to US (short) ton is $1 : 1.10231$.

[29] For example, see Shapiro (2016, 2021).

measure the costs by running a computable general equilibrium (CGE) model. The main difference of this approach compared to the former one as well as my own is that environmental outcomes do not enter into utility directly but affect the overall economy through production. The social cost of carbon (SCC) is typically calculated in this framework as the differential of GDP that occurs from an additional ton of CO_2 emission (Nordhaus, 2017). The approach taken in this paper is closer to the first one, but the main difference is that the welfare from emissions appears in the multiplicative form, which allows me to decompose the changes in utility into the one driven by consumption and by emission.

2.3.4 Quantification results

Table 2.8 presents the change in emission intensity, total emissions, and welfare from the shock in the emission factor, regulation stringency, and intermediate import cost. In Panel A, I show the equilibrium outcomes that are obtained from applying each shock separately to the baseline. While all three shocks bring a reduction in emission intensity, they have heterogeneous impacts on total emissions and welfare.

First of all, the decrease in the emission factor brings a reduction in total emissions comparable to its effect on emission intensity, indicating the minimal impact on the economy's size. The increased regulation stringency, however, brings a larger decrease in total emissions than in emission intensity. Stricter regulation increases the cost of production, thus shrinking the competitiveness and production as well as reducing welfare with respect to consumption. The decrease in intermediate import cost lowers both emission intensity and total emissions, but the latter is smaller due to the increased size of production. The welfare gains from the lower intermediate import cost mainly come from higher real income.

Table 2.8: Change in the US emissions and welfare

(%)	Emission intensity	Total emissions	Welfare	Welfare (con)	Welfare (env)
Panel A. Separate shock					
Emission factor	-4.80	-4.77	0.05	0.01	0.04
Regulation	-2.36	-3.23	-0.21	-0.24	0.03
Int. import cost	-1.87	-1.18	5.27	5.25	0.01
Panel B. Impact of intermediate import cost					
Emission factor & regulation	-6.95	-7.71	-0.16	-0.22	0.06
+ Int. import cost	-1.78	-1.11	5.30	5.29	0.01
Total	-8.73	-8.82	5.14	5.07	0.07

Panel B identifies the effect of the change in intermediate import cost by comparing the two counterfactual outcomes. The first row shows the change in emissions and welfare that would occur with the change in emission factor and regulation stringency, and the third row shows the outcomes when I also incorporate the change in intermediate import cost. The gap between the first and the third row is the implied effect of intermediate import cost, as presented in the third row. The change in import cost explains a 1.8% decrease in aggregate emission intensity and brings 5.3% gains in welfare, mostly coming from the higher real income. To give a reference point for the magnitude, this is about 8.5% of the observed technique effect that is due to the energy usage change (21%), as shown in the previous chapter's Section 1.3.

Lastly, the similar magnitude of the effect of intermediate import cost between Panel A and Panel B suggests that the effect does not interact much with the underlying regulation stringency or emission factor.

Decomposition: within-across and across-firm

I decompose the total change (-1.8%) into the within-firm and across-firm channels. Formally, I use the following decomposition of the change in Z_Q

$$\Delta Z_Q = \underbrace{\int_{\varphi_o}^{\infty} \left(z_q(\varphi)' - z_q(\varphi)\right) \omega(\varphi) dG(\varphi)}_{\text{Within-firm}} + \underbrace{\int_{\varphi_{o'}}^{\infty} \left(\omega(\varphi)' - \omega(\varphi)\right) z_q(\varphi)' dG(\varphi)}_{\text{Reallocation}}$$
$$- \underbrace{\int_{\varphi_o}^{\varphi_{o'}} z_q(\varphi)\omega(\varphi) dG(\varphi)}_{\text{Selection}}$$

where $z_q(\varphi)$ and $\omega(\varphi)$ is the emission intensity and market share of a firm with φ, and φ_o is the entry cutoff. The variables with $'$ superscript are the value after the shock. Table 2.9 shows the change coming from each component (in percentage) in column 1. Column 2 shows the share of each channel.

Table 2.9: Change in emission intensity

(%)	% change from the initial	
Total	***-1.78***	***100%***
Intensive	**-1.21**	**68.1%**
Input substitution	-1.04	58.3%
Global sourcing	-0.16	9.2%
Technology adoption	-0.01	0.6%
Selection	**-0.53**	**30.0%**
Reallocation	**-0.03**	**1.9%**

In my calibrated model, 68% of the reduction in aggregate emission intensity comes from within-firm changes. This includes the change in emission intensity among the firms that do not change their sourcing and adoption decisions due to the change in relative input prices, as well as the change that is due to some firms' starting to source globally or use technology or both. The selection effect explains 30% of the decrease, and less than 2% comes from the reallocation effect. The finding that the intensive margin plays the largest role is worth noting since this margin is less discussed in the model without input-output linkage and, thus, intermediate trade. The main channel in such an alternative model is across-firm effects (Shapiro and Walker, 2018).

Decomposition: direct vs. indirect effect

I also present an alternative decomposition of the change driven by lower intermediate import cost. Recall that the last term in the expression of aggregate emission intensity (Equation 1.11), $MAcost = \frac{X_d + X_f \tau_f^{1-\sigma}}{X_d + X_f \tau_f^{-\sigma}}$, captures the average cost of market access. While exporting cost (τ_f) does not change, the market demand from domestic and foreign countries (X_d and X_f) changes in the general equilibrium. With the lower intermediate import cost, domestic producers increase their usage of foreign intermediates and decrease that of domestic intermediates, which decreases X. At the same time, foreign producers' demand for domestic intermediates increases due to lower domestic producer price, thus X_f increases.

In summary, the relative size of foreign market demand compared to domestic market demand ($\frac{X_f}{X_d}$) decreases. As more sales are made in markets with higher market access costs ($\tau_f > 1$), the average market access cost increases, and aggregate emission intensity increases accordingly.

Table 2.10 shows the decomposition of the 1.8% decrease in emission intensity into the change resulting from the change in $MAcost$ and the rest. The latter can be interpreted as the change in emission intensity when there is no change in market access cost. The decomposition illustrates that if there was no indirect effect on market access cost arising from increased relative foreign sales, emission intensity would decrease by 2.7%.[30]

[30] It is important to note that this decomposition is not equivalent to calculating the decrease in emission intensity when there is no extra market access cost – either because there is no export cost or because no firms export.

Table 2.10: Change in emission intensity

		% change from initial	
Total		*-1.78*	*100%*
Indirect:	Increase in market access cost	0.90	-50.3%
Direct:	Decrease in Z_Q with no change in market access cost	-2.68	150.3%

Impact on foreign country by home country's policies

Although this paper focuses on understanding what happened in the US (i.e., home country) and the model is structured for that purpose mainly, it is still useful to track what happens in foreign countries in response to the reduction of US input import cost. Table 2.11 reports the change in emissions and welfare, showing that both emission intensity and total emissions increase in response to the decrease in the home country's cost of importing intermediates. This contrasts with the change in the home country's emission intensity and total emissions (as shown in Panel B of Table 2.8) although the magnitude of the change is much smaller in foreign countries. As three foreign countries are symmetric, I discuss in terms of one foreign country without loss of generality.

Table 2.11: Change in a foreign country

(%)	Emission intensity	Total emission	Welfare	Welfare (con)	Welfare (env)
Emission factor & regulation (ϵ, t)	0.72	0.99	0.06	0.07	-0.01
+ Int. import cost (τ)	0.06	0.39	0.63	0.64	-0.003
Total	0.78	1.38	0.70	0.71	-0.01

The increase in the foreign country's total emissions is based on two changes. One is that its production increases as the exporting cost to the home country decreases. In addition, the production itself becomes more energy-intensive as the relative cost of energy input to non-energy inputs becomes lower, mainly driven by the rise in the wage in the foreign country.[31] This is in contrast to the higher cost of energy input to non-energy inputs in the home country, which pushes down the energy intensity of the home country.

Figure 2.3: Change in home and foreign countries

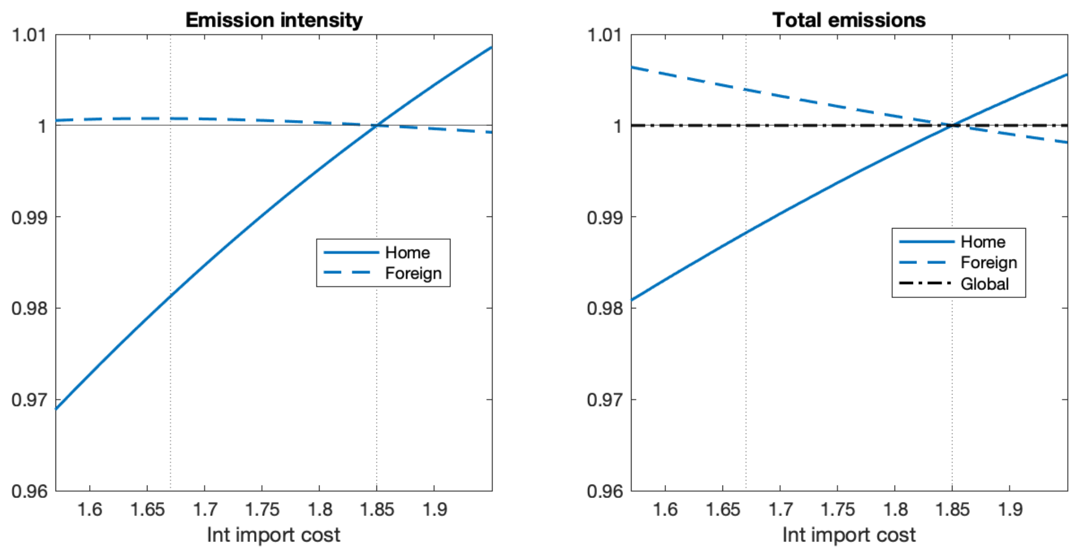


Figure 2.3 shows the change in energy intensity and total emissions in home and foreign countries on a wider range of the home's intermediate input import cost τ. The right figure shows the opposite pattern of total emissions in home and foreign countries. Notably, the level of global emissions stays constant due to the model's simplifying assumption that the global energy consumption stays the same. The limitation of such an assumption is that it automatically makes one part of the world emit more while the other part less.

[31]The cost of intermediates available in the foreign country do go down, but the increase in the wage is larger and drives firms to be more energy-intensive.

2.3.5 Robustness results

I test the sensitivity of the baseline results, using various parameter values, and show that the overall magnitude of the change in emission intensity is robust across calibrations. Table B.6 presents the results. The reduction is larger with more dispersion in productivity (smaller $\theta = 4$). More effective technology (higher β) also increases the magnitude of the decrease in emission intensity – although the change is modest.

I also calculate the welfare gains from the decrease in total emissions, using alternative values for the disutility paramter δ to examine how the welfare impact is sensitive to parameter assumptions. Specifically, I use the minimum and maximum value of the marginal social cost of NO_x from Heo et al. (2016). The calculated welfare impact increases with social cost, but the magnitude of the wealth gains from emission reductions is still much lower than that from the real income changes.[32] Appendix B.3.1 has more detailed discussions on the robustness results.

2.3.6 Additional analyses

I conduct additional counterfactual experiments to study the implications of different policies, using the current model framework. I first run a scenario in which both home and foreign countries reduce their intermediate import costs. This, by nature, eliminates the concern of pollution relocation and explores whether global liberalization in intermediate trade brings improvement in the overall environment. I also run a counterfactual scenario of a trade war on intermediate

[32]The relatively small welfare gains from the emission-related component can be attributed to a few factors. First, the marginal social cost is estimated by monetizing the premature mortality caused by marginal emission but not other welfare losses. Thus, it is highly likely that the welfare changes obtained from using the current social cost estimate are the lower bound. Second, the marginal social cost largely depends on the estimate of the value of statistical life (VSL), which itself is the subject of long-standing and ongoing discussion. Given this limitation, some papers emphasize the physical decrease of air pollution more than the welfare implication (Shapiro, 2021).

imports, motivated by the recent US-China trade war that was mostly focused on intermediate import tariffs. I show the change in emissions and welfare when the US increases the import cost on intermediates and when foreign countries retaliate. Lastly, I discuss the impact of lower export costs in comparison with the impact of lower intermediate import costs. While increased market access from a lower export cost is not the focus of this paper, it is helpful to see its impact in comparison with a lower import cost since it is not uncommon to have trade liberalization in both directions. The third exercise is discussed in Appendix B.3.2.

2.3.6.1 Symmetric policy changes

The previous subsections discuss the consequence of changing only the US intermediate import cost. In Table 2.12, I consider a counterfactual scenario in which all four countries experience the same shock to the emission factor, regulation stringency, and intermediate import cost. This is intended to address the potential concerns about pollution relocation resulting from policy changes in one country (henceforth, the 'unilateral policy change' case). This symmetric scenario by nature eliminates the pollution haven effect.

Table 2.12: Changes from symmetric policy change

(%)	Emission intensity	Total emissions	Welfare	Welfare (con)	Welfare (env)
Emission factor & regulation	-4.88	-4.88	0.05	0.01	0.040
+ Int. import cost	-1.79	0.00	7.70	7.70	0.000
Total	-6.67	-4.88	7.75	7.70	0.040

The combined impact of the emission factor and regulation is smaller than that in the unilateral policy change case. When all countries impose higher taxes on energy, the global price of energy falls due to a global decrease in demand for energy. This partially offsets the effect of regulation.

The impact of the intermediate import cost is similar to that of the baseline. While in this symmetric policy change setting the price of intermediates goes down further than in the baseline, the cost of energy also decreases by a larger extent due to a larger decrease in its demand. So the change in the relative price of intermediates to energy is not much larger. Nonetheless, the result shows that production becomes less emission-intensive in all countries, without creating winners and losers, under a symmetric liberalization.[33]

2.3.6.2 Trade war

I present counterfactual policy experiments in which the US increases import costs on intermediates from *all* its trading partners. I first show the results when only the US imposes the increase. Then I show the results when *all* foreign countries *retaliate* with the same policy toward the US intermediates.

I use the magnitude of the increase in import costs as characterized by the recent US-China trade war. The average import tariff rate imposed by the US on Chinese exports increased from 3% to 19%. Converting them into an iceberg cost term that is consistent with my model (i.e., $\tau = 1 + \text{tariff}$) and calculating the change in ratio indicates that this was a 16% increase in import cost. I impose the shock to the equilibrium that is calibrated to the 2014 US data.

Table 2.13: Changes from trade war

(%)	Emission intensity	Total emissions	Welfare	Welfare (con)	Welfare (env)
US only	2.78	1.51	-6.99	-6.98	-0.012
Foreign countries retaliate	1.48	-0.56	-7.15	-7.16	0.004

When the US increases its intermediate import cost, both emission intensity and total

[33]Note that total emissions do not change (in all countries), as the amount of total global emissions is fixed in the current model assumption due to the fixed global supply of energy.

emissions increase, presenting the opposite direction of the change from the decrease in import cost. The emission intensity increases by 2.8% while total emissions increase by 1.5%, indicating that US production decreases by 1.3%. US production decreases as US firms' production cost and price increase. This also means lower real income and, thus, welfare loss to be around 7%.

With foreign countries' retaliation, the emission intensity is still higher than the value without a trade war, but the increase is smaller than the previous scenario. While different indirect forces are in effect in the general equilibrium, one factor that makes the increase in this case smaller is the decrease in export sales. With all partner countries imposing higher import costs on US intermediates, US sales in foreign markets shrink, which decreases the average market access cost and the extra emissions made from exporting. This effect of decreased production results in a total emissions decrease of 0.6%. Combined with a 1.5% increase in emission intensity, the end result is a 2.1% decrease in total output. So in this case, the decrease in production size is sufficiently large enough to offset the increase in emission intensity. The welfare from environmental disutility improves, but this is insufficient to offset the welfare loss from increased prices and lower real incomes.

2.4 Conclusion

In this chapter, I run empirical and quantitative analyses to test the theoretical model from the previous chapter against the US manufacturing data. In the empirical analysis, I estimate the model prediction, which states that industry-level emission intensity can be expressed in the producer price index when the cost of energy and market access are controlled, using the industry-level panel data between 1998 and 2014. By using the import price of intermediates as an instrumental variable for the producer price index, I find evidence that a lower producer price, driven by a lower intermediate import price, leads to lower emission intensity. The reduced-form evidence supports the model mechanism that states that a lower import price of intermediates decreases emission intensity.

I then calibrate the model to 1998 aggregate US manufacturing and quantify the change in emission intensity driven by the change in intermediate import cost. The quantification shows that the fall in intermediate import cost between 1998 and 2014 explains about a 1.8-2% decrease in emission intensity, which is 8-10% of the observed technique effect. 68% of the decrease comes from the within-firm changes via firms' substituting away from energy inputs, global sourcing, and adopting energy-saving technology. This finding highlights the importance of taking within-firm channels into account to understand the effects of trade policies on emissions.

I also conduct additional counterfactual experiments to study the implications of different policies. The symmetric reduction in intermediate import costs brings all countries toward less energy-intensive, and therefore less emission-intensive, production. In addition, the scenario of a trade war over intermediates shows that the emission intensity of a country increases with higher intermediate import cost due to the shift towards higher energy intensity production in aggregate.

In summary, this chapter finds support for the mechanism discussed in the previous chapter's theoretical model and analyzes the magnitude of such mechanism in the observed trajectory of the US emissions. More broadly, this chapter, along with the previous chapter, shows a multifaceted impact of trade policies, highlighting the impact on firms' input sourcing costs, and adds to the recent discussions on the total effects of trade policies on firms through their supply chains (Handley et al., 2020). Future works can build on my findings to study the implications of international policies that touch on both trade and emissions, such as the EU's Carbon Border

Adjustment Mechanism (CBAM) or a Climate Club suggested by Nordhaus (2015).

Chapter 3: Welfare gains from trade across space with transboundary air pollutants

3.1 Introduction

This paper re-examines the welfare gains from international trade by incorporating the transboundary nature of air pollutants. Air pollutants, such as particulate matters, sulfur dioxide, and nitrogen oxides, are called "local pollutants" since they are considered to have localized effects in both environmental and health aspects, unlike "global pollutants" including greenhouse gases. Thus, it is common that the literature that studies the change in these local air pollutants has focused on the region- or country-level local effects (Duarte and Serrano, 2021; He, 2005; Vennemo et al., 2008). However, these pollutants actually do travel across the border, which is known as their "transboundary" nature. The atmospheric science literature shows that the transboundary air pollution is not just a matter of countries that share borders (Lee et al., 2017) and shows that air pollutants make a long-distance transport, for example between China and the US (Lin et al., 2014; Zhang et al., 2017).

The consideration of transboundary nature is important when we try to understand the welfare implications of trade policies since it affects the size and heterogeneity of welfare gains across countries. For example, in the gravity model, being close to large trade partners means lower aggregate trade costs and higher gains from trade. But the welfare implications of proximity to large countries can be offset by higher transboundary pollution from them if we take this aspect into account.

In this paper, we build the transboundary nature of local pollutants into a general equilibrium model of trade and the environment. This model allows us to quantify the welfare consequences of trade shocks and decompose the spatially heterogeneous welfare gains into a few sources, including real income, own emissions, and transboundary pollution. We use the model to investigate the welfare effects of two trade liberalization episodes, China's joining the world market at lower trade costs (henceforth, China shock) and the EU 2004 enlargement, considering the environmental externality from particulate matter 2.5 ($PM_{2.5}$) pollution. Specifically, we show that there arise not only the relocation of production and emissions to liberalized countries but also heterogeneous welfare implications across countries depending on their economic and geographic proximity to liberalized countries. This sheds light on the importance of understanding multiple layers of environmental externalities of trade policies.

To motivate this paper's focus on transboundary transport of air pollution, we run a set of multi-country panel regressions that explore the linkage between economic activities, $PM_{2.5}$ emissions, and $PM_{2.5}$ concentration, using a balanced panel on 42 countries from 2000 to 2014. We run two separate regressions: one linking trade and emissions and the other linking concentration with own emissions and transboundary pollution. While this is not a two-stage analysis, strictly speaking, by running two separate regressions we can break down how trade and concentration are linked, which are through changing its own emissions and through others' emissions that may travel across the border. We construct a variable that measures the exposure to transboundary pollution from other countries for each country, by summing up other countries' emissions adjusted by emitting countries' size and the distance between emitting and receiving countries. The regression result shows that a country's concentration is correlated with this transboundary transport measure – even after we control for multiple factors that affect concentration, such as meteorology, own emissions, and the density of industrial activities. This suggests the role of transboundary pollution from other countries in a country's $PM_{2.5}$ concentration level and underlines the need to incorporate it in understanding the role of trade policies on air pollutant concentration.

We then build a general equilibrium model of international trade and environmental externality from local pollutants of transboundary nature. The objective of the model is to introduce a framework to think about how the transboundary nature of local pollutants shapes the heterogeneous welfare effect of trade shocks across countries as well as to lay a framework for counterfactual analyses. We build on Caliendo and Parro (2015) and introduce environmental externality, similar to that in Shapiro (2016). The novelty of our model is that we allow the concentration of a country to be affected by both its own and other countries' emission, thus incorporating the transboundary nature of local pollutants. The model shows that the change in welfare can be decomposed into the change in real income and the change in air pollutant concentration, the latter of which can further be decomposed into that driven by own emissions and by other countries' emissions.

We use this model to quantitatively assess the welfare implications of trade shocks after taking the environmental externality including transboundary pollution into account. We parametrize the formation of air pollutant concentration, using the estimates from the motivational regression, and calibrate the model to the year 2000's multi-country dataset.

We study two counterfactual exercises: China shock and EU 2004 enlargement. The China shock makes a useful counterfactual scenario since it has been discussed extensively in the literature on its consequences in various aspects and also because there have been discussions on transboundary air pollution within the region. EU enlargement also makes an apposite scenario since both new and existing member countries are all close to each other, so the magnitude of transboundary transport of air pollution would be large. Our focus of the counterfactual exercises is to study the change in welfare and decompose such change into different drivers – including real income, own emissions, and transboundary pollution – and see how they shape heterogeneous welfare consequences across countries. In addition, by running an additional scenario for each event, in which we impose more stringent environmental regulations on China and new EU members, respectively, we investigate the effect and welfare implications of combining trade and environmental policies.

In the China shock exercise, with a cut in trade costs to and from China, most countries experience welfare gains but in a heterogeneous magnitude. The decomposition shows that the gains from the increased real income are partially offset by the rise in concentration in some countries. These countries include not only China, whose comparative advantage improve due to the cut in trade costs and production increase, but also neighboring countries, such as Japan and Korea. The latter group's concentration levels increase due to both increased their own emissions and increased transboundary pollution from countries in proximity including China. When an additional environmental regulation is imposed on China, we see a smaller increase in concentration and, thus, smaller welfare loss from the environmental aspect, in both China and these neighboring countries.

In the EU enlargement counterfactual exercise, we impose the actual decrease in tariff rates between new and existing EU member countries. This counterfactual has a similar set of results to the ones from the China shock. First, while both new and existing members experience welfare gains, the former gains much more than the latter, mostly driven by larger increases in real income. Second, production increases in both new members and the countries that source cheaper inputs from new members. Emissions and concentration increase in these countries, which lowers their environmental utility. The level of concentration increases in many of the existing member countries as well, since the increased emissions from neighboring countries travel across borders, indicating that the effect of pollution relocation is abated. When new members are imposed stricter environmental regulations at joining the EU, the concentration levels of both new and existing members are lower than the scenario without additional regulations, as both the emissions made within borders and that travel across borders decrease. Thus, the overall welfare gains among existing members are larger while the gains among new members are smaller, the latter of which is due to higher production costs and deteriorated competitiveness.

The counterfactual results highlight potentially important policy implications of incorporating environmental policies into trade agreements (or vice versa). Pollution relocation effects of trade agreements are often the subject of heated discussions. In the context of local pollutants, the discussion over pollution relocation centers on the unequal environmental consequences between developed and developing countries, the latter of which usually have laxer regulation and attract emission-intensive industries at the event of trade liberalizations. But our paper shows that due to the transboundary nature of local pollutants, the concentration and, thus, environmental aspect of welfare in developed countries are also affected by the increase in emissions in developing countries that join trade agreements. Thus, there exist incentives among a larger group of countries to consider including environmental provisions in trade agreements to find a balance between excessive environmental harm and economic gains.

Related Literature

This paper is related to several strands of literature. First, this paper builds on a large body of literature on trade and the environment. We follow the model framework from Copeland and Taylor (2003) in which emissions are generated as a byproduct of production (Cherniwchan et al. 2017; Copeland and Taylor 2004; Forslid et al. 2018; Shapiro 2021, 2016; Shapiro and Walker 2018). It allows us to incorporate emissions into a macro-trade framework in a simple and tractable way to understand the impact of trade liberalization on countries' emission-generating activities and, thus, air pollution. In particular, our paper builds on the recent works that add environmental aspects into a structural gravity framework (Shapiro 2021, 2016; Shapiro and Walker 2018). These works study the impact of trade policies on emissions and welfare in a general equilibrium, quantitative setting, building on either Eaton and Kortum (2002) or Melitz (2003) frameworks. They quantify the change in emissions and welfare driven by either historical or counterfactual trade policies. For example, Shapiro and Walker (2018) decompose the role of trade in the clean-up of US manufacturing air pollutant emissions, and Shapiro (2016) quantifies the change in carbon emissions from international trade liberalizations.

Our contribution is that we consider the transboundary nature of local air pollutants, such as nitrogen oxides (NO_x), sulfur dioxides (SO_2), and particulate matters (PM_{10} and $PM_{2.5}$). In the existing works in this literature, emissions are modeled as either completely local or completely global. On one hand, the papers that study local air pollutants focus on how the change in market size or production cost or both affect emission-generating activities in a country – for example, see Shapiro and Walker (2018). On the other hand, greenhouse gases are completely global; in other words, the impact of emissions on one country does not depend on the source of emissions.[1] Thus, what matters in those papers that study global pollutants is the sum of all countries' emissions (Akerman et al. 2021; Forslid et al. 2018; Shapiro 2021, 2016).

While local air pollutants are 'more local' than global pollutants, they do travel across borders. Thus, it is important to take such transboundary spillovers into account to capture environmental externalities comprehensively. To address this, we estimate the extent of transboundary transport across countries, using a reduced-form regression, and incorporate the estimates into our quantitative analyses to quantify the welfare impact of trade liberalizations via own emissions and transboundary pollution. Especially, we add emissions and transboundary pollution to Caliendo and Parro (2015), which incorporate an input-output linkage in a multi-country, multi-industry setting. Although we use a simplified version of the input-output linkage, having an intermediate input in the model is important since input sourcing and transboundary pollution are closely related to the distance between countries. Countries tend to form a production cluster with those in proximity – for example, think of those in Europe or Asia – and these countries are also more likely to be affected by cross-border pollution.

This paper is not the first paper in the literature to acknowledge and study the transboundary transport of air pollution. Extant work shows that transboundary pollution spillover exists, estimating the change in one region's concentration caused by a change in another region's emissions or concentration (Fu et al. 2022; Zheng et al. 2014). Moreover, some papers study the impact of such air pollution spillover on economic and health outcomes (Jia and Ku 2019; Jung et al. 2022; Sheldon and Sankaran 2017) or how local governments' pollution regulations respond to such

[1] But this does not mean that the welfare impact of additional emissions should be the same across countries. The consequences of global warming can be realized in a different manner and magnitude geographically. In addition, countries may experience a heterogeneous degree of disutility from the same environmental shock according to their income level or other elements in the utility function.

spatial externalities (Boskovic 2015; Wang and Wang 2021).[2] We make two contributions to this body of literature. First, unlike these papers that estimate the transboundary pollution across cities within a country, we find evidence for cross-border pollution transport, using multi-country panel data.[3] Second, our paper complements the existing studies, which focus on empirical evidence, by incorporating the idea of transboundary transport into a tractable, structural model and quantifying the impact of different policy scenarios. To our best knowledge, this paper is the first to apply the transboundary nature in the context of understanding the interaction between trade and the environment in a quantitative setting.

Lastly, this paper contributes to the body of literature that looks at the pollution haven hypothesis (PHH) prediction of trade liberalizations (Brander and Scott Taylor 1998; Chichilnisky 1994; Copeland and Taylor 1994, 1995, 2003; Grossman and Krueger 1993). The PHH claims that pollution-intensive industries would move to countries with lax environmental regulations after trade barriers are reduced. There has been scant evidence and little consensus on the PHH. One reason is that there are other factors that affect countries' comparative advantage, such as factor abundance, which may offset the pollution haven effect (see Taylor (2005) for a more detailed discussion on the PHH).[4] This paper presents another aspect to consider when we discuss potential environmental consequences of trade liberalizations, including the PHH. We show that even if pollution-intensive industries are relocated to those countries with less

[2]In the science literature, the transboundary nature of air pollution has been heavily discussed (Lin et al. 2014; Liu et al. 2009; Verstraeten et al. 2015; Zhang et al. 2017). They use chemical transport models (CTMs) to relate source emissions and receptor concentrations, which are usually computationally expensive and specific.

[3]Many works in the environmental science literature find evidence of cross-border pollution transport (Akimoto 2003; Jaffe et al. 1999; Lin et al. 2014; Liu et al. 2009; Verstraeten et al. 2015; Zhang et al. 2017). For example, Lin et al. (2014) show that 3-10% of sulfate concentrations in the western US are from the transport of the trade-related Chinese air pollution in 2006.

[4]The pollution haven effect (PHE) argues that less stringent environmental policy improves comparative advantage. The PHE is a necessary condition for the PHH to hold.

stringent environmental regulation – that is, *even if* the PHH holds initially – we should take how the "relocated" emissions travel across borders into consideration to capture the ultimate heterogeneous welfare implications across countries.

Specifically, several papers discuss the environmental consequences of two trade liberalization episodes that we look at in our counterfactual: China's WTO accession and EU enlargement. For example, Chen et al. (2020) empirically find that trade expansion increased $PM_{2.5}$ and SO_2 pollution in China, using county-level panel data between 2000 and 2013. They show that trade expansion has contributed to a 60% and 20% increase in those two pollutants' concentration levels, respectively. Levitt et al. (2019) look at the other side of the story by estimating the impact on China's WTO trade partner countries. They find that the consumption-based greenhouse gas (GHG) emissions increased in these countries while the production-based emissions decreased. Specifically, they show that the emissions embodied in imports increased in total and became dirtier, highlighting that this indicates GHG emissions offshoring. Our contribution to these works is that we combine these two sides of a coin by building a tractable quantative model, which allows us to dissect the multi-facted linkages between countries.

In addition, a few papers decompose the actual change in emissions after these trade liberalizations to understand the sources of the change. For instance, de Araujo et al. (2020) divide the change in CO_2 emissions into the change in technology, sourcing, and consumption and show that the sourcing-related emissions increased in the new EU members and China while decreased in the old EU members and the USA between 1995 and 2007. Duarte and Serrano (2021) conduct a similar decomposition but focus on the $PM_{2.5}$ emissions embodied in exports from the new EU member countries to the old EU countries.[5] We complement these works by

[5] In addition, a few papers use an environmental computable general equilibrium (CGE) model to simulate the

providing a decomposition of the change in concentration in each country into the change in own emissions and the change in emissions that travel from other countries. By doing so, we highlight that we need to consider the transboundary transport of pollution to truly understand the environmental implications of these liberalization events on both liberalized and partner countries. Moreover, this paper can be used or easily adjusted to study the implications of any future liberalization events.

3.2 Motivational Evidence

To motivate our consideration of transboundary transport, we establish the relationship between trade participation and $PM_{2.5}$ concentration by running two panel regressions. First, we establish a linkage between a country's participation in trade and its own emission (step 1). Then we show the role of a country's own emissions and the emissions from other countries that travel across borders on a country's concentration (step 2). Breaking down our analysis into two steps allows us to understand the separate channels that trade affects a country's concentration – through changing its own emissions as well as others' emissions that may travel across the border. It is important to emphasize again that this section is purely motivational and is not making any causal statements. Before going into specifications in more detail, we discuss data and measurements in the following section.

change in emissions based on scenarios of China's liberalization or EU enlargement (He, 2005; Vennemo et al., 2008; Zhu and van Ierland, 2006). But these papers do not analyze concentration changes. They also look at the limited set of countries – only China (He, 2005; Vennemo et al., 2008) or the EU countries (Zhu and van Ierland, 2006) – and, thus, are abstract from heterogeneous consequences across countries.

3.2.1 Data and Measurement

We combine multiple data sources to have balanced panel data on $PM_{2.5}$, trade, and other country-level features. We include not only trade and other economic activities but also several factors that affect the level of emissions and concentration. Our sample is a balanced panel of 42 countries from 2000 to 2014.[6] Table C.1 in the Appendix shows the list of sample countries.

PM 2.5

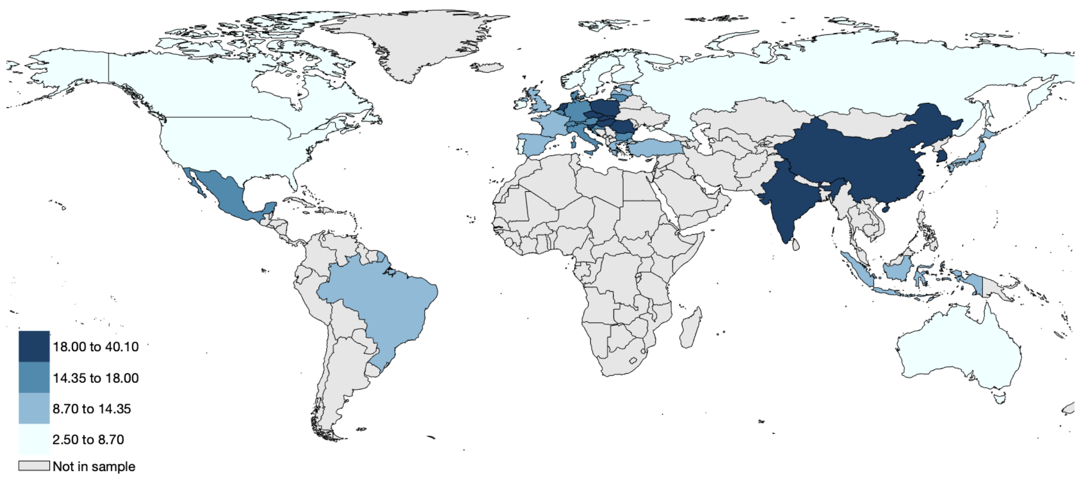
First of all, we need the level of both emissions and concentration of $PM_{2.5}$ for each country. Country-level $PM_{2.5}$ emissions are from the Emission Database for Global Atmospheric Research (EDGAR) 5.0 version (Crippa et al. 2020), which provides emissions for greenhouse gases and local air pollutants, including $PM_{2.5}$, per sector and country for 1970-2015. EDGAR calculates emissions based on the emission factor approach, using the detailed information on the emission factor of each activity and different emission-reducing technology installations.[7] We aggregate the country-sector-level information to the country-level and convert the unit of emissions from gigagram (gG) to metric ton (ton).

Country-level $PM_{2.5}$ concentration is obtained from Atmospheric Composition Analysis Group's $PM_{2.5}$ Global Estimates (Hammer et al. 2020), which estimates $PM_{2.5}$ concentration by combining Aerosol Optical Depth (AOD) retrievals from satellite with the GEOS-Chem chemical transport model and calibrating to ground-based observations. The dataset provides the country-level annual average of concentration measures, measured in microgram per meter cubed ($\mu g/m^3$)

[6] The sample countries are composed of the countries from the World Input-Ouput Database (WIOD) except for Taiwan which does not have meteorology data.

[7] In other words, the database is not direct observations of emissions. See the dataset's web page for more details.

Figure 3.1: Level of concentration (2000)



Note: This figure illustrates the level of concentration for the year 2000. *Source*: Atmospheric Composition Analysis Group.

at 0.01×0.01 resolution from 1998 to 2018 for 238 countries.[8] Figure 3.1 shows the level of concentration of our sample countries in the year 2000. There is a wide dispersion in the level of concentration across countries. China, India, and South Korea as well as a few Eastern European countries are much more polluted than other countries, and the level of their concentration ranges a great deal – from $18\mu g/m^3$ to $40.1\mu g/m^3$. In contrast, the level of concentration is low in Northern European countries as well as those that have a large share of land area with a low level of industrial activities, including but not limited to Canada, the US, and Australia.

Trade

As we estimate how a country's participation in trade is correlated with its emissions, we use trade openness in the empirical specification. For trade openness, we use the ratio of exports to GDP and imports to GDP, obtained from the World Bank World Development Indicators (WDI) database. For the baseline specification, we use the ratio of total trade to GDP by summing the

[8]We use the estimates that are obtained after applying Geographically Weighted Regression (GWR) and removing dust and sea-salt. Annual averages correspond to a simple mean of within-grid values. According to EPA, $PM_{2.5}$ remains airborne for up to weeks, thus the annual measure mostly captures the flow value rather than the stock value.

two ratios. In an additional regression, we use export ratio and import ratio as separate variables to estimate the heterogeneous roles of the two.

GVC

A country's position on the global value chain determines the specialization patterns and, thus, affects the distribution of emission-intensive industries across countries. Recent studies find that more upstream industries are more emission-intensive (Copeland et al. 2022; Shapiro 2021). In order to evaluate the role of country-level upstreamness on emissions – on its own and by interacting with trade's role – we include a country-level GVC position in our step 1 regression.

To construct a country-level GVC position, we use the World Input-Output Database (WIOD). It contains the intra- and inter-country input-output information for 56 industries in 44 countries for from 2000 to 2014. We follow Antràs and Chor (2018) to calculate the measure of countries' GVC positioning. Specifically, we collapse the WIOD to the country-by-country level and compute the distance from final use. The country i's upstreamness, U_{it}, is calculated by the i-th element of

$$\frac{[I - D]Y}{Y_{it}} \tag{3.1}$$

where I is an identity matrix, D is an N-by-N matrix whose (i, j) element, d_{ijt}, is the dollar amount of country i's output needed to produce one dollar's worth of country j's output at time t. Y is a column matrix with country i's gross output Y_{it} in row i. Table 3.1 shows the countries with top and bottom 5 upstreamness values in the year 2000. A higher value indicates more upstream (farther from consumers) country. Our measures are similar with those in Antràs and Chor (2018), whose measures are 2011 values, indicating that countries' GVC position has not changed much between 2000 and 2011.[9]

Table 3.1: Upstreamness values by country

Rank	Country	Upstreamness (2000)
	Top 5	
1	China	2.54
2	Luxembourg	2.35
3	Russia	2.32
4	Czech Republic	2.23
5	Australia	2.16
	Bottom 5	
38	Lithuania	1.82
39	India	1.81
40	United States	1.80
41	Greece	1.71
42	Mexico	1.64

Notes: The table presents the top and bottom 5 countries in terms of 2000 upstreamness, measured following Antras and Chor (2018). Only our regression sample countries are included.

Preferential Trade Agreements (PTA)

Trade can affect emissions by moving the location of production – mostly, emission-generating – activities. If countries are part of the PTAs that have environmental provisions and, thus, aim to address environmental concerns, the impact of trade on the environment would be different. To capture such heterogeneous effects, we include the information on countries' participation in such PTAs.

The World Bank's Deep Trade Agreements (DTA) dataset provides detailed information on country-pair-level PTA status and provisions included in each PTAs. One of the provision categories is 'environment' which includes the development of environmental standards, enforcement of national environmental laws, establishment of sanctions for violation of environmental laws,

[9] Both in our paper and Antràs and Chor (2018), the US, Greece, and Mexico are in the bottom 5 (i.e., most downstream), and China, Luxembourg, and Czech Republic are in the top 5 (i.e., most upstream).

and publications of laws and regulations (Hofmann et al. 2019). To capture the extent of each country to which trade flows are under these environmental provisions, we use the share of trade flows made with partner countries of PTAs that have such environmental provisions.[10]

Meteorology

Meteorological factors affect the formation of air pollution concentration, so we include them in the step 2 regression. The information on temperature and precipitation is from the World Bank Climate Change Knowledge Portal (CCKP). The dataset provides temperature and precipitation on a monthly basis for 196 countries. Using the monthly information, we calculate the simple average and standard deviation of temperature and precipitation at the annual level for each country.

Environmentally-related technology

$PM_{2.5}$ has end-of-pipe technologies available, which can reduce the amount of emissions generated from certain economic activities. Thus, the countries with a higher level of such technologies would have lower emissions from the same level of industrial activities. In order to control for such differences across countries, we include the variable that captures the state of technological development of each country.

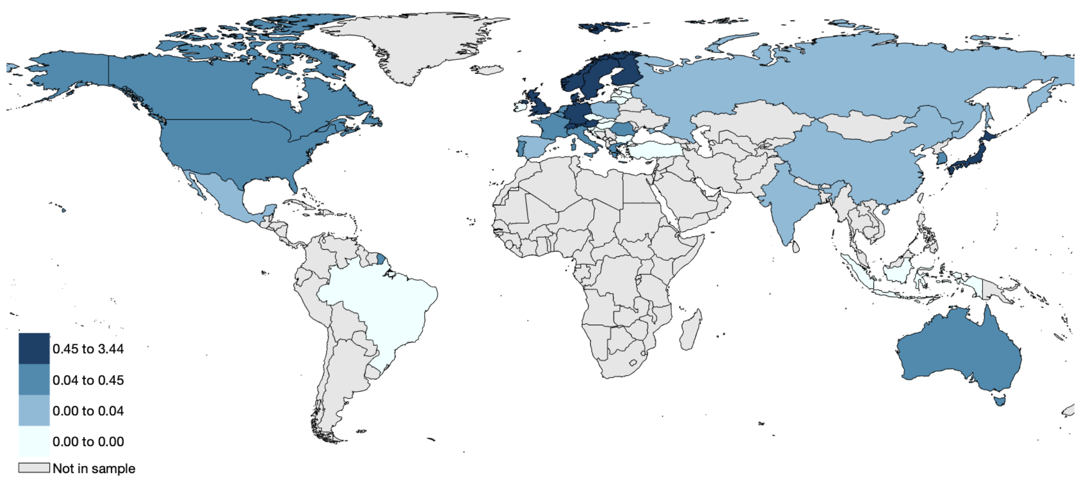
The OECD Environmental Statistics database provides the number of environment-related patents, including abatement, climate change management, greenhouse gases, and environment monitoring. To control for the difference in patent capacities coming from the size of countries we use the number of patents per capita. For the first regression, we use the number of patents

[10]We use the bilateral trade flows from the CEPII's Gravity dataset to calculate the share of trade flows with PTA partner countries among the total trade flows.

related to the abatement of stationary source emissions, and for the second regression, we use the number of environmental management patents per capita to proxy the overall development of the technologies relevant to air pollution management.

Figure 3.2 shows the number of abatement-related patents per capita in the year 2000. European countries are more advanced in the technology related to air pollution abatement than other countries. Especially, Northern European countries have the largest number of patents per capita.[11] The maximum of the group is Luxembourg, which has 3.44 patents per 1000 persons, although this may be more attributed to its small population size. Figure C.1 in the Appendix shows the number of patents on environmental management, which shows a similar pattern across countries although the overall level is higher.

Figure 3.2: Number of patents on abatement (per 1000 persons)



Note: This figure illustrates the number of patents on abatement per 1000 persons for each country.
Source: OECD Environmental Statistics database.

Transboundary transport of $PM_{2.5}$

We include a measure of transboundary transport of pollution in order to capture how much

[11]Sweden has 0.79 patents per 1000 persons, Norway 1, and Finland 1.74.

each country is exposed to other countries' emissions. By using this in the step-2 regression, we can explore how a country's concentration moves with its exposure to other countries' (adjusted) emissions.

The transboundary transport of $PM_{2.5}$ from other countries to country i is measured by the sum of foreign emissions that are adjusted by foreign countries' land area size and the square of the distance between i and each foreign country i'.

$$PolTransport_{it} = \sum_{i' \neq i} \frac{E_{i't}}{land_{it'}} \times \frac{1}{distance_{ii't}^2} \tag{3.2}$$

Land area is from the World Bank's World Development Indicators (WDI), and the distance between countries is from the CEPII GeoDist dataset. We use the distance between the most populated cities in each of two countries, instead of the simple distance between two countries' center points, to capture the distance from emission sources proxied by the most populated locations.

Two adjustments to foreign emissions are made to capture the degree of transmission from one country to another. Dividing by land area (of an emitting country) captures the degree to which emission is dispersed before crossing the border to other countries. Dividing the emission by the squared term of distance captures the degree of cross-border transport. Intuitively, the farther two countries are apart, the less pollution reaches from one to the other. We choose to use the square term of distance based on the findings from the atmospheric science literature that pollution transport decays faster at a larger distance (Fu et al. 2022; Requia and Koutrakis 2018).[12] We also run a sensitivity analysis regression, using the cubed term.

[12]To the best of our knowledge, there is no existing study that estimates the distance elasticity of transboundary pollutants at the cross-country level. The scientific literature uses chemical transport model, which is based on

Table 3.2 shows the countries with the 5 highest and 5 lowest values for $PolTransport$ of the year 2000. As the countries with higher $PolTransport$ is more exposed to other countries' emissions, $PolTransport$ represents the proximity to foreign emission sources. The list shows that European countries tend to have a higher value of $PolTransport$ while the countries that are relatively distant from the rest of the world – for example, Australia or those in North America– are located at the bottom of the list.

Table 3.2: Countries with top and bottom 5 $PolTransport$

Top 5		Bottom 5	
1	Austria	38	Mexico
2	Slovak Republic	39	Canada
3	Germany	40	United States
4	Belgium	41	Australia
5	Netherlands	42	Brazil

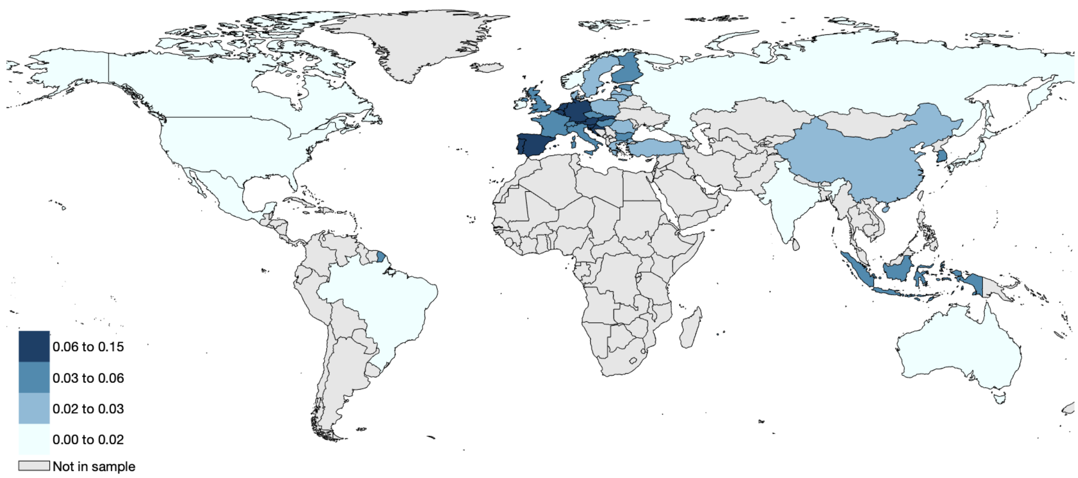
Notes: The table presents the top and bottom 5 countries in terms of $PolTransport$ of 2000. Only our regression sample countries are included.

Figure 3.3 shows $PolTransport$ of all of our sample countries. It is noteworthy that the values vary even between the countries that share the same neighbor countries. For example, both India and South Korea are close to China, one of the largest emitters, but South Korea's $PolTransport$ is much higher than that of India. The reason is that China is most populated and, thus industrialized, on the east coast, so the distance from the east coast of China matters rather than whether a country shares borders with – or is physically close to – China or not.

It is crucial to note an important element that is missing from the current specification of

atmospheric processes in the three-dimension grid models and requires highly disaggregated geographic data (Lin et al., 2014; Liu et al., 2009; Zhang et al., 2017). There are a few papers in the economics literature that estimate the pollution decay function and see how one region's pollution affects the other region (Fu et al., 2022; Zheng et al., 2014). They show that the effect of other cities' (or regions') pollution decreases with distance. But as their analyses are intra-national, thus having shorter distance values only, and high-frequency, it is hard to make direct comparisons with our approach of discounting transboundary transport with distance.

Figure 3.3: Level of $PolTransport$



Note: This figure illustrates the number of patents on abatement per 1000 persons for each country.
Source: Authors' calculation based on the World Bank WDI, CEPII Geo Dist, and EDGAR.

$PolTransport$: the role of wind. As wind affects the direction and degree of transboundary pollution, it has been included as a determinant of transboundary pollution in several papers in both economic and atmospheric science literature (Fu et al., 2022; Kim, 2019; Reuther, 2000; Zheng et al., 2014). Our unit of analysis – annual frequency and country-level – is more aggregate than what is ideal to appropriately use wind direction, which is usually measured at high frequency and varies with distance. In addition, it is not simple to define a dominant wind direction for countries with large land areas, such as Russia, the United States, and Canada. Nonetheless, recognizing the importance of wind as a key factor, we plan to augment the $PolTransport$ variable by using wind direction between countries in the next version of the paper.[13] Furthermore, we can crosscheck how $PolTransport$ measures the degree of transboundary pollution by comparing it with the source-receptor matrix information in the future.

[13] A few papers incorporate wind in their otherwise-low-frequency analyses. For example, Fu et al. (2022) use the mixed two-stage least square (M2SLS) method to incorporate high-frequency (daily) wind data with low-frequency (annual) economic outcome data. Zheng et al. (2014) use monthly wind direction data and define dominant wind direction as monthly main wind direction(s) that appear the most in 12 months.

Other country-level characteristics

We use several country-level characteristics to capture the size and industrial development of a country – other factors that would affect emissions and concentration – including GDP per capita, population density, urban population share, and rail infrastructure. GDP per capita and population density, and urban population share are from the WDI. The urban population share is measured as the share of the population in urban agglomerations, defined as the areas with more than 1 million people, in total population. We also include the railway density, defined as the length of rail lines (km) per land area (100 km^2), to proxy the dispersion in industrial development within a country.[14] The railway density is obtained from the OECD Infrastructure Transport dataset.

3.2.2 Specification

In this section, we introduce two specifications, each of which explores the linkage between trade and emissions and the linkage between emissions and concentrations, respectively. Specifically, we first establish a linkage between a country's participation in trade and its own emission (step 1). Then we show the role of a country's own emissions and the emissions from other countries that travel across borders on a country's concentration (step 2).

While this is not a two-stage analysis, strictly speaking, running two separate regressions allows us to break down how trade and concentration are linked, which are through changing its own emissions and through others' emissions that may travel across the border.

[14]The dispersion in industrial activities is controlled to capture potential chemical reactions between pollutants that occur after emissions due to clustered industiral activities (e.g., secondary $PM_{2.5}$ formation).

3.2.2.1 Regression on $PM_{2.5}$ emissions

To test the determinants of $PM_{2.5}$ emission, we estimate the following country-level panel regression:

$$\begin{aligned} ln(Emissionpc)_{it} = \zeta + \chi_1 GDPpc_{it} + \chi_2 GDPpc_{it}^2 + \chi_3 Tech_{it} + \beta_1 Trade_{it} + \beta_2 Upstream_{it} \\ + \beta_3 PTAenv_{it} + \beta_4 Trade_{it} \times PTAenv_{it} + \rho_i + \rho_t + \epsilon_{it} \end{aligned} \tag{3.3}$$

The dependent variable $\ln(Emissionpc)_{it}$ is the natural log of emission per capita for country i in year t. The real GDP per capita ($GDPpc_{it}$) controls the role of economic development and income. Our estimation incorporates the idea of the Environmental Kuznets Curve (EKC) by including the square of $GDPpc_{it}$. The EKC states that economic growth deteriorates the environment during the beginning of industrialization, but after reaching a certain level, further economic development reduces the environmental damage. Thus, $\chi_1 > 0$ and $\chi_2 < 0$ are expected.

The level of emission-reducing technology ($Tech_{it}$) controls for the difference in the amount of emissions resulting from the presence and usage of abatement technologies. Countries with a higher level of such technologies would have a smaller amount of emissions generated from the same economic activities ($\chi_3 < 0$).

The main explanatory variables of our interest are a country's trade intensity ($Trade_{it}$) and GVC position ($Upstream_{it}$). As $Trade_{it}$ includes both import and export, its coefficient β_1 represents the net effect of trade on emissions. A large body of literature studies the effect of trade on air pollution, but there is no consensus established, as trade affects a country's emissions (and concentration accordingly) through multiple channels and the net effect is determined by the magnitude of each channel (Antweiler et al. 2001; Frankel and Rose 2005; Grossman and Krueger 1993; Heil and Selden 2001; Li and Reuveny 2006).[15] Another aspect to consider is a country's position on the global value chain, which determines specialization patterns across countries and, thus, affects emission intensity. Recent studies find that more upstream industries are more emission-intensive (Copeland et al. 2022; Shapiro 2021). The coefficient β_2 tests if such a relationship holds at the country level as well. Positive β_2 means that more upstream countries are dirtier on average after their economic growth and participation in trade are controlled.

Lastly, we explore whether the participation in PTAs with environmental provisions affects the level of emissions as well as how trade affects emissions. With the environmental standards or regulations agreed upon among members, PTAs may mitigate environmental damage that trade brings to some countries – via pollution offshoring, for example. The coefficient on the interaction term, β_4, captures that role and is expected to have the opposite sign to β_2 if PTAs fix some of the environmental externalities.

3.2.2.2 Role of pollution remoteness on concentration

As the previous section illustrates, we first estimate how a country's emission is associated with its size, level of abatement technology, and participation in trade and GVC position. Then we link country-level emissions with concentrations, which is the mechanism by which emissions

[15] In a sense, our specification is similar to that of Copeland and Taylor (2003), as we estimate the partial effect of trade intensity when the economy's size, industrial composition, and emission intensity – respectively, scale, composition, and technique aspect – are controlled. Recall that the emission measures are not observations but calculated values. So our specification tests if trade affects any of the factors that are used in the calculation of emissions – for example, share of dirty industries or firms' abatement decisions.

affect welfare ultimately. Using Equation 3.4, we estimate not only the role of a country's own emissions but also those of other countries' $PM_{2.5}$ emissions, the latter of which motivates our focus on transboundary travel of pollutants.

$$ln(concentration)_{it} = \psi + \lambda_1 ln(E/land)_{it} + \lambda_2 Meteo_{it} + \kappa \ln(PolTransport)_{it} + \delta_i + \delta_t + \xi_{it} \tag{3.4}$$

The right-hand side of Equation 3.4 shows a few determinants of a country's concentration. First of all, it would increase with its own emission level (normalized by the size of land area), $E_{it}/land_{it}$. In addition, it would also be affected by meteorological factors ($Meteo$), including temperature and precipitation.[16] For example, higher temperature dissipates pollution faster, and more consistent precipitation washes down concentration. In order to capture such effects on concentration, we include the average and standard deviation of temperature and precipitation in the $Meteo$ vector.

Lastly, the main variable of interest is $PolTransport$, which measures the degree of transboundary pollution that each country is exposed to. The coefficient on $PolTransport$, κ, tests whether $PM_{2.5}$ emissions travel across border and affect other countries' concentration. For example, if $PM_{2.5}$ travels across the border, κ would be positive.

One limitation of this chapter is that it focuses on the role of primary $PM_{2.5}$ and abstracts from secondary $PM_{2.5}$, which are formed by chemical reactions of precursor gases, including nitrogen oxides (NO_x), ammonia (NH_3), and sulfur dioxide (SO_2), in the atmosphere.[17] As the

[16] In the atmospheric science literature, air pollutant transport and concentration are simulated based on emissions and meteorological and tropospheric chemical processes (Lin et al. 2014; Liu et al. 2009; Verstraeten et al. 2015; Zhang et al. 2017).

[17] EPA (2018) states that a great portion of fine PM ($PM_{2.5}$) contains secondary particles, more than in the case of coarse PM (PM_{10}).

concentration data includes the pollution formed by secondary processes, the role of secondary formation would be captured in the coefficient of either own emission or transboundary pollution or both as well as the error term in our specification.[18] Thus, we include controls that proxy the dispersion of industrial activities, such as population density, the share of the urban population, and rail density, in the additional specification to capture the degree of secondary formation of $PM_{2.5}$. Alternatively, we could explicitly include the emissions of precursor pollutants, but that would result in including too many regressors that are highly correlated to each other. Also, we would, then, have to take into account the chemical processes of secondary formation of PM 2.5, which is outside this paper's scope.

3.2.3 Results

In this section, we present the results from running Equation 3.3 and 3.4. These two steps of regressions are useful to understand the linkage between economic activities, including trade, and air pollution. In two steps, we not only check whether our sample shows a similar pattern of the linkage from what the existing literature finds but also highlight the importance of transboundary pollution in air pollution concentration. For all specifications, we use country-level and year-level fixed effects to absorb unobserved factors determining emissions and concentration. We also cluster standard errors at the region-year-level since our dependent variables may not be independent – in particular, concentration in a setting with transboundary spillovers.[19]

[18]Copeland et al. (2022) find that different pollutants' emissions are highly correlated to each other.

[19]We use the region classification provided by the World Bank, which divides countries into 7 regions, including East Asia and Pacific, Europe and Central Asia, Latin America the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa.

3.2.3.1 Determinants of $PM_{2.5}$ emission per capita

Table 3.3 reports the step 1 results: the determinants of $PM_{2.5}$ emissions.[20] Column 1 shows that emission increases with economic growth and that the coefficient on the squared GDP is negative, supporting the EKC hypothesis. It also shows the emission-reducing effect of abatement-related technologies. The role of total trade intensity is positive, but the estimate is not statistically significant, which is consistent with the lack of consensus on the net effect of trade in the literature. Of equal interest is the coefficient on $Upstream$, which shows how a country's positioning in the GVC affects emissions when its trade participation is controlled. The estimate is positive and significant, suggesting that the countries located farther from final consumer demand (i.e., more upstream) are more emission-intensive. This is analogous to the industry-level findings that more upstream industries are dirtier (Copeland et al. 2022; Shapiro 2021).

Columns 2 and 3 add $PTAenv$ and the interaction of $PTAenv$ and $Trade$. The magnitude of coefficient estimates from column 1 decreases overall as PTA terms are added, implying that their roles were absorbed by the existing regressors in column 1. The negative coefficient on the interaction term in column 3 shows that the role of trade on emissions is heterogeneous and depends on a country's participation in PTAs that have environmental provisions. Specifically, countries that are bound by PTA environmental provisions experience less emission-increasing impact from trade.

We also run the regression after separating trade openness into export intensity and import intensity, defined as the ratio of export to GDP and import to GDP respectively. Table 3.4 shows

[20] Appendix Table C.3 shows the summary statistics.

Table 3.3: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
$GDPpc$	30.149***	20.620**	18.867*
	(8.849)	(9.735)	(9.960)
$GDPpc^2$	-244.977***	-163.162**	-147.311**
	(66.072)	(65.267)	(66.497)
$Tech$	-33.906***	-27.102**	-28.520**
	(11.167)	(11.003)	(11.236)
$Trade$	0.073	0.017	0.130
	(0.069)	(0.061)	(0.097)
$Upstream$	0.300***	0.268***	0.247**
	(0.089)	(0.093)	(0.098)
$Trade$		0.155***	0.323***
		(0.040)	(0.094)
$Trade \times PTAenv$			-0.156**
			(0.071)
Number of observations	630	630	630
Within Adj. R-squared	0.111	0.142	0.151

Notes: The dependent variable is the log of emission per capita. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *$<$ .1, **$<$ .05, ***$<$ .01.

that the emission-increasing effect of trade openness is driven by the export side of it. In contrast, import is negatively associated with emission. This is not surprising given that exporting requires additional production in a country and importing eliminates the need for emission-generating activities in a country. The emission-increasing and emission-decreasing effects of export and import are muted by PTA, respectively, but the coefficients are insignificant.

Another notable difference is that the coefficient on GVC participation is estimated less significantly while the positive estimate remains. In column 3, it loses significance. One way to interpret this is that splitting trade intensity into export and import sides captures the pattern of specialization of each country, which is closely related to its position in the global value chain. In all columns, the coefficients on $GDPpc$, $GDPpc^2$, and $Tech$ remain similar to those in Table

3.3.

Table 3.4: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
$GDPpc$	32.317***	21.339*	20.563*
	(9.699)	(11.586)	(11.631)
$GDPpc^2$	-257.295***	-168.854**	-157.227**
	(67.695)	(74.844)	(75.833)
$Tech$	-32.600***	-26.638**	-27.479**
	(11.680)	(11.451)	(11.600)
$Export$	0.431*	0.270	0.577**
	(0.231)	(0.238)	(0.254)
$Import$	-0.342	-0.296	-0.387
	(0.296)	(0.282)	(0.277)
$Upstream$	0.220**	0.237**	0.193
	(0.109)	(0.113)	(0.117)
$PTAenv$ (ex)		0.290**	0.471**
		(0.123)	(0.211)
$PTAenv$ (im)		-0.151	-0.185
		(0.123)	(0.213)
$Export \times PTAenv$ (ex)			-0.411*
			(0.244)
$Import \times PTAenv$ (im)			0.113
			(0.214)
Number of Observations	630	630	630
Within Adj. R-squared	0.116	0.148	0.155

Notes: The dependent variable is the log of emission per capita. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *$<$ .1, **$<$ .05, ***$<$ .01.

In summary, the results in this section show that the role of trade on emissions is not clear, as it is composed of opposing forces, but that the role is heterogeneous according to countries' participation in PTAs that include environmental provisions. In addition, whether a country is export-intensive or import-intensive also has different implications on its emissions.

3.2.3.2 Determinants of $PM_{2.5}$ concentration

Table 3.5 shows the results of the second regression, which tests how each country's $PM_{2.5}$ concentration is determined by its own and others' emissions.[21] The first column shows the role of each country's own emission and meteorological factors on concentration. The coefficients confirm the existing understanding of the impact of temperature and rainfall. Both the increase in average temperature and rainfall decrease concentration (conditional on the emissions from own and foreign countries), and the estimates are significant.

Our main variable of interest, $PolTransport$, is added in the second column. When we include $PolTransport$, the coefficients on the meteorological regressors barely change. But the coefficient on own emissions, $\ln(emission/land)$, decreases. Combining it with a positive and significant coefficient on $\ln(PolTransport)$ indicates that a country's concentration is correlated with other countries' emissions, which was partly absorbed by the coefficient on own emissions in the first column. The coefficients – 0.144 and 0.333 – suggest that a within standard deviation increase in $PolTransport$ is associated with a 2.3% increase in concentration while a within standard deviation increase in own emission is associated with a 1.6% increase in concentration.[22] At the same time, this means that the impact of 1% increase in all other countries' emissions – thereby an 1% increase in $PolTransport$ – is similar with the impact of 2% increase in own emission of a country on average. This suggests that the transboundary transport of foreign emissions has a comparable role to a country's own emissions on its concentration level.[23]

[21] Appendix Table C.4 shows the summary statistics of the regression sample.

[22] The within standard deviation of $\ln(emission/land)$ is 0.11, and that of $\ln(PolTransport)$ is 0.07.

[23] Although existing studies use different measures for transboundary pollution, it is useful to compare the magnitude of its role. For example, Zheng et al. (2014) show that the 10% decrease in neighboring cities' smoke emission – weighted by wind direction – reduces the PM_{10} concentration of a country by 1.7%.

Table 3.5: Determinants of $PM_{2.5}$ concentration

	(1)	(2)	(3)
ln(emission/land)	0.197***	0.144***	0.177***
	(0.038)	(0.039)	(0.058)
Temp Ave	-0.042*	-0.042*	-0.032
	(0.022)	(0.022)	(0.028)
Temp SD	0.021	0.022	0.028
	(0.025)	(0.024)	(0.025)
Rain Ave	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)
Rain SD	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)
ln(PolTransport)		0.333***	0.291***
		(0.087)	(0.088)
ln(population density)			0.119
			(0.173)
Share of urban population			1.665**
			(0.787)
ln(rail density)			0.482***
			(0.101)
Technology			-4.216
			(4.169)
Number of Observations	630	630	429
Within Adj. R-squared	0.101	0.131	0.166

Notes: The dependent variable is log of $PM_{2.5}$ concentration. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value $*< .1$, $**< .05$, $***< .01$.

In the third column, we add more controls that may affect $PM_{2.5}$ concentration. Specifically, we add the log of population density, the share of urban agglomeration population, and the log of rail density to capture the density of industrial activities within a country. We also put the level of technology to capture a country's capability to control air pollution. Specifically, we use the number of environmental management patents per capita to proxy the overall development of the technologies relevant to air pollution management.[24] The positive and significant coefficient

[24] Note that this is different from the technology control variable used in the previous section, which is measured as the ratio of the number of patents related to stationary source emission abatement to the total number of patents.

on $PolTransport$ remains after adding these controls. In the Appendix Table C.5, we present the results obtained from using $PolTransport$ calculated from using cubed distance instead of squared distance to discount the emissions from foreign countries. The results remain similar.

The results of this section show that the role of transboundary pollution is substantial and robust, which motivates us to take the transboundary transport of pollution into consideration when we analyze the impact of trade on air pollution. In addition, the estimates from the regressions are used for calibration in the later quantitative section.

3.3 Model

Motivated by the empirical evidence presented in the previous section, we build a general equilibrium model of international trade and environmental externality from local pollutants that travel across borders. Our model builds on Caliendo and Parro (2015), a multi-industry extension of Eaton and Kortum (2002) with an input-output linkage. We introduce environmental externality to our multi-country general equilibrium trade model following a similar approach to Shapiro (2016) but allow local pollutants to travel across space. The transboundary nature is an important characteristic for pollutants such as particulate matters. Our model shows how the transboundary nature of local pollutants shapes the heterogeneous welfare effect of trade shocks across countries, when the environmental externality is taken into consideration.

3.3.1 Basic Setup

There are N countries in the model, and each country is indexed by either i or n. Consumers in country i have an identical preference summarized by the following utility function which takes into account disutility from concentration of local pollutants:

$$U_i = \left(\prod_j (C_i^j)^{\phi_i^j}\right)\left(\frac{1}{1+\left(\frac{1}{\mu_i} g_i(E_1,\ldots,E_N)\right)^2}\right), \tag{3.5}$$

where $C_i^j = \left(\int_0^1 C_i(e^j)^{\frac{\eta-1}{\eta}} de^j\right)^{\frac{\eta}{\eta-1}}$ is a consumption bundle for sector j aggregating product varieties $e^j \in [0,1]$ with the elasticity of substitution $\eta > 1$ between them. We assume that there are J industries in this economy, with the expenditure share on each industry from each country is given by $\phi_i^j \in [0,1]$ with $\sum_j \phi_i^j = 1$ for each i.

The term in the second parenthesis of equation (3.5) describes the disutility from concentration of local pollutants regardless of the origin. In other words, our local pollutants are not entirely local in a sense that we allow these pollutants to travel across space. When we take our model to data, we focus on PM 2.5 as the measure of local pollutants. We denote the total emission of local pollutants from country i by E_i, and $g_i(\cdot)$ captures the concentration level of the local pollutants. Consistent with the transboundary nature that we allow for the local pollutants, $g_i(\cdot)$ is a function of the emission level from all countries around the world. We will parametrize this function when we quantify the model in the next section. Lastly, μ_i is the parameter that captures the social cost of emission of transboundary pollutants. Following Shapiro (2016), we assume that consumers consider concentration of transboundary pollutants as a pure externality which they take as given in their utility maximization problem.

We assume perfect competition for both goods and factor markets as in Eaton and Kortum (2002, EK, hereafter). The producer of a product e^j of sector j uses labor, capital, and intermediate goods as core production inputs. Production process leads to emission of transboundary pollutants for which producers in country i have to pay an environment tax to the government with the rate t_i set by country i's government. Following Copeland and Taylor (2003), we assume that the production technology for a variety e^j in country i has the following Cobb-Douglas form which combines the potential output from core inputs with emission:

$$Q_i^j(e^j) = \left[E_i^j(e^j)\right]^{\alpha_i^j} \left[z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}\right]^{1-\alpha_i^j}, \tag{3.6}$$

where L_i^j, K_i^j, and M_i^j are labor, capital, and intermediate input bundle, respectively. We assume that both labor and capital is perfectly mobile across varieties and sectors. The cost shares for labor and capital are given by $\gamma_{i,l}^j, \gamma_{i,k}^j \in (0,1)$, respectively. These cost shares are assumed to vary by country and sector, since we relate the capital intensity to the emission intensity when quantifying the model. The emission level from production of variety e^j is denoted by $E_i^j(e^j)$, and α_i^j stands for the emission elasticity of sector j in country i. Following EK, we assume that the factor neutral productivity for variety e^j in country i, $z_i(e^j)$, is randomly drawn from a Fréchet distribution specified as $F_i^j(z) = \exp\left(-A_i^j z^{-\theta^j}\right)$. In this distribution function, $A_i^j > 0$ denotes country i's absolute advantage in sector j, and $\theta^j > 0$ captures the degree of the Ricardian comparative advantage for sector j. As in variations of EK, θ^j is essentially a sector-specific trade elasticity.

3.3.2 Emission, Environmental Tax, and Abatement

Producers' decision on the emission level is tied with how much to abate and also internalizes the environmental tax they have to pay for their emission of local pollutants. We follow Copeland and Taylor (2003) to model how these decisions are related. First, we denote the potential output from core inputs by $F_i^j(e^j) \equiv z_i(e^j) \left(L_i^j\right)^{\gamma_{i,l}^j} \left(K_i^j\right)^{\gamma_{i,k}^j} \left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}$ for notational simplicity. The producer of variety e^j can use a fraction $\kappa_i^j(e^j) \in [0,1]$ her potential output for abatement. Then, the net output in equation (3.6) can be re-written as

$$Q_i^j(e^j) = \left(1 - \kappa_i^j(e^j)\right) F_i^j(e^j). \tag{3.7}$$

We denote the emission intensity of the producer of variety e^j in country i with respect to the potential output by $\tilde{\varphi}_i^j(e^j)$, and by using equation (3.7), we can derive $\tilde{\varphi}_i^j(e^j)$ as follows:

$$\tilde{\varphi}_i^j(e^j) \equiv \frac{E_i^j(e^j)}{F_i^j(e^j)} = \left(1 - \kappa_i^j(e^j)\right)^{\frac{1}{\alpha_i^j}}. \tag{3.8}$$

The emission elasticity α_i^j captures the responsiveness of emission with respect to abatement. The emission intensity with respect to potential output is larger if producers devote a smaller fraction of their potential output for abatement conditional on the emission elasticity. Denoting the marginal emission tax rate in country i by t_i, the emission intensity can be also written with respect to the net output,

$$\varphi_i^j(e^j) \equiv \frac{E_i^j(e^j)}{Q_i^j(e^j)} = \frac{\alpha_i^j p_i^j(e^j)}{t_i}. \tag{3.9}$$

We assume that the environmental tax rate for emission varies by country but not by sector within a country. The emission intensity with respect to the net output increases in the emission elasticity and decreases in the environmental stringency of the country which is captured by a higher environmental tax rate.

Combining equations (3.7)-(3.9), we can derive the optimal abatement decision of producers as follows:

$$\kappa_i^j(e^j) = 1 - \left(\frac{\alpha_i^j p_i^j(e^j)}{t_i}\right)^{\frac{\alpha_i^j}{1-\alpha_i^j}}, \tag{3.10}$$

and thus the optimal abatement cost is given by

$$\left(\frac{\alpha_i^j p_i^j(e^j)}{t_i}\right)^{\frac{\alpha_i^j}{1-\alpha_i^j}} F_i^j(e^j). \tag{3.11}$$

Intuitively, producers devote a larger fraction of their potential output for abatement if the environmental tax rate is higher and the emission decreases more with abatement.

3.3.3 International Trade

All product varieties are tradable between countries subject to iceberg trade costs $d_{in}^j \geq 1$ for products in sector j shipped from country i to country n. It means that firms need to produce extra units to deliver goods to markets, which also implies they need to generate extra amounts of emissions due to iceberg trade costs. One way to interpret this is the emissions arising from global transportation.[25] We make a simplifying assumption on the input-output structure that the final good bundle can be used either for final consumption by consumers or as intermediate input M_i^j in production function (3.6). With this assumption, the unit price for the intermediate input bundle is equal to the exact price index of the country. From producer's profit maximization, the unit cost of production for all producers in industry j of country i is

$$c_i^j = \Upsilon_i^j t_i^{\alpha_i^j} \left(w_i^{\gamma_{i,l}^j} r_i^{\gamma_{i,k}^j} P_i^{(1-\gamma_{i,l}^j-\gamma_{i,k}^j)} \right)^{(1-\alpha_i^j)}, \tag{3.12}$$

[25] Cristea et al. (2013) and Shapiro (2016) explicitly model the emissions of greenhouse gases based on different modes of freight shipping, including both domestic and international. According to the US EPA, transportation (including both freight and personal transport) is responsible for less than 10% of $PM_{2.5}$ emissions.

where Υ_i^j is a Cobb-Douglas constant; w_i is wage; r_i is rental rate of capital; and P_i is the aggregate price index for country i. Following EK, the equilibrium share of trade of sector j goods from country i to country n (X_{in}^j) in country n's total expenditure in sector j (X_n^j) is given by

$$\pi_{in}^j = \frac{A_i^j \left(c_i^j d_{in}^j\right)^{-\theta^j}}{\sum_{i'} A_{i'}^j \left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}} = \frac{X_{in}^j}{X_n^j}. \tag{3.13}$$

The sector-level exact price index is

$$P_n^j = \left[\Gamma\left(\frac{\theta^j + 1 - \sigma}{\theta^j}\right)\right]^{1/(1-\sigma)} \left[\sum_{i'} A_{i'}^j \left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}\right]^{-1/\theta^j}, \tag{3.14}$$

for which we assume $\sigma < \theta^j + 1$ for all j. Using the assumption of Cobb-Douglas aggregation across sectors in consumer's utility, the aggregate price index can be derived as $P_n = \prod_{j'} \left(\frac{P_n^{j'}}{\phi_i^{j'}}\right)^{\phi_i^{j'}}$.

The effect of international trade on sector-level and aggregate emissions is summarized by

$$E_i^j = \frac{\alpha_i^j}{t_i} \sum_{n'} \pi_{in'}^j X_{n'}^j, \tag{3.15}$$

where the country i's aggregate emission is simply $E_i = \sum_{j'} E_i^{j'}$. As a country exports more to other countries, its gross output increases, which in turn leads to a higher level of emission conditional on the emission elasticity and the environmental tax rate. Since sectors vary by emission elasticity, the same change of gross output may lead to different degrees of change in emission across sectors. In particular, a sector with a higher emission elasticity sees a larger increase in emission from the same percentage change of gross output. The government of each country collects the environmental tax whose total revenue is t_iE_i for each country i, and we assume that this tax revenue is rebated to the total income of consumers.

3.3.4 Market Clearing

To close the model for the general equilibrium, we first need to derive the equilibrium expenditure for each sector from each country. The expenditure function also needs to take the intermediate input demand into account. From the production function in equation (3.6), the sectoral expenditure is derived as

$$X_n^j = \phi_n^j \sum_{j'} (1-\alpha_n^{j'})(1-\gamma_{n,l}^{j'}-\gamma_{n,k}^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'} + \phi_n^j I_n, \tag{3.16}$$

where the total income of country n is given by

$$I_n = w_n L_n + r_n K_n + t_n \sum_{j'} E_n^{j'} + D_n. \tag{3.17}$$

In the total income, the first two terms are incomes of the owners of the core value-added production inputs, labor and capital; $t_n \sum_{j'} E_n^{j'}$ is the total tax revenue that is rebated to consumers; and D_n is the aggregate trade deficit of country n, which we treat as an exogenous policy variable.[26] Finally, the general equilibrium factor prices $\{w_n, r_n\}_{n=1}^N$ solve the following system of market clearing conditions:

$$w_n L_n = \sum_{j'} \gamma_{n,l}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'} \tag{3.18}$$

$$r_n K_n = \sum_{j'} \gamma_{n,k}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'}. \tag{3.19}$$

[26] By having exogenous trade deficit, our model underestimates the increases in emissions of those with current account surplus and overestimates the increases in emissions of those with current account deficit. For example, China experienced the continuous rise in trade surplus after joining WTO. This indicates the production activities and, thus, emissions in China have grown more than what is allowed in our model setting.

3.3.5 Welfare

Our model framework enables us to derive a closed-form expression for the aggregate welfare for consumers of each country and exactly decompose the welfare expression into real income and environmental externality. Consumer's utility maximization with the preference given by equation (3.5) gives the following expression for indirect utility:

$$W_i = \left(\frac{I_i}{P_i}\right)\left(\frac{1}{1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2}\right), \tag{3.20}$$

where the expression in the first parenthesis is real income which is based on the expressions (3.14) and (3.17); and the expression in the second parenthesis is the externality from concentration of local pollutants sourced from all countries including its own emission.

A trade shock potentially has two opposite effects on the welfare. A decline in export trade cost for a particular country, for example, is likely to increase the real income of the country by increasing the world demand for the goods produced in that country. The same trade shock, however, would increase the emission from the country, which eventually increases the environmental disutility. In addition, the transboundary nature of the pollutants can show a richer effect of a trade shock on welfare. If a trade shock hits a country, the change in emission of transboundary pollutants induced by the shock in that country affects the level of concentration of the transboundary pollutants in neighboring countries as captured by the function $g(\cdot)$. The exact degree of the spillover effects depends on the functional form of $g(\cdot)$ which we will specify in the next section based on our empirical findings from Section 3.2. Also, the pattern of intermediate input sourcing matters for the spillover effect. If country A is physically close to country B and country A imports a lot of intermediate inputs from country B, a decline in export trade cost from country B would increase production, and thus emission, from not just country B but also from country A, because producers in country A can source inputs more cheaply and thus increase their production.

3.4 Quantification

We quantify the model presented in the previous section to understand the effect of changes in trade environment and the stringency of environmental regulations on the spatial distribution of emission, concentration, and welfare. First, we re-write the model in terms of difference between two steady state equilibria. We then calibrate the baseline equilibrium to match the data in 2000. The quantification of the model also relies on the additional parametrization for the transboundary nature of pollutants.

3.4.1 Model in Changes and the Decomposition of Changes in Welfare

As the first step of the quantification of the model, we re-formulate the model we presented in Section 3.3 in terms of changes between the initial steady state equilibrium and the new steady state equilibrium after an exogenous shock is introduced to the model in the same spirit as the exact hat algebra of Dekle et al. (2008). For any variable x of the model, we denote the level of x at the new equilibrium after a shock to the baseline economy by x' then define $\hat{x}$ as the ratio of x' to the initial level x, i.e., $\hat{x} \equiv x'/x$. We can then re-write all equilibrium conditions of the model in terms of $\hat{x}$. For example, the sector-level unit cost in change is

$$\hat{c}_i^j = \hat{t}_i^{\alpha_i^j} \left(\hat{w}_i^{\gamma_{i,l}^j} \hat{r}_i^{\gamma_{i,k}^j} \hat{P}_i^{(1-\gamma_{i,l}^j - \gamma_{i,k}^j)} \right)^{(1-\alpha_i^j)}, \tag{3.21}$$

where $\hat{t}_i$ is an exogenous change in the environmental tax rate which is one of the counterfactual shocks we introduce in the next section. We assume that the cost share parameters and the emission elasticity are both time-invariant. The other hat variables in equation (3.21) are changes in endogenous variables which respond to the shock introduced to the model.

The sectoral expenditure at the new equilibrium can be written

$$X_n'^j = \phi_n^j \sum_{j'} (1-\alpha_n^{j'})(1-\gamma_{n,l}^{j'} - \gamma_{n,k}^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}'^{j'} + \phi_n^j I_n', \tag{3.22}$$

where the total income of the new equilibrium is

$$I_n' = w_n \hat{w}_n L_n + r_n \hat{r}_n K_n + t_n \hat{t}_n \sum_{j'} E_n'^{j'} + D_n'. \tag{3.23}$$

In our counterfactual exercises, we assume that labor and capital endowments as well as the sectoral expenditure shares in consumer's utility do not vary over time. The emission level of sector j of country i at the new equilibrium is then written as

$$E_i'^j = \frac{\alpha_i^j}{t_i'} \sum_{n'} \pi_{in'}^j \hat{\pi}_{in'}^j X_{n'}'^j. \tag{3.24}$$

The derivation of changes of other model variables including $\hat{\pi}_{in}^j$, $\hat{P}_n^j$, and $\hat{P}_n$ is in the Appendix. Lastly, the labor market and capital market clearing conditions at the new equilibrium are written as

$$w_n \hat{w}_n L_n = \sum_{j'} \gamma_{n,l}^{j'} (1 - \alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}^{\prime j'} \tag{3.25}$$

$$r_n \hat{r}_n K_n = \sum_{j'} \gamma_{n,k}^{j'} (1 - \alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}^{\prime j'}. \tag{3.26}$$

The welfare equation in (3.20) is written in changes as follows:

$$\hat{W}_i = \underbrace{\left(\frac{\hat{I}_i}{\hat{P}_i} \right)}_{\text{changes in real income}} \underbrace{\left(\frac{1 + \left(\frac{1}{\mu_i} g_i(E_1, \ldots, E_N) \right)^2}{1 + \left(\frac{1}{\mu_i} g_i(E_1', \ldots, E_N') \right)^2} \right)}_{\text{changes in environmental utility}}, \tag{3.27}$$

which is a function of changes in other variables that have been derived above. Equation (3.27) enables us to conveniently quantify the welfare effect of a counterfactual shock while taking into account the general equilibrium effect of the shock on income and emission as well as the associated environmental externality. For the rest of the paper, we will call the term in the second parenthesis of equation (3.27) as changes in environmental *utility*, which a slight abuse of language. We can also decompose the change in the environmental utility into changes in utility coming from own emission and changes in utility from the pollutants that travel from other countries around the world. First, denote the initial environmental utility from concentration of transboundary pollutants for country i by W_i^D, i.e., $W_i^D \equiv \frac{1}{1+\left(\frac{1}{\mu_i} g_i(E_1,\ldots,E_N)\right)^2}$. By totally differentiating W_i^D, the change in W_i^D can be decomposed as follows:

$$\hat{W}_i^D - 1 = \underbrace{\frac{\partial}{\partial E_i}\left(1 + \left(\frac{1}{\mu_i} g_i(E_1, \ldots, E_N)\right)^2\right) \frac{E_i(\hat{E}_i - 1)}{W_i^D}}_{\text{from own emission}} + \underbrace{\sum_{i'' \neq i} \frac{\partial}{\partial E_{i''}}\left(1 + \left(\frac{1}{\mu_i} g_i(E_1, \ldots, E_N)\right)^2\right) \frac{E_{i'}(\hat{E}_{i'} - 1)}{W_i^D}}_{\text{from others' emission}}. \tag{3.28}$$

The exact functional form of (3.28) depends on the parametrization of the $g(\cdot)$ function which is discussed in the next subsection. Given the initial emission data, we compute E_i, $g_i(E_1, \ldots, E_N)$, and W_i^D. After solving the model for $\{\hat{w}_n, \hat{r}_n\}_{n=1}^N$ which is the solution of the system of equations (3.25) and (3.26), we compute $\hat{E}_i$ by using (3.24) and the initial emission data.

3.4.2 Parametrization of the Travel of Local Pollutants

We parametrize the $g(\cdot)$ function, using the empirical results (step 2) from Section 3.2. Specifically, we use the coefficient estimates from column 2 of Table 3.5, which is a baseline specification that includes a transboundary transport term. Recall that the empirical specification looks like

$$ln(concentration)_{it} = \psi + \gamma_1 ln(E/land)_{it} + \gamma_2 Meteo_{it} + \kappa \ln(PolTransport)_{it} + \delta_i + \delta_t + \upsilon_{it}$$

Putting both sides as the power to the exponentials, we get the following function for a country's concentration, $g_i(E_1, \ldots, E_N)$.

$$g_{it}(E_1, \ldots, E_N) = e^{\left(\hat{\psi} + \hat{\gamma_1} ln(E/land)_{it} + \hat{\gamma_2} Meteo_{it} + \hat{\kappa} \ln(PolTransport)_{it} + \hat{\delta_i} + \hat{\delta_t}\right)}$$

The meteorological vector $Meteo$ includes the average of temperature, standard deviation of temperature, average of precipitation, and standard deviation of precipitation, and $PolTransport$ is the degree to which a country is exposed to other countries' emissions. As we discussed in Section 3.2, we use the following functional form for $PolTransport_{it}$.

$$PolTransport_{it} = \sum_{i' \neq i} \frac{E_{i't}}{land_{i't}} \times \frac{1}{distance^2_{ii't}}$$

The division by land area of an emitting country captures the dispersion of its emissions before crossing borders, and the division by the distance between two countries captures the phenomenon that pollution transport decays with distance nonlinearly.

The coefficient estimates obtained from column 2 are illustrated in Table 3.6. Note that δ_i is country-specific and we use the coefficient of year fixed effects δ_t corresponding to the year 2000 as the model is calibrated to the year 2000's data. Lastly, we use the year 2000's information on country-level temperature, precipitation, land area as well as the distance between countries from our empirical dataset used in Section 3.2. Emissions E_i are computed from the model.

Table 3.6: $g(\cdot)$ parameters

$\hat{\psi}$	$\hat{\gamma}_1$	$\hat{\gamma}_2$				$\hat{\kappa}$	$\hat{\delta}_i$	$\hat{\delta}_{2000}$
		Temp Ave	Temp SD	Rain Ave	Rain SD			
-0.329	0.144	-0.042	0.022	-0.003	0.001	0.333	*varies*	0.12

3.4.3 Calibration

In this section, we introduce the data and methods used for calibrating the model. We combine a few different datasets for calibration, and our base year is 2000, which is before China's accession to WTO and EU 2004 enlargement, our two main counterfactual scenarios.

Our sample includes 38 individual countries and the rest of the world (ROW). We started from 43 countries and ROW as presented in the WIOD, which is our main dataset, and merged those 5 countries without much data coverage with ROW. In addition, based on the sector list from the WIOD, we made a few modifications and ended up with 24 sectors. Specifically, we combined A01-A03 into A and merged D, E, and F into one sector. Also, we put other service sectors than D/E/F and H as other services, so we have 3 service sectors, all of which are non-tradable. Sample countries and sectors are presented in Table C.1 and C.2.

The WIOD provides country-sector-level gross output and value-added as well as a multi-country, multi-sector input-output table. We also use the KLEMS for country-sector-level capital and labor expenditures, EDGAR for country-sector-level emissions, and OECD for the country-level ratio of environmental tax revenue to GDP.

3.4.3.1 Environment-related parameters

In addition to $g(\cdot)$ function as discussed in the previous section, we have three environment-related parameters that need to be calibrated. They are the disutility parameter μ_i, environmental tax t_i and country-sector-level emission intensity α_i^j.

Disutility parameter

We calibrate the disutility parameter, μ_i, so that the welfare decrease by a one-ton increase in $PM_{2.5}$ emissions matches the social cost of $PM_{2.5}$ of each country. Specifically, we take the following steps. First, using the US estimate of $PM_{2.5}$'s social cost, we impute the social cost for other countries. Heo et al. (2016) provide the estimated range for the marginal social cost of $PM_{2.5}$ emission, calculated for the US in 2005. We use the median of the range, which is

$109,000$ 2005 USD per metric ton.[27] Non-US countries' social costs, $sc_{i \neq US}$, are estimated by adjusting for their relative population density and GNI per capita (with elasticity ν) compared to the US, as shown in Equation 3.6.

$$sc_{i \neq US} = sc_{US} \times \frac{popdensity_i}{popdensity_{US}} \times \left(\frac{GNIpc_i}{GNIpc_{US}} \right)^{\nu} \tag{3.29}$$

This is based on the notion that marginal social cost is estimated by measuring the damage incurred by an additional emission through increased mortality risks and expressing it in a monetized value using the value of statistical life (VSL). The implicit assumption is that the demographics composition of each country and the health effect of pollution are common across countries. A higher level of population density increases the degree to which the population is exposed to a marginal emission, thus increasing total mortality risks.[28] In addition, VSL is based on the willingness to pay to reduce mortality risk and increases with income level (OECD, 2012; Viscusi and Masterman, 2017). We use the income elasticity of VSL $\nu = 1.103$, following (Viscusi and Masterman, 2017).[29] The resulting estimated values of the social cost of $PM_{2.5}$ are reported in Appendix Table C.6.

Then we solve for μ_i which makes the marginal social cost of $PM_{2.5}$ emission match each country's estimated social cost, following Bockstael and Freeman (2005). We define the marginal social cost as the willingness to pay to avoid marginal emission as follows with $dE_k = 1$ for all

[27] The minimum is $88,000$ 2005 USD, and the max $130,000$ 2005 USD.

[28] Ideally, we want to use the exact measure of population exposure to $PM_{2.5}$ pollution, which needs information on the location of emission sources and population density within a country.

[29] This is the estimate for non-US countries.

k.[30]

$$sc_i = -\frac{dI_i}{\sum_{\forall k} dE_k} = \frac{\sum_{\forall k} \partial W_i/\partial E_k}{\partial W_i/\partial I_i} = \sum_{\forall k} \frac{\partial W_i}{\partial g_i}\left(\frac{\partial W_i}{\partial I_i}\right)^{-1} \frac{\partial g_i}{\partial E_k} dE_k \tag{3.30}$$

It is worth to note that this is a general form that allows a range of assumptions on the degree of transboundary transport. In a model that does not take transboundary pollution into account (equivalently, $\frac{\partial g_i}{\partial E_{k\neq i}} = 0$), the marginal social cost is, and Equation 3.30 becomes $sc_i = \frac{\partial W_i}{\partial g_i}\left(\frac{\partial W_i}{\partial I_i}\right)^{-1} \frac{\partial g_i}{\partial E_i}$.

Putting Equation 3.20 and the functional form of $g(\cdot)$ specified in the previous section into Equation 3.30, we get the following expression for the environmental disutility parameter, μ_i, squared.

$$\mu_i^2 = -\frac{2g_i I_i}{sc_i} \times \sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k - g_i^2 \tag{3.31}$$

where

$$\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k = \frac{g_i}{E_i}\hat{\gamma}_1 dE_i + \hat{\eta}_1 \frac{g_i \sum_{i'\neq i}(land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{\sum_{i'\neq i} \frac{E_{i'}/land_{i'}}{d_{i'i}^2}} \tag{3.32}$$

We assume that μ_i^2 is time-invariant and use the 2005 data to calculate μ_i^2 since the social cost values we take from Heo et al. (2016) are estimated for the year 2005. Putting Equation 3.32 into Equation 3.31 and using the data as well as parameter values for $g_i(\cdot)$ as discussed in the previous section, we obtain the values of μ_i^2 for each country. Equation 3.27 shows that countries with larger μ_i^2 experience a smaller welfare loss from the same increase in concentration. Appendix C.2.1 shows detailed steps for the derivation, and Table C.7 reports the estimated μ_i^2 values.[31]

[30] We interpret marginal social cost in a different way from how Shapiro (2016) does. He defines social cost as the change in welfare with respect to the change in (global) CO_2 emission. Following such definition, $sc_i = \frac{\partial W_i}{\partial E}$ where E is the level of global emissions.

[31] We also obtain alternative social cost and disutility parameter values by using alternative measures for population exposure, which are reported in Table C.8 and C.9. Population density may not perfectly capture the degree of the population's exposure to pollution. For example, if the population is concentrated in one part of a country whereas polluting sources are concentrated at another end of the country, then using population density overestimates the exposure of the population to increased emission and concentration. Ideally, we need information on the location of

If $PM_{2.5}$ pollution sources are located mostly in these areas, then they may capture a closer picture of people's exposure to pollution. But some industrial activities are located far from residential areas. In addition, both measures are not available for all of our sample countries.[32] Thus, we present them as robustness checks. Appendix Table C.8 and C.9 report the resulting social cost and μ_i^2 values from these two approaches, showing that the estimates are similar in most countries. One notable exception is Australia, whose urban version has a much smaller μ_i^2 estimate as the population is highly concentrated in urban areas (thus, much higher urban population density compared to overall and rural population density).

Environmental regulation

We calibrate the level of emission tax for each country by matching the ratio of emission tax revenue to value-added $\frac{t_i E_i}{VA_i}$ to the data. Specifically, we use the environmental tax revenue per GDP from OECD.[33] As we have the data for E_i and VA_i, we can easily solve for t_i for each country.

Emission elasticity

The emission elasticity α_i^j captures the responsiveness of emission with respect to abatement. We calibrate the value of emission elasticity α_i^j by using 3.33, which is obtained from rearranging

emission sources and population density within each country, but such information is not easy to attain. Thus, we use population density for urban areas and population density for urban and rural areas combined as two alternative measures of exposure.

[32] We use the population and surface area of urban and rural areas, obtained from the World Bank's WDI. Austria, the Czech Republic, Hungary, and Taiwan do not have the data.

[33] We use the tax revenue for all categories, which include the tax on energy, transport, resources, and air pollution. For the countries that provide huge subsidies for energy – resulting in a negative value for this ratio – we exclude energy subsidies and include the tax on the remaining categories. The model does not allow the negative regulation (i.e., subsidies) as Equation 3.33 does not make sense with $t_i < 0$.

Equation 3.9.

$$\alpha_i^j = \frac{E_i^j t_i}{GO_i^j} \tag{3.33}$$

It shows that emission intensity can be calculated as the share of tax expenditures in gross output. In other words, it is as though emission is a type of input and α_i^j represents a Cobb-Douglas input share for emission, which is consistent with how Equation 3.6 shows the Cobb-Douglas production technology using emission as an input. As sector-level emissions E_i^j and gross output GO_i^j are observed in the data, we can obtain the value of α_i^j, using the calibrated value of t_i.

3.4.3.2 Other calibration

We match input expenditure shares ($\gamma_{i,l}^j$, $\gamma_{i,k}^j$, $1 - \gamma_{i,l}^j - \gamma_{i,k}^j$) from the WIOD and KLEMS. Specifically, we first obtain the ratio of value-added and intermediate expenditures to gross output from the WIOD. Then, we divide the value-added share into labor and capital expenditure shares, using the information from the KLEMS.

Sectoral expenditure share, trade share, and trade deficit match the data from the WIOD. To calculate the sectoral expenditure share ϕ_i^j, we divide the total final expenditure on sector j goods by country i's total final expenditures.[34] The bilateral trade share π_{in}^j is obtained by dividing n's imports of sector j goods from i by n's total absorption of sector j goods. Trade deficits are given by subtracting total exports from total imports.

Lastly, we use the estimates from Caliendo and Parro (2015) for the sector-level trade

[34] We follow Costinot and Rodríguez-Clare (2014) to eliminate the negative inventories so that both expenditure share and trade share are all nonzero. Specifically, for negative inventories, the authors assume that the products expressed in the negative inventories were produced in the previous period, thus replacing the negative inventory values with zero and adding the absolute value of the negative inventories to the gross output. For a static model setting, like ours, they assume that they were produced in the same, concurrent period.

elasticity (θ^j).[35] While most sectors correspond 1-to-1 between their and our classifications, three sectors from theirs are matched with one sector in ours.[36] The sector C26 (Manufacturer of computer, electronic, and optimal products) in our sample is matched with Office, Communication, and Medical Manufacturing in their sector list. We use the weighted average of the three elasticities to get the one for C26, using the world total trade flows. The elasticities are presented in the Appendix Table C.10.

3.5 Counterfactuals

What would be the welfare effect of trade liberalization after taking the environmental externality from transboundary pollutants into account? Is that effect quantitatively different if a particular trade liberalization episode involves more stringent environmental regulations for participating countries? We can use our model to answer these policy questions based on counterfactual exercises. These exercises not only shed light on important policy questions about trade and the environment but also highlight the key mechanism of the model.

We study two counterfactual scenarios. First, we quantify the welfare effect of the China shock by exogenously lowering trade costs to and from China by 20%—i.e., $\hat{d}_{i,China} = \hat{d}_{China,i} = 0.8$ for all $i \neq China$. Second, we explore the welfare effect of EU enlargement in 2004 with the actual changes in tariffs between existing and new EU member countries as the exogenous shock of the counterfactual scenario. For each scenario, we compute changes in total welfare for all countries in our sample and decompose them into changes in real income and changes in environmental externality. The former is a conventional measure of welfare gains from trade

[35] We use their 99% sample estimates.

[36] We use the ISIC Rev. 4 classification while they use the ISIC Rev. 3 classification.

in a model with identical and homothetic demand, while the latter is the new component in our framework.

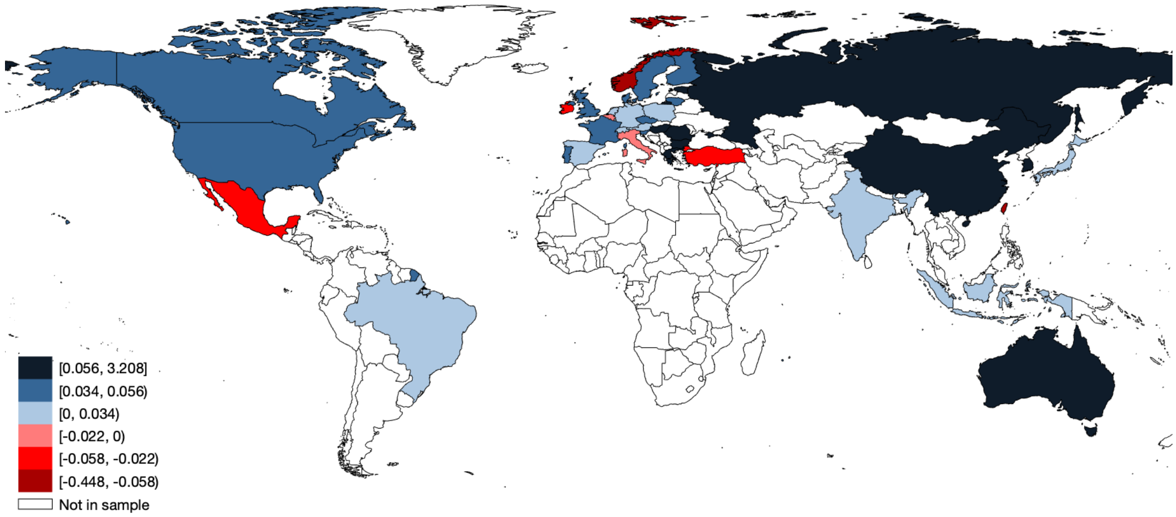
Also, we augment each scenario by introducing hypothetically more stringent environmental regulations. More recent trade agreements tend to include environmental provisions to ensure participating countries' commitment to a clean environment. To study how such provisions may change the welfare effect of trade liberalization, we put an additional shock of a 20% exogenous increase of environmental tax for China in the first scenario, and for new EU member countries in the second scenario. The 20% of increase in the tax is meant to capture the change in regulation stringency in various forms, both tax and non-tax, that may follow the trade liberalization. The additional shock is to highlight the model mechanism but not to exactly capture the actual change in regulation stringency that occurred in China's accession and the EU enlargement.[37]

3.5.1 China shock

Since China joined the WTO in 2001, most countries around the world have seen a large increase in trade with China, especially imports from China. There has been a lot of research on the welfare consequences of China's joining the world market from various perspectives. Our focus in this paper is to revisit the welfare effect of trade shocks with the environmental externality from transboundary pollutants taken into account. We introduce the so-called China shock to the baseline model by plugging in $\hat{d}_{i,China} = \hat{d}_{China,i} = 0.8$ for all $i \neq China$, which implies that trade costs to and from China are exogenously lowered by 20%. All the other model parameters remain unchanged. This counterfactual shock will affect trade patterns

[37]Candidate countries must apply all EU legislation and policy on the environment by their date of accession. For example, they must enforce emission sources to meet EU standards, including but not limited to monitoring and data collection, and reduce emissions. As such, the heightened stringency takes different forms.

Figure 3.4: Changes in aggregate welfare from the China shock (% change)



between China and each of the other countries in the sample. Changes in trade patterns will affect each country's production patterns across industries, and depending on each industry's emission intensity, the aggregate emission of $PM_{2.5}$ will change. While we should expect each country's own emission to be the most important determinant of the concentration level of the same pollutant in the country, changes in the emission level of neighboring countries will also matter due to the transboundary nature of the pollutant. Therefore, the environmental externality is expected to show spatial heterogeneity.

Figure 3.4 shows the changes in aggregate welfare for each country in our sample from a 20% decrease in trade costs to and from China. The results in numbers are reported in Table C.11 of the Appendix. Not surprisingly, we see that aggregate welfare increases in most countries with the largest increase for China.[38] The results also show that the welfare effect of the China shock is significantly heterogeneous across countries in terms of both directions and magnitudes.

[38]China's welfare gain is an outlier. It gains by 3.2% whereas the next highest welfare gain is that of Australia, which is just 0.31%.

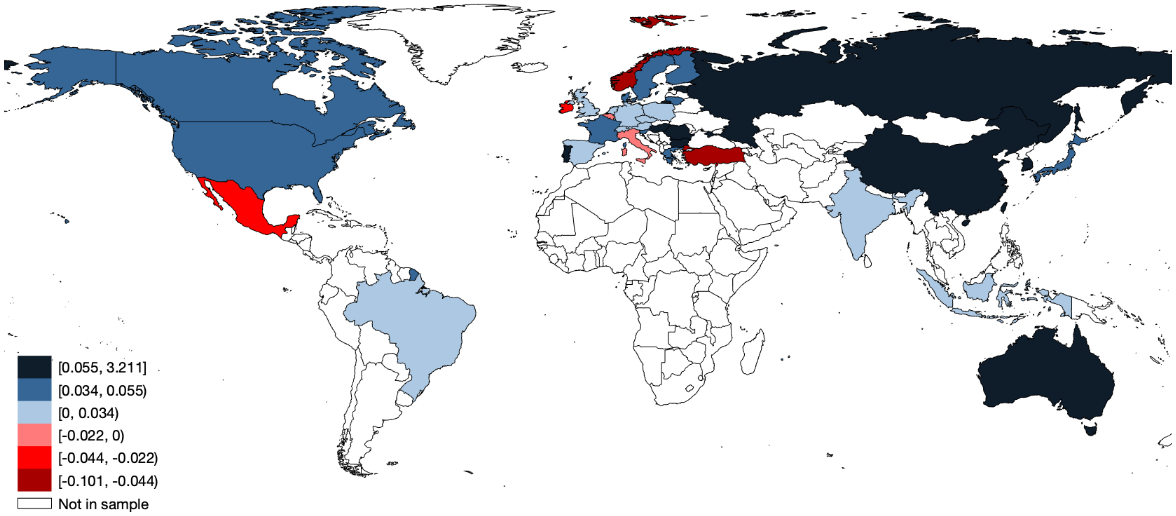
Where does this heterogeneous welfare response across countries come from? A standard trade model without environmental externality would answer this question solely based on changes in real income of each country from the change in trade costs with China. The sign and the magnitude of the changes depend on various factors such as each country's industry composition, China's comparative advantage across industries, and each country's initial trade shares with China. The welfare response in our model, on the other hand, has an additional component that captures changes in environmental externality for each country. As shown in equation (3.27), the total changes in welfare in response to the China shock can be exactly decomposed into changes in real income as captured in standard trade models, and changes in environmental externality from transboundary pollutants.

Figure 3.5 shows the decomposition results for each country. Columns (2) and (3) of Appendix Table C.11 report the results in numbers. The first notable pattern is that changes in welfare measures reported in Figure 3.4 are predominantly determined by changes in real income reported in Figure 3.5 (a). While there is sizable disutility from transboundary pollutants, the magnitude of the environmental externality is relatively smaller compared to that of changes in real income.[39]

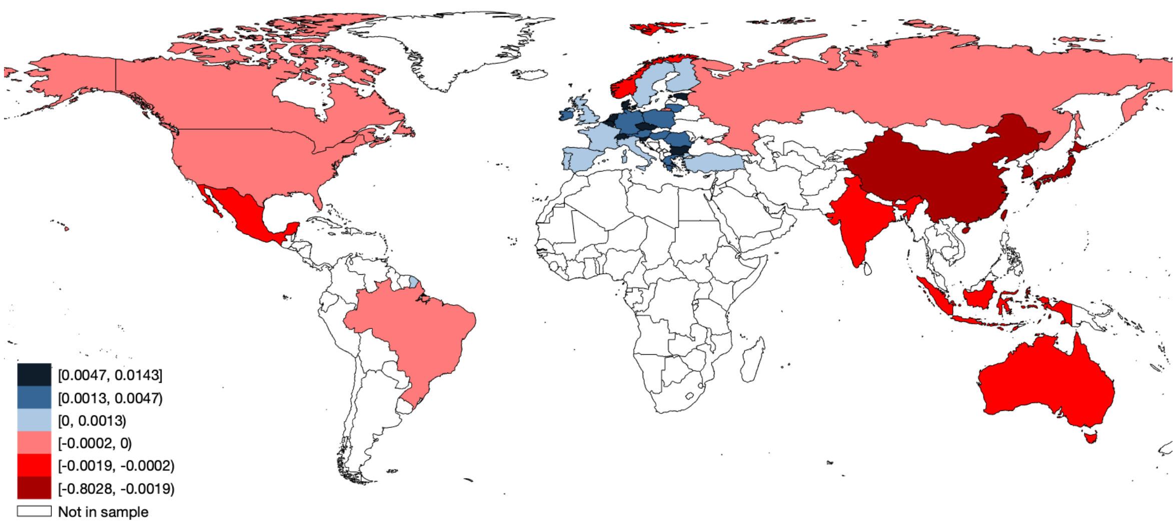
The second pattern to note is that changes in environmental externality – i.e., changes in utility from the concentration of $PM_{2.5}$ in air – also contribute to the heterogeneous welfare effects across countries, but that the pattern of heterogeneity is significantly different between changes in real income and changes in environmental externality. In fact, many countries have welfare losses from increases in environmental disutility due to the decrease in trade costs with

[39] Recent few papers also find that the environmental aspect of welfare changes from trade policies is much smaller than the real-income counterpart (Shapiro, 2021, 2016).

Figure 3.5: Decomposition of the welfare effect from the China shock



(a) Changes in real income (%)



(b) Changes from environmental externality (%)

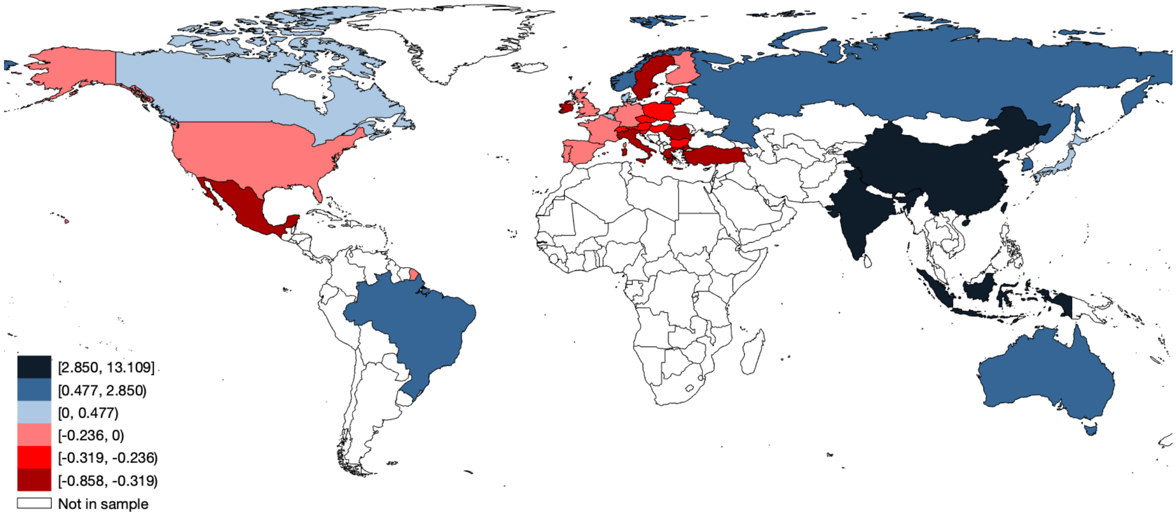
China, as reported in Figure 3.5 (b). There are three effects combined in this result. First, as China joins the world market, the conventional pollution haven effect would come into play. In other words, production is reallocated from other countries, especially from other developed countries such as North-American or European countries, to China after the shock, which increases the emissions of $PM_{2.5}$ in China and decreases them in those other countries. Second, due to the transboundary nature of $PM_{2.5}$, an increase in emissions from China can have spillover effects on its neighboring countries in East and Southeast Asia. This spillover effect is captured by the decrease in environmental externality in countries like Korea, Japan, India, Taiwan, and Russia in Figure 3.5 (b). Lastly, the China shock can also increase other countries' own emissions. For example, if country A specializes in the industry X which heavily uses intermediate inputs for which China has a comparative advantage, an increase in trade with China may increase country A's production in industry X. If the technology of country A for industry X has a high emission intensity, an increase in trade with China will increase country A's own emission.

To disentangle these three effects more clearly, we decompose changes in environmental utility into changes in environmental utility from a country's own emission and those from all the other country's emissions, based on the analytical decomposition in equation (3.28). Columns (4) and (5) of Appendix Table C.11 report the decomposition results. In response to a decrease in trade costs to and from China, the environmental utility from $PM_{2.5}$ in China decreases by 0.0025%, and we show that 84% of that decrease is from an increase in own emission. In other neighbors of China, the patterns are starkly different. In Korea, for example, the China shock decreases the environmental utility by 0.1411%, but only 3.5% of that decrease is from its own emission. The rest of the decrease is from other countries' emissions in which the increase in emissions from China plays a dominant role. The fact that the magnitude of the negative welfare effect from emission is larger in Korea than in China reflects that the marginal disutility from emission can be different across countries, as captured by the country-specific parameter μ_i. In other words, an additional emission brings smaller welfare loss in China given the current calibration of the disutility parameter.

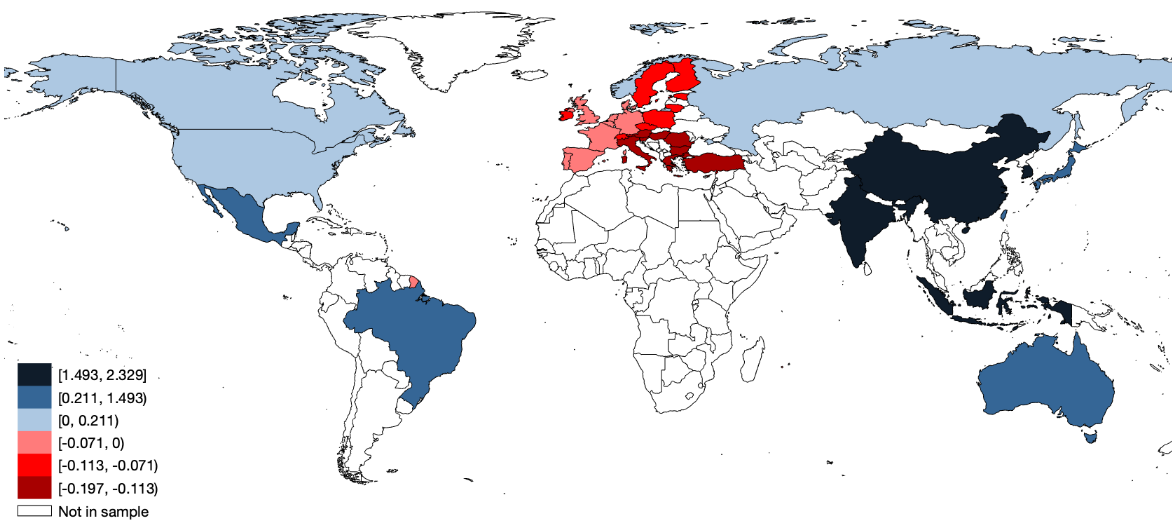
Lastly, our model also shows how much each country's own emission and concentration level of PM2.5 change in response to the China shock. While the emission level depends on each country's own production level, the concentration level of a country depends on how much other countries' emission levels change in addition to the changes in its own emissions, due to the transboundary nature of PM2.5. Figure 3.6 show changes in emission and concentration in each country in response to an exogenous decrease of trade costs to and from China, and columns (6) and (7) of Appendix Table C.11 report the results in numbers. The results show that both the emission level and the concentration level increase in the neighboring countries of China. A decrease in trade costs with China makes it possible for those countries to import cheaper inputs from China, which would increase their own production level as well. Therefore, the emission level of those countries close to China increases from the increase in their production level. In addition, since China experiences a large increase in production scale and thus a large increase in emission due to their high emission intensity, the neighboring countries of China have spillover effects from the increased emission from China. As a result, the countries geographically close to China experience increases in both their own emissions and concentration of $PM_{2.5}$ due to their geographical proximity to China. European countries, on the other hand, show a relatively strong pollution haven effect, which is represented by significant decreases in their own emissions. Also, the European countries are relatively further from China compared to their direct neighbors of China. Therefore, they see decreases in both emission and concentration of $PM_{2.5}$ in response to the China shock.

Since different countries have different levels of stringency for environmental regulations, many recent trade agreements try to address this discrepancy with additional provisions related to environmental regulations. These environmental provisions are often a subject of heated debates

Figure 3.6: Changes in emission and concentration from the China shock



(a) Changes in emission (%)



(b) Changes in concentration (%)

between developed and developing countries, because more stringent environmental regulations may increase the effective cost of production for developing countries, which would limit the potential benefit from trade liberalization for them. From developed countries' perspectives, they have an incentive to include strict environmental provisions not only to level the playing field but also to reduce future harm to global environmental conditions. In order to assess the welfare effect of trade liberalization accompanied by stricter environmental regulations, we consider a counterfactual scenario where bilateral trade costs to and from China decrease by 20% as in the previous scenario and there is an exogenous 20% increase in the environmental tax rate in China. This scenario characterizes a situation where China is required to implement more stringent environmental regulations when it joins the world market.

Table C.12 in the appendix show the effect of this counterfactual scenario on aggregate welfare, real income, environmental utility, and emission and concentration levels of $PM_{2.5}$. The welfare increase for China is about 3.4% smaller with a higher environmental tax, compared to the first counterfactual scenario without additional environmental regulations. When we decompose the welfare increase, the result shows that the smaller welfare effect is from the smaller increase in real income, as China is not able to expand its production as much as in the first counterfactual scenario with higher effective production costs due to the higher environmental tax. Since producers are required to pay higher environmental tax, the environmental utility in China increases after this counterfactual shock, which is exactly the opposite result of the counterfactual scenario with only trade liberalization without additional environmental regulations. Another thing to note is that even though the concentration level of $PM_{2.5}$ decreases by 0.30% in China with the stricter environmental regulations, the environmental utility increases only by 0.0003%. This result is because the marginal disutility from $PM_{2.5}$ concentration is relatively smaller in China, compared to other developed countries in our sample.

The effects on the other countries' real income do not vary much between the two scenarios. The effects on the other countries' environmental utility, on the other hand, are significantly different depending on whether China's joining the world market is accompanied by stricter environmental regulations imposed on China. In all countries of our sample, the effect of the shock on the environmental utility is larger with a higher environmental tax imposed on China, because fewer emissions of $PM_{2.5}$ from China decrease the concentration level of $PM_{2.5}$ everywhere. This effect is more pronounced in the countries that are geographically close to China. For example, in Korea, the environmental utility decreases by 0.14% in the first counterfactual scenario without environmental regulations for China, but it decreases by only 0.007% with environmental regulations. Therefore, all countries, especially the neighboring countries to China, have a large incentive to actively engage in negotiations about requiring stricter environmental regulations in China. The welfare loss from additional environmental regulations accompanying trade liberalization for China is also not large.

3.5.2 EU Enlargement

The spillover effect of transboundary pollutants is likely to be more problematic in regions where a large number of countries with potentially different incentives for environmental protection are geographically clustered. The European Union (EU) enlargement that occurred in 2004 is an ideal event to study this effect through the lens of our model since the level of economic development between the new EU member countries and the existing EU member countries was sizable and EU countries are geographically close to one another, which made the spillover effect of transboundary pollutants more important. To study the effect of the trade liberalization that accompanied the EU enlargement on welfare and environmental utility, we introduce the actual changes in tariff rates between new and existing EU member countries between 2000 and 2010 as a counterfactual shock to the model. Other model parameters are assumed to be unchanged.

Figure 3.7: Changes in aggregate welfare from the EU enlargement (% change)

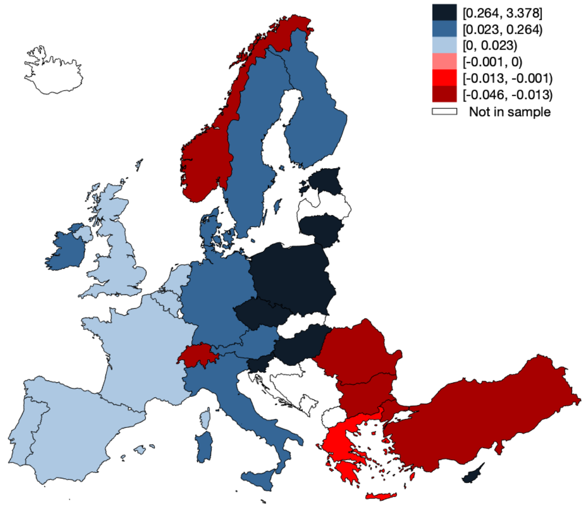
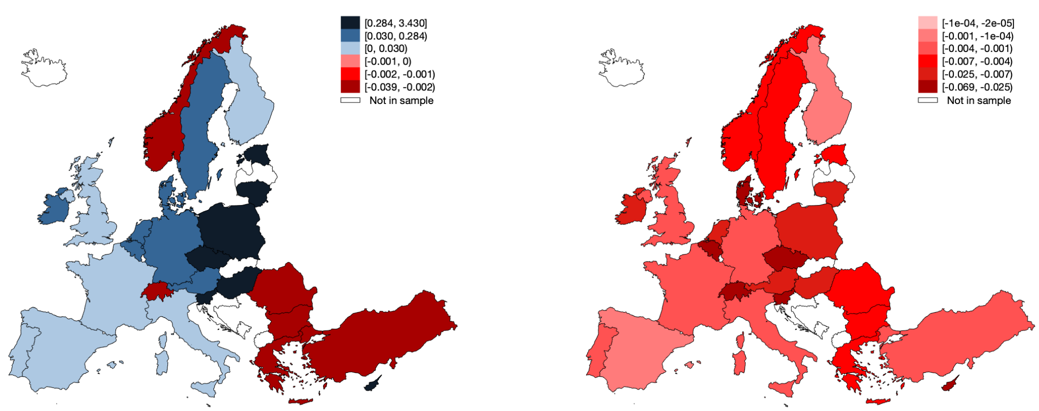


Figure 3.7 shows counterfactual changes in aggregate welfare in European countries in response to the trade liberalization that followed the EU enlargement. We report the results in numbers in column (1) of Table C.13 in the appendix. The most notable pattern is that new EU member countries experience larger welfare gains than existing EU member countries. As shown in columns (2) and (3) of Table C.13, this result is driven by larger increases in real income that the new EU member countries experience as a result of their newly acquired access to the larger European market.

As the next step, we decompose the welfare effect of the EU enlargement into changes in real income and changes in environmental utility. Figure 3.8 show the decomposition results for countries in Europe, and columns (2) and (3) of Table C.13 report the full results in numbers. As discussed previously, the effect of the EU enlargement on real income plays a dominant role in its effect on aggregate welfare. Panel (b) of Figure 3.8 shows that there is significant spatial heterogeneity in counterfactual changes in environmental utility across European countries and that the pattern is consistent with the pollution haven effect as well as the transboundary nature of $PM_{2.5}$. This pattern can be more easily seen with counterfactual changes in emission and concentration levels of $PM_{2.5}$, which are reported in Figure 3.9 for European countries. As the new EU member countries gain better access to the large markets of higher-income European countries, their production level increases. Since these countries have a relatively higher level of emission intensity, $PM_{2.5}$ emissions increase significantly in these countries. On the other hand, some existing EU member countries experience a decrease in emissions, as they produce less in dirtier industries and import from new EU member countries instead. For the other existing EU member countries, having new EU member countries may increase their own production due to cheaper input imports, which increases their own emission level. However, in terms of the magnitude, the increase in emission is much larger for the new EU member countries than for the existing members. An increase in $PM_{2.5}$ emissions from new EU member countries increases the concentration level in most European countries due to the transboundary nature of $PM_{2.5}$. For example, in Greece, the own emissions of $PM_{2.5}$ in fact decrease by 0.14% after the EU enlargement, but the concentration level of $PM_{2.5}$ increases by 0.31% as the emission levels increase a lot in the new EU member countries that are geographically close to Greece.

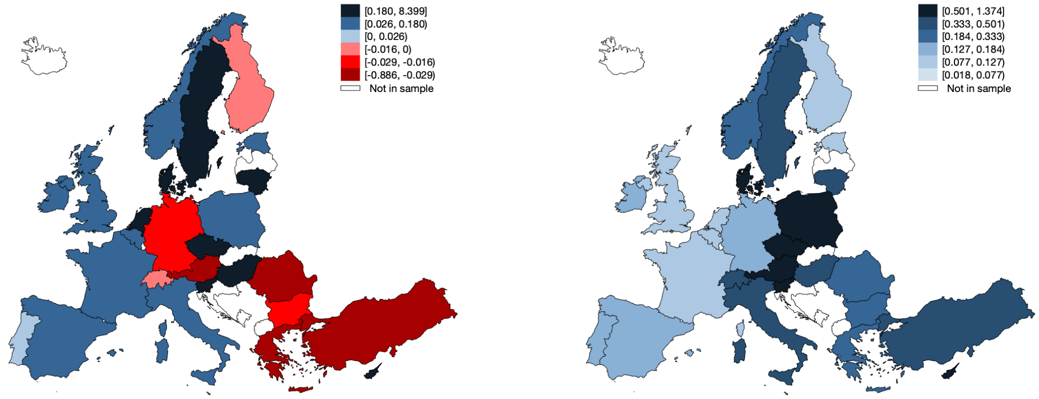
Figure 3.8: Decomposition of the welfare effect from the EU enlargement



(a) Changes in real income (%)

(b) Changes from environmental externality (%)

Figure 3.9: Changes in emission and concentration from the EU enlargement



(a) Changes in emission (%) (b) Changes in concentration (%)

Joining the European Union does not only mean that the new member countries must lower trade barriers but also they have to comply with many other rules including environmental regulations. The environmental implication of the EU enlargement discussed above highlights that the existing EU member countries have an incentive to enforce a higher level of environmental regulations on new member countries, especially regarding the air pollutants of transboundary nature, due to their spillover effects. To quantitatively assess how such environmental regulations may change the welfare effect of the trade liberalization that followed the EU enlargement, we add another shock which increases the environmental tax rates for the new EU member countries by 20% from their baseline levels. In other words, this scenario introduces both lower trade costs and higher environmental tax for the new EU member countries, similarly to the exercise we did for the case of China in the previous subsection.

Table C.14 in the appendix reports the counterfactual results. The results highlight the differential incentives that new and existing EU member countries may have for environmental regulations imposed on the new member countries. Compared to the results from the counterfactual scenario without additional environmental regulations, the welfare gains of the new EU member countries are smaller, and those of the existing member countries are larger. Higher environmental tax rates on the new EU member countries increase the environmental utility for all European countries, but the limited gains in real income for the new member countries partially offset the gains in the environmental utility. With a similar intuition discussed in the case of China, with higher environmental tax rates, the effective production cost increases in the new EU member countries, which limits the expansion of their production in response to the access to the European market. The existing EU member countries benefit from this trade liberalization with new member countries accompanied by stricter environmental regulations because the new member countries need to reduce the emission of transboundary pollutants, which significantly decreases the concentration level of such pollutants in the existing member countries as well.

3.6 Conclusion

This paper develops a general equilibrium model to quantify the welfare implications of international trade policies incorporating the transboundary nature of air pollutants. As air pollutants travel across borders, the environmental consequences of trade are not solely determined by the location of emission-generating activities; the emissions of neighboring countries are also an important factor. To motivate this paper's focus on transboundary transport of air pollution, we run multi-country panel regressions and find that a country's concentration is correlated with its exposure to other countries' emissions – our measure of transboundary transport of pollution – which is suggestive of the importance of taking this additional externality into account to understand the welfare consequences of trade policies. By building a multi-country general equilibrium trade model with environmental externality, we show how trade shocks affect a country's welfare via changes in real income and its own emissions as well as other countries' emissions that may travel to a country.

We quantify the model to examine how such multiple channels come into play and determine welfare gains from trade shocks. The model is calibrated to the year 2000, and the transboundary travel of local pollutants is parametrized by using the estimates from a multi-country panel regression on the determinants of concentration. We run two counterfactual exercises, using the scenarios that show both large-scale economic integration and potential transboundary spillovers: the China shock and the EU 2004 enlargement. In each of the counterfactuals, we examine the welfare impact of a trade shock only and the welfare impact of a combination of trade shock and tighter environmental regulations. The latter is to explore the welfare implications of combining trade and environmental policies.

Both counterfactual results show a few similar patterns. First, liberalizing countries experience an increase in emissions due to an increase in production. Second, among the rest of countries, some experience decreases in emissions as emission-generating production activities relocate to liberalized countries while others experience increases in production and emissions due to increased access to cheaper inputs from liberalized countries. Third, the levels of concentration increase not only in liberalized countries but also in some other countries, the latter of which are due to the increase in own emissions as well as transboundary pollution. Lastly, the change in real income is much larger than the change in environmental utility, thus determining the overall welfare gains, for most countries. These multiple channels shape heterogeneous welfare consequences across countries. With more stringent environmental regulations imposed on China and new EU members, trade shocks bring smaller environmental welfare losses in both these liberalizing countries and neighboring countries via lower levels of emissions and transboundary pollution. In the meantime, the gains in real income are not reduced much. This additional counterfactual result shows the potential effects of incorporating environmental provisions into trade liberalization agreements or, more broadly speaking, combining international trade and environmental policies.

In summary, this paper provides a general, tractable framework to study spatial heterogeneity in the welfare impact of trade shocks. The general framework of our model can be applied to a wide range of pollutants, from strictly local pollutants to global pollutants, such as greenhouse gases, which makes it a useful tool to study the environmental consequences of trade. For example, we can use the model to look at the effects of the Carbon Border Adjustment Mechanism (CBAM), which aims to tackle carbon leakage by putting a price on the carbon content of imports. Although CBAM focuses on carbon, it would affect a wide range of emissions since many types of pollution are highly correlated (Copeland et al., 2022). One could use this model to study the effects of CBAM across multiple pollutants by considering their different emission intensities as well as the degree of transboundary transport.

In addition, this model can be used to study the optimal trade policy or the optimal combination of trade and environmental policies. For example, if there was no transboundary pollution externality, it would be more beneficial to trade with nearby countries than with countries farther apart. But with transboundary pollution into consideration, there can be a different optimal set of trade partner countries. Moreover, the consequences of a trade war could be smaller for some countries because of the environmental improvement from less transboundary pollution. More broadly, this paper provides a basis to understand the global optimal policy for local pollutants, which has not been studied much unlike the one for carbon (Farrokhi and Lashkaripour, 2021), or the linkage between trade and environmental negotiations in the presence of global environmental externalities (Abrego et al., 2001; Limão, 2005; Nordhaus, 2015; Venables, 1999).

Lastly, this model can be extended to incorporate input-output linkages between sectors to study how such linkages amplify the size of environmental externality. If two countries that are geographically close to each other are also linked with tight input-output connections, one's trade policy would affect the other's pollution not only through the channels discussed in this paper but additionally through the amplification effect via sectoral interrelations.

Appendix A: Appendix for Chapter 1

A.1 Additional tables and figures

Table A.1: Supplementary regression result

	(1)	(2)	(3)
β	0.110**	0.105**	0.105**
	(0.050)	(0.051)	(0.052)
Observations	6480	6480	6480
R-squared	0.051	0.053	0.062
Year FE	O	O	O
NAICS-3 FE		O	
NAICS-6 FE			O

Notes: The estimating equation is $\Delta_t \ln(\text{Intermediate/Energy})_j = \beta\Delta_t \ln(\text{Import penetration})_J + \delta_t + \epsilon_{jt}$ where $\Delta_t x = x_t - x_{t-1}$ is the first-difference, j denotes the NAICS 6-digit level, and J denotes the NAICS 3-digit level. The sample includes annual manufacturing observations in the NAICS 6-digit level, covering from 1997 to 2014.

Table A.2: Change in the US NO_x emission intensity (1998-2014)

(1) Emission/Y	(2) (minus) TFP	(3) Energy/$\bar{Y}$	(4) Emission factor	(5) Residual
-0.63	0.04	-0.25	-0.05	-0.37

Notes: The decomposition is based on $\Delta \ln \frac{\text{Emission}}{Y} = -\Delta \ln TFP + \Delta \ln \frac{\text{Energy}}{\bar{Y}} + \Delta \ln(\text{Emission factor}) + \Delta \ln(1 - \text{Abatement})$. The numbers are the change from 1998 to 2014 in log-points. Emission is total emission, Y is real gross output value, TFP total factor productivity, $\bar{Y}$ denotes the change in the real gross output after subtracting the change of TFP (5-factor-based measure), and Energy measures the non-electricity consumption used for fuel purpose. Note that US manufacturing experienced a decline in TFP on average between 1998 and 2014 and, thus, we see a positive value in the second column. The average change is, like others, calculated by using the 1998 value of shipments as weights.
Sources: MECS, NBER-CES, and NEI.

Figure A.1: US manufacturing non-electricity consumption per real gross output

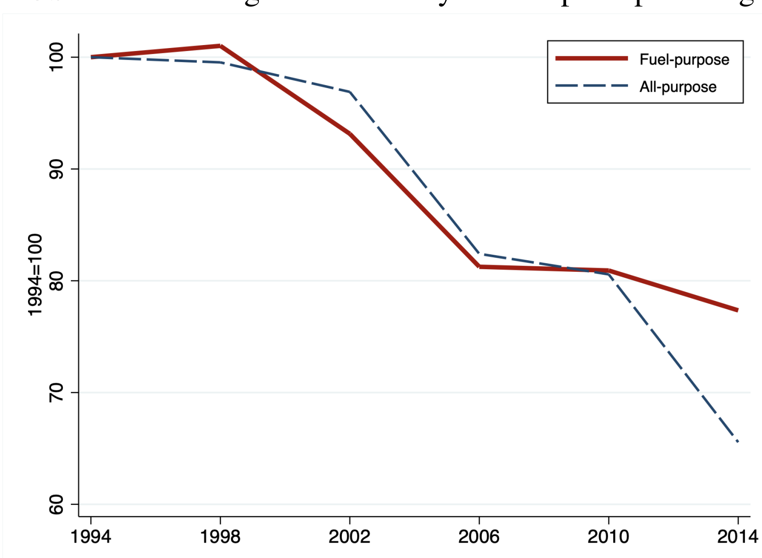
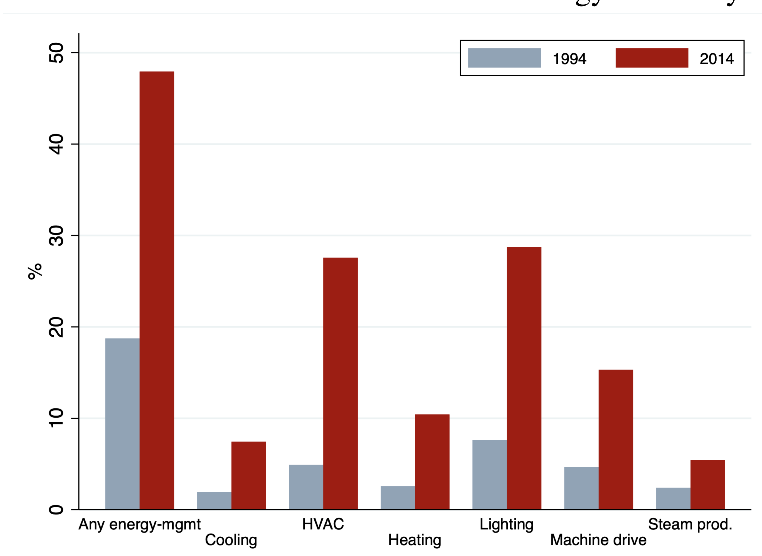


Table A.3: Industry list for Figure 1.3

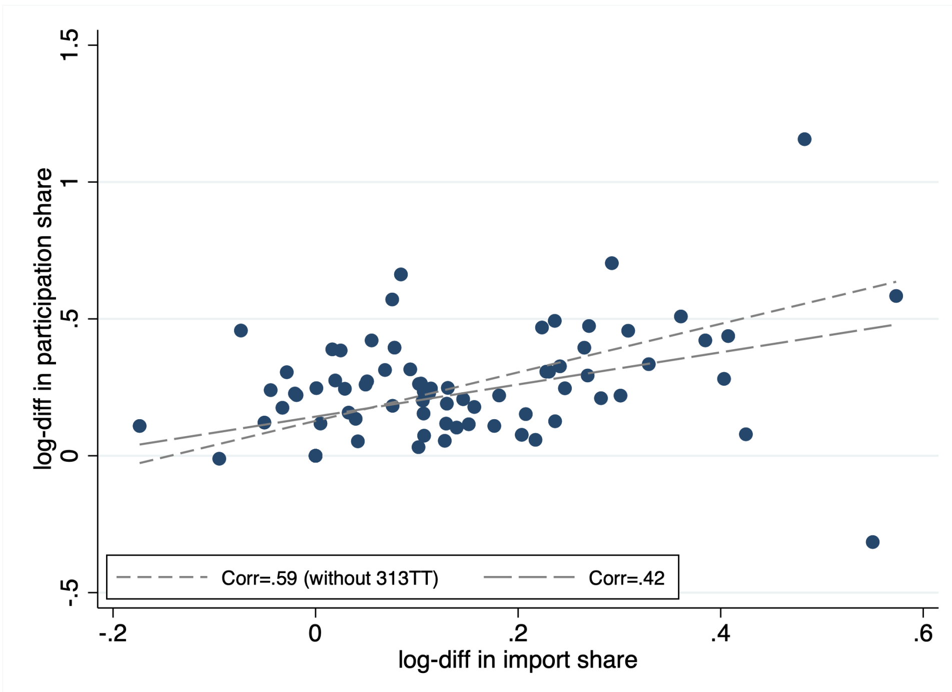
311FT	Food and beverage and tobacco products
313TT	Textile mills and textile product mills
315AL	Apparel and leather and allied products
321	Wood products
322	Paper products
323	Printing and related support activities
324	Petroleum and coal products
325	Chemical products
326	Plastics and rubber products
327	Nonmetallic mineral products
331	Primary metals
332	Fabricated metal products
333	Machinery
334	Computer and electronic products
335	Electrical equipment, appliances, and components
336	Transportation equipment
337	Furniture and related products
339	Miscellaneous manufacturing

Figure A.2: Share of establishments that installed energy-efficiency equipment



Note: The bars present the ratio of the establishments that installed or retrofitted equipment for the primary purpose of improving energy efficiency among the total number of establishments participating the MECS survey. *Source*: Author's calculation from using the MECS.

Figure A.3: Change between 1998 and 2014



Note: The vertical axis represents the log-difference of the share of establishments that installed energy-management equipment. The horizontal axis represents the log-difference of the share of expenditures on foreign inputs in the total input expenditures. *Source*: Author's calculation from using the MECS, BEA Supply-Use Tables, and BEA Import Matrix.

A.2 Proofs and derivations

A.2.1 Proof of Proposition 1: (g, a) decision cases and order

In this section, I lay out the conditions that determine how firms' (g, a) decision looks like in the economy, which I call as 'case'. I first show that any economy should have only one from $(g, a) = (1, 0)$ and $(0, 1)$ but not both. I prove this by showing that if there exists a productivity that a firm finds it indifferent between $(0, 0)$and $(1, 0)$ then all firms with higher productivity than that point will prefer $g = 1$ to $g = 0$. In other words, if there exists a firm that chooses $(1, 0)$ then there is no firm choosing $(0, 1)$ in this environment. Assume that φ_g is the level of productivity over which firms find it more profitable to operate with $(g, a) = (1, 0)$ than with $(g, a) = (0, 0)$. Then with $\varphi' > \varphi_g$,

$$
\begin{aligned}
&\pi(\varphi_g; 1, 0) = \pi(\varphi_g; 0, 0) \\
\Leftrightarrow &\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi_g^{\sigma-1} s_g - f_g w = \sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi_g^{\sigma-1} \\
\Leftrightarrow &\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi_g^{\sigma-1}(s_g - 1) = f_g w \\
\Leftrightarrow &\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi'^{\sigma-1}(s_g - 1) > f_g w \\
\Leftrightarrow &\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi'^{\sigma-1} s_g - f_g w > \sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} \varphi'^{\sigma-1} \\
\Leftrightarrow &\pi(\varphi'; 1, 0) > \pi(\varphi'; 0, 0)
\end{aligned}
$$

Thus $\pi(\varphi'; 1, 0) > \pi(\varphi'; 0, 0)$ for all $\varphi' > \varphi_g$. Analogously, if φ_a is the productivity level over that all firms with higher productivity choose $(1, 0)$ over $(0, 0)$. Then $\pi(\varphi''; 0, 1) > \pi(\varphi''; 0, 0)$ for all $\varphi'' > \varphi_a$.

Next, define the zero-profit cutoff for each of (g, a) choices.

$$\varphi^*_{(0,0)} = \left[\frac{f_o w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma}}\right]^{\frac{1}{\sigma-1}}$$
$$\varphi^*_{(1,0)} = \left[\frac{(f_o + f_g) w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} s_g}\right]^{\frac{1}{\sigma-1}}$$
$$\varphi^*_{(0,1)} = \left[\frac{(f_o + f_a) w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} s_a}\right]^{\frac{1}{\sigma-1}}$$
$$\varphi^*_{(1,1)} = \left[\frac{(f_o + f_g + f_a) w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} s_g s_a}\right]^{\frac{1}{\sigma-1}}$$

The above productivity cutoffs are the level at which the firm with each (g, a) choice makes zero profit. As the total profit increases with productivity, φ, the firms with higher productivity make positive profits at respective (g, a) choice.

If $\varphi^*_{(1,1)}$ is the smallest among the four zero-profit cutoffs, it means that the productivity cutoff at which firms would choose to operate with $(1, 1)$ is lower than those of other (g, a) choices. Then it should be that any operating firms (in other words, making non-negative profits) choose $(g, a) = (1, 1)$ over other (g, a) choices. If $\varphi^*_{(1,1)}$ is smaller than the minimum productivity b from the given Pareto distribution, it means that all firms choose to operate after their productivity draw and optimally choose $(1, 1)$ for sourcing and technology adoption. Thus, if $\varphi^*_{(1,1)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$, then the operating productivity cutoff is $\min(\varphi^*_{(1,1)}, b)$ and all operating firms choose $(g, a) = (1, 1)$. Let me call this *case E*.

Now, define these additional cutoffs. φ_g is the productivity cutoff at which the firm becomes indifferent between $(g, a) = (0, 0)$ and $(1, 0)$. Similarly, φ_a is the productivity cutoff at which the firm becomes indifferent between $(g, a) = (0, 0)$ and $(0, 1)$. φ_{ga} is the productivity cutoff at which the firm becomes indifferent between $(g, a) = (1, 0)$ and $(1, 1)$. Lastly, φ_{ag} is the productivity cutoff at which the firm becomes indifferent between $(g, a) = (0, 1)$ and $(1, 1)$. In essence, these are the values that would be productivity level at which firms start making different (g, a) decision. Note that I do not make restriction on whether the firm's profit should be positive when it make any of these changes.

$$\varphi_g = \left[\frac{f_g w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} (s_g - 1)}\right]^{\frac{1}{\sigma-1}}$$
$$\varphi_a = \left[\frac{f_a w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} (s_a - 1)}\right]^{\frac{1}{\sigma-1}}$$
$$\varphi_{ga} = \left[\frac{f_a w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} s_g(s_a - 1)}\right]^{\frac{1}{\sigma-1}} > \varphi_g$$
$$\varphi_{ag} = \left[\frac{f_g w}{\sum_i X_i \tilde{\sigma} \left(c/\tau_i^x\right)^{1-\sigma} s_a(s_g - 1)}\right]^{\frac{1}{\sigma-1}} > \varphi_a$$

Consider the case when $\varphi^*_{(0,0)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$. If $b < \varphi^*_{(0,0)}$, the marginally operating firms (with the lowest productivity among the operating firms) will choose $(g, a) = (0, 0)$. Whether $(0, 0)$ switches to $(1, 0)$ or $(0, 1)$ depends on the size of φ_g and φ_a.[1] If $\varphi_g < \varphi_a$, then there comes a cutoff at which the optimal (g, a) switches from $(0, 0)$ to $(1, 0)$ at the lower productivity level. So the relevant cutoffs will be φ_g and φ_{ga}, respectively at which the (g, a) changes $(0, 0) \to (1, 0)$ and $(1, 0) \to (1, 1)$. Recall that there is no firm that chooses $(0, 1)$ in this case, as shown in the beginning of this section. Similarly, if $\varphi_a < \varphi_g$, then (g, a) is composed of $(0, 0) \to (0, 1) \to (1, 1)$. Lastly, again, I need to check where the minimum productivity level from the Pareto draw locates at compared to these cutoffs. For example,

[1]Note that since $\varphi^*_{(0,0)} < \varphi^*_{(1,0)}$ it follows that $f_o < \frac{f_g}{s_g - 1}$ and, thus, $\varphi^*_{(0,0)} < \varphi_g$. Similarly, $\varphi^*_{(0,0)} < \varphi_a$. So marginal firms will always choose $(0, 0)$.

if $\varphi_{ga} < b$, then all operating firms ($\varphi \geq b$) have $(g,a) = (1,1)$. In summary, if $\varphi^*_{(0,0)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$ and $\varphi_g < \varphi_a$ the (g,a) distribution is

$$\begin{cases} \textit{case A} \text{ with operating cutoff at } \varphi^*_{(0,0)} & \text{if } b < \varphi^*_{(0,0)} < \varphi_g < \varphi_{ga} \\ \textit{case A} \text{ with operating cutoff at } b & \text{if } \varphi^*_{(0,0)} \leq b < \varphi_g < \varphi_{ga} \\ \textit{case C} \text{ with operating cutoff at } b & \text{if } \varphi^*_{(0,0)} < \varphi_g \leq b < \varphi_{ga} \\ \textit{case E} \text{ with operating cutoff at } b & \text{if } \varphi^*_{(0,0)} < \varphi_g < \varphi_{ga} \leq b \end{cases}$$

After repeating the similar procedure for other possibilities, I can compile the conditions for (g,a) distribution cases in terms of the size of zero-profit cutoffs, $\varphi^*$and decision i cutoffs, φ_i, as well as the Pareto minimum productivity, b. The full list of conditions is as follows.

- If $\varphi^*_{(0,0)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$, or equivalently if $f_o = \min(f_o, \frac{f_o+f_g}{s_g}, \frac{f_o+f_a}{s_a}, \frac{f_o+f_g+f_a}{s_g s_a})$,
  - If $\varphi_g < \varphi_a$ or equivalently if $\frac{f_g}{s_g-1} < \frac{f_a}{s_a-1}$,

$$\begin{cases} \textit{case A} \text{ with operating cutoff at } \max(b, \varphi^*_{(0,0)}) & \text{if } b < \varphi_g < \varphi_{ga} \\ \textit{case C} \text{ with operating cutoff at } b & \text{if } \varphi_g \leq b < \varphi_{ga} \\ \textit{case E} \text{ with opearting cutoff at } b & \text{if } \varphi_g < \varphi_{ga} \leq b \end{cases}$$

  - If $\varphi_a \geq \varphi_g$ or equivalently if $\frac{f_g}{s_g-1} \geq \frac{f_a}{s_a-1}$,

$$\begin{cases} \textit{case B} \text{ with operating cutoff at } \max(b, \varphi^*_{(0,0)}) & \text{if } b < \varphi_a < \varphi_{ag} \\ \textit{case D} \text{ with operating cutoff at } b & \text{if } \varphi_a \leq b < \varphi_{ag} \\ \textit{case E} \text{ with opearting cutoff at } b & \text{if } \varphi_a < \varphi_{ag} \leq b \end{cases}$$

- If $\varphi^*_{(1,0)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$, or equivalently if $\frac{f_o+f_g}{s_g} = \min(f_o, \frac{f_o+f_g}{s_g}, \frac{f_o+f_a}{s_a}, \frac{f_o+f_g+f_a}{s_g s_a})$,

$$\begin{cases} \textit{case C} \text{ with operating cutoff at } \max(b, \varphi^*_{(1,0)}) & \text{if } b < \varphi_{ga} \\ \textit{case E} \text{ with operating cutoff at } b & \text{if } \varphi_{ga} \leq b \end{cases}$$

- If $\varphi^*_{(0,1)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$, or equivalently

  if $\frac{f_o+f_a}{s_a} = \min(f_o, \frac{f_o+f_g}{s_g}, \frac{f_o+f_a}{s_a}, \frac{f_o+f_g+f_a}{s_g s_a})$,

$$\begin{cases} \textit{case D} \text{ with operating cutoff at } \max(b, \varphi^*_{(0,1)}) & \text{if } b < \varphi_{ag} \\ \textit{case E} \text{ with operating cutoff at } b & \text{if } \varphi_{ag} \leq b \end{cases}$$

- If $\varphi^*_{(1,1)} = \min(\varphi^*_{(0,0)}, \varphi^*_{(1,0)}, \varphi^*_{(0,1)}, \varphi^*_{(1,1)})$, or equivalently

  if $\frac{f_o+f_g+f_a}{s_g s_a} = \min(f_o, \frac{f_o+f_g}{s_g}, \frac{f_o+f_a}{s_a}, \frac{f_o+f_g+f_a}{s_g s_a})$,

  - *case E* with operating cutoff at $\max(b, \varphi^*_{(1,1)})$

Case A and *C* constitute the case 1 in Proposition 1, *case B* and *D* constitute the case 2 in Proposition 1, and *case E* is included in both cases – that is, when $\varphi_o = \varphi_g = \varphi_a$.

A.2.2 Output share

Quantity share of firms with productivity φ when there are multiple markets denoted by d is as follows.

$$\omega_q(\varphi) = \frac{\left(\sum_d q(\varphi)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_d Q_d^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}$$

In each market d, the share of firms with φ is

$$\frac{q_d(\varphi)}{Q_d} = \left(\frac{M p_d(\varphi)}{P_d}\right)^{-\sigma}$$

so $q_d(\varphi)$ can be written as

$$q_d(\varphi) = \left(\frac{Mp_d(\varphi)}{P_d}\right)^{-\sigma} Q_d$$

Putting this into the numerator and using that the price of serving market d is same as the price of serving domestic market multiplied by exporting cost – i.e. $p_d(\varphi) = p(\varphi)\tau_d$ – the numerator becomes

$$\begin{aligned}
\left(\sum_d q(\varphi)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} &= \left[\sum_d M^{1-\sigma} p_d(\varphi)^{1-\sigma} P_d^{\sigma-1} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= M^{-\sigma} p(\varphi)^{-\sigma} \left[\sum_d \tau_d^{1-\sigma} P_d^{\sigma-1} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= M^{-\sigma} p(\varphi)^{-\sigma} \left[\sum_d \tau_d^{1-\sigma} \left\{M \int_\varphi p_d(\varphi)^{1-\sigma} dG(\varphi)\right\}^{-1} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= M^{-\sigma} p(\varphi)^{-\sigma} \left[\sum_d \tau_d^{1-\sigma} \left\{M \int_\varphi (\tau_d p(\varphi))^{1-\sigma} dG(\varphi)\right\}^{-1} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= M^{-\sigma} p(\varphi)^{-\sigma} \left[\sum_d \left\{M \int_\varphi p(\varphi)^{1-\sigma} dG(\varphi)\right\} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= M^{-\sigma} p(\varphi)^{-\sigma} \left[\sum_d P^{\sigma-1} Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= \left(\frac{Mp(\varphi)}{P}\right)^{-\sigma} \left[\sum_d Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

Thus, the multi-market weight becomes

$$\omega_q(\varphi) = \frac{\left(\sum_d q(\varphi)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_d Q_d^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}} = \frac{\left(\frac{Mp(\varphi)}{P}\right)^{-\sigma} \left[\sum_d Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_d Q_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}} = \left(\frac{Mp(\varphi)}{P}\right)^{-\sigma}$$

A.2.3 Derivation of CES price index

Start with the case 1, in which $\varphi_o \leq \varphi_g \leq \varphi_a$.

$$
\begin{aligned}
P =& \left[M \int_{\varphi} p(\varphi)^{1-\sigma} dG(\varphi)\right]^{\frac{1}{1-\sigma}} \\
=& \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} \times \left[\int_{\varphi} \varphi^{\sigma-1} B(\varphi)^{\eta_e(1-\sigma)} P(\varphi)^{\eta_m(1-\sigma)} dG(\varphi)\right]^{\frac{1}{1-\sigma}} \\
=& \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} \times \\
& \left[\int_{\varphi_o}^{\varphi_g} \varphi^{\sigma-1} P^{\eta_m(1-\sigma)} dG_o(\varphi) + \int_{\varphi_g}^{\varphi_a} \varphi^{\sigma-1} (P^G)^{\eta_m(1-\sigma)} dG_o(\varphi) + \int_{\varphi_a}^{\infty} \varphi^{\sigma-1} \beta^{-\eta_e(1-\sigma)} (P^G)^{\eta_m(1-\sigma)} dG_o(\varphi))\right]^{\frac{1}{1-\sigma}} \\
=& \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} P^{\eta_m} \times \\
& \left[\int_{\varphi_o}^{\varphi_g} \varphi^{\sigma-1} dG_o(\varphi) + \int_{\varphi_g}^{\varphi_a} \varphi^{\sigma-1} \left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)} dG_o(\varphi) + \int_{\varphi_a}^{\infty} \varphi^{\sigma-1} \beta^{-\eta_e(1-\sigma)} \left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)} dG_o(\varphi)\right]^{\frac{1}{1-\sigma}} \\
=& \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} P^{\eta_m} \times \left(\frac{\theta}{\theta-\sigma+1}\right)^{\frac{1}{1-\sigma}} \varphi_o^{-1} \times \\
& \left[1 + \left\{\left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)} - 1\right\} \left(\frac{\varphi_g}{\varphi_o}\right)^{\sigma-\theta-1} + \left(\frac{P^G}{P}\right)^{\eta_m(1-\sigma)} \left\{\beta^{-\eta_e(1-\sigma)} - 1\right\} \left(\frac{\varphi_a}{\varphi_o}\right)^{\sigma-\theta-1}\right]^{\frac{1}{1-\sigma}} \\
=& \frac{\sigma}{\sigma-1} M^{\frac{1}{1-\sigma}} w^{\eta_l} r^{\eta_e} (1+t\epsilon)^{\eta_e} P^{\eta_m} \times \left(\frac{\theta}{\theta-\sigma+1}\right)^{\frac{1}{1-\sigma}} \varphi_o^{-1} \times \left[1 + \left(\frac{\varphi_g}{\varphi_o}\right)^{-\theta} \frac{f_g}{f_o} + \left(\frac{\varphi_a}{\varphi_o}\right)^{-\theta} \frac{f_a}{f_o}\right]^{\frac{1}{1-\sigma}}
\end{aligned}
$$

I use the Pareto distribution assumption to move from the 4th to the 5th expression, and I use the expression of global sourcing and adoption cutoff for the case 1 to obtain the last expression from the 5th one. The expression for the price index in case 2 is obtained from taking the analogous steps. It results in the same expression.

A.2.4 Proof of the effect on operation cutoff (i.e. selection effect)

Recall the free entry condition.

$$f_e w = \int_{\varphi_o}^{\infty} \pi(\varphi; g(\varphi), a(\varphi))\, dG(\varphi)$$

For case 1, the right hand side can be expanded as

$$\begin{aligned}\int_{\varphi_o}^{\infty} \pi(\varphi; g(\varphi), a(\varphi))\, dG(\varphi) = & \int_{\varphi_o}^{\infty} \pi(\varphi; 0, 0)\, dG(\varphi) + \int_{\varphi_g}^{\infty} \pi(\varphi; 1, 0) - \pi(\varphi; 0, 0)\, dG(\varphi) \\ & + \int_{\varphi_a}^{\infty} \pi(\varphi; 1, 1) - \pi(\varphi; 1, 0)\, dG(\varphi)\end{aligned}$$

which is written as the sum of incremental profits for the productivity above each cutoffs. To re-write each of the terms above,

$$\begin{aligned}\int_{\varphi_o}^{\infty} \pi(\varphi; 0, 0)\, dG(\varphi) &= \int_{\varphi_o}^{\infty} \tilde{\pi}(\varphi; 0, 0) - f_o w\, dG(\varphi) \\ &= f_o w \int_{\varphi_o}^{\infty} \frac{\tilde{\pi}(\varphi; 0, 0)}{\tilde{\pi}(\varphi_o; 0, 0)} - 1\, dG(\varphi) \\ &= f_o w \int_{\varphi_o}^{\infty} \left(\frac{\varphi}{\varphi_o}\right)^{\sigma-1} - 1\, dG(\varphi)\end{aligned}$$

The second equality uses the zero profit condition, given by $\tilde{\pi}(\varphi_o;0,0) = f_o w$. Similarly,

$$\begin{aligned}
\int_{\varphi_g}^{\infty} \pi(\varphi;1,0) - \pi(\varphi;0,0)\, dG(\varphi) &= \int_{\varphi_g}^{\infty} \tilde{\pi}(\varphi;1,0) - \tilde{\pi}(\varphi;0,0) - f_g w\, dG(\varphi) \\
&= f_g w \int_{\varphi_g}^{\infty} \frac{\tilde{\pi}(\varphi;1,0) - \tilde{\pi}(\varphi;0,0)}{\tilde{\pi}(\varphi_g;1,0) - \tilde{\pi}(\varphi_g;0,0)} - 1\, dG(\varphi) \\
&= f_g w \int_{\varphi_g}^{\infty} \frac{(s_g - 1)\tilde{\pi}(\varphi;0,0)}{(s_g - 1)\tilde{\pi}(\varphi_g;0,0)} - 1\, dG(\varphi) \\
&= f_g w \int_{\varphi_g}^{\infty} \left(\frac{\varphi}{\varphi_g}\right)^{\sigma-1} - 1\, dG(\varphi) \\
\int_{\varphi_a}^{\infty} \pi(\varphi;1,1) - \pi(\varphi;1,0)\, dG(\varphi) &= \int_{\varphi_a}^{\infty} \tilde{\pi}(\varphi;1,1) - \tilde{\pi}(\varphi;1,0) - f_a w\, dG(\varphi) \\
&= f_a w \int_{\varphi_a}^{\infty} \frac{\tilde{\pi}(\varphi;1,1) - \tilde{\pi}(\varphi;1,0)}{\tilde{\pi}(\varphi_a;1,1) - \tilde{\pi}(\varphi_a;1,0)} - 1\, dG(\varphi) \\
&= f_a w \int_{\varphi_a}^{\infty} \frac{(s_a - 1)\tilde{\pi}(\varphi;1,0)}{(s_a - 1)\tilde{\pi}(\varphi_a;1,0)} - 1\, dG(\varphi) \\
&= f_a w \int_{\varphi_a}^{\infty} \left(\frac{\varphi}{\varphi_a}\right)^{\sigma-1} - 1\, dG(\varphi)
\end{aligned}$$

Combining the above equations (for the RHS of FE) and dividing both sides by w produces a *modified FE condition* as below.

$$f_e = \sum_{k=o,g,a} f_k \int_{\varphi_k}^{\infty} \left(\frac{\varphi}{\varphi_k}\right)^{\sigma-1} - 1\, dG(\varphi)$$

The modified FE can be re-expressed as below after using the Pareto distribution assumption.

$$f_e = \frac{\sigma - 1}{\theta - \sigma + 1} \times \left\{ f_o \left(\frac{b}{\varphi_o}\right)^{\theta} + f_g \left(\frac{b}{\varphi_g}\right)^{\theta} + f_a \left(\frac{b}{\varphi_a}\right)^{\theta} \right\}$$

Using the expression of $\frac{\varphi_g}{\varphi_o} = \left(\frac{f_g/f_o}{s_g-1}\right)^{1/(\sigma-1)}$ and $\frac{\varphi_a}{\varphi_o} = \left(\frac{f_a/f_o}{s_g(s_a-1)}\right)^{1/(\sigma-1)}$ and rearranging the above equation, I can express the operationg cutoff as

$$\varphi_o = \left[\frac{\sigma-1}{\theta-\sigma+1} \times \frac{b^\theta}{f_e} \times \left\{ f_o + f_g \left(\frac{f_g}{f_o}\right)^{\frac{\theta}{1-\sigma}} (s_g-1)^{\frac{\theta}{\sigma-1}} + f_a \left(\frac{f_a}{f_o}\right)^{\frac{\theta}{1-\sigma}} (s_g(s_a-1))^{\frac{\theta}{\sigma-1}} \right\}^{\frac{1}{1-\sigma}}\right]^{1/\theta}$$

Note that s_g is the only term that τ affects. Before deriving $\frac{\partial \ln \varphi_o}{\partial \ln \tau}$, let me make some definitions that will be used throughout the derivations to come: μ is the foreign input share in global bundle (i.e. trade share of f in h bundle), and Λ is an auxiliary term which constitutes the aggregate productivity along with the operation cutoff, φ_o.

$$\begin{aligned}
\mu &= \frac{\tau^{1-\sigma} P^{*1-\sigma}}{P^{1-\sigma} + \tau^{1-\sigma} P^{*1-\sigma}} \\
\Lambda_h &= 1 + (s_g-1)\Big(\frac{\varphi_g}{\varphi_o}\Big)^{\sigma-\theta-1} + s_g(s_a-1)\Big(\frac{\varphi_a}{\varphi_o}\Big)^{\sigma-\theta-1} \\
&= 1 + \left(\frac{f_g}{f_o}\right)^{\frac{\sigma-\theta-1}{\sigma-1}} (s_g-1)^{\frac{\theta}{\sigma-1}} + \left(\frac{f_a}{f_o}\right)^{\frac{\sigma-\theta-1}{\sigma-1}} (s_g(s_a-1))^{\frac{\theta}{\sigma-1}} \qquad \text{(A.1)}
\end{aligned}$$

I will use $\frac{\partial \ln s_g}{\partial \ln \tau} = \eta_m(1-\sigma)\mu$ repeatedly throughout the following derivations. The rearranged expression of φ_o and the partial effect of τ on φ_o are as follow.

$$\varphi_o = \left[\frac{\sigma-1}{\theta-\sigma+1} \times \frac{b^\theta}{f_e} \times f_o \times \Lambda\right]^{1/\theta} \qquad \text{(A.2)}$$

$$
\begin{aligned}
\frac{\partial \ln \varphi_o}{\partial \ln \tau} &= \frac{1}{\theta}\frac{s_g}{\Lambda}\frac{\partial \Lambda}{\partial s_g}\frac{\partial \ln s_g}{\partial \ln \tau} \\
&= \frac{1}{\theta}\frac{s_g}{\Lambda}\eta_m(1-\sigma)\mu \times \frac{\partial \Lambda}{\partial s_g} \\
&= \frac{1}{\theta}\frac{s_g}{\Lambda}\eta_m(1-\sigma)\mu \times \frac{\theta}{\sigma-1}\left\{\left(\frac{f_g}{f_o}\right)^{\frac{\sigma-\theta-1}{\sigma-1}}(s_g-1)^{\frac{\theta-\sigma+1}{\sigma-1}} + \left(\frac{f_a}{f_o}\right)^{\frac{\sigma-\theta-1}{\sigma-1}}(s_g(s_a-1))^{\frac{\theta-\sigma+1}{\sigma-1}}\right\} \\
&< 0
\end{aligned}
$$

A.2.5 Proof of the partial elasticity of aggregate emission intensity

I illustrate the proof using the case of when $\varphi_o \leq \varphi_g \leq \varphi_a$. The proof for the other case is analogous. First, holding the aggregate prices, the potential entrepreneur mass, and the market access term fixed, I get the expression below from $\ln Z_Q$ that changes with τ.

$$
\begin{aligned}
&\ln\left[\varphi_o^{\frac{\theta-\sigma+1}{\sigma-1}} \times \left[1+\left\{\left(\frac{P_g}{P}\right)^{\eta_m(1-\sigma)}-1\right\}\left(\frac{\varphi_g}{\varphi_o}\right)^{\sigma-\theta-1}+\left\{\beta^{-\eta_e(1-\sigma)}-1\right\}\left(\frac{\varphi_a}{\varphi_o}\right)^{\sigma-\theta-1}\right]^{\frac{1}{1-\sigma}}\right] \\
&= -\frac{1}{\theta}\frac{\theta-\sigma+1}{\sigma-1}\ln\left(\frac{\sigma-1}{\theta-\sigma+1}\frac{b^\theta f_o}{f_e}\right) - \frac{\theta+\sigma-1}{\theta(\sigma-1)}\ln\Lambda
\end{aligned}
$$

Simple algebra gives

$$
\begin{aligned}
\frac{\partial \ln \Lambda}{\partial \ln s_g} &= \frac{\theta}{\sigma-1}\tilde{\lambda}_g > 0 \\
\frac{\partial \ln s_g}{\partial \ln \tau} &= \eta_m(1-\sigma)\tilde{\mu} < 0 \\
\frac{\partial \ln s_g}{\partial \ln P} &= \eta_m(\sigma-1)\tilde{\mu} > 0 \\
\frac{\partial \ln s_g}{\partial \ln P^*} &= \eta_m(1-\sigma)\tilde{\mu} < 0
\end{aligned}
$$

Since $\frac{\partial \ln Z_Q}{\partial \ln \tau} = \frac{1}{1-\sigma}\frac{\partial \ln \Lambda}{\partial \ln \tau}$, $\frac{\partial \ln Z_Q}{\partial \ln \tau} > 0$. Note that I hold the aggregate prices of the two countries (P and P^*) but not the global bundle price (P^G), for P^G changes with τ.

A.3 Model assumptions on policy instruments

Policy instruments for regulating air pollution can be broadly categorized into three types: command and control, emission tax (or subsidies on abatement, equivalently), and tradable permits (Phaneuf and Requate 2017). Command and control requires specific standards, either in technology or performance (e.g. emission per output or total emission). For example, US EPA's New Source Review (NSR) requires new plants or modifications located in nonattainment areas to install the lowest achievable emission rate. Emission tax is a price-based instrument, which levies tax on air pollution emitted. Examples include the emission tax on SO_2 and NO_x in Sweden and France. Under tradable permits, firms trade emission allowances which they are either given for free or through auction. This is a quantity-based regulation. The examples include US' Acid Rain Program, NO_x Budget Trading Program, and EU Emissions Trading System.

To be accurate, my model does not take any of the above three types. In the model, I assume emission is regulated through taxing energy on its emission content, so it is actually closer to to how many countries put price on carbon. For example, France levies tax on energy products based on the content of CO_2 on fossil fuel. In addition, I assume that tax is levied as ad-valorem, which simplifies the model analysis but does not affect the overall implications. As Equation A.3 shows, firms face the tax-inclusive cost of energy, $\tilde{e}$, for using fuel that has emission content of ϵ.

$$\tilde{e} = e(1 + t\epsilon) \tag{A.3}$$

Since the model assumes that using energy is the only source of emission, energy and emission are linked one-to-one (in the ratio of $1 : \epsilon$). Thus the tax in my model essentially can be interpreted as emission tax with the effective tax rate at et.

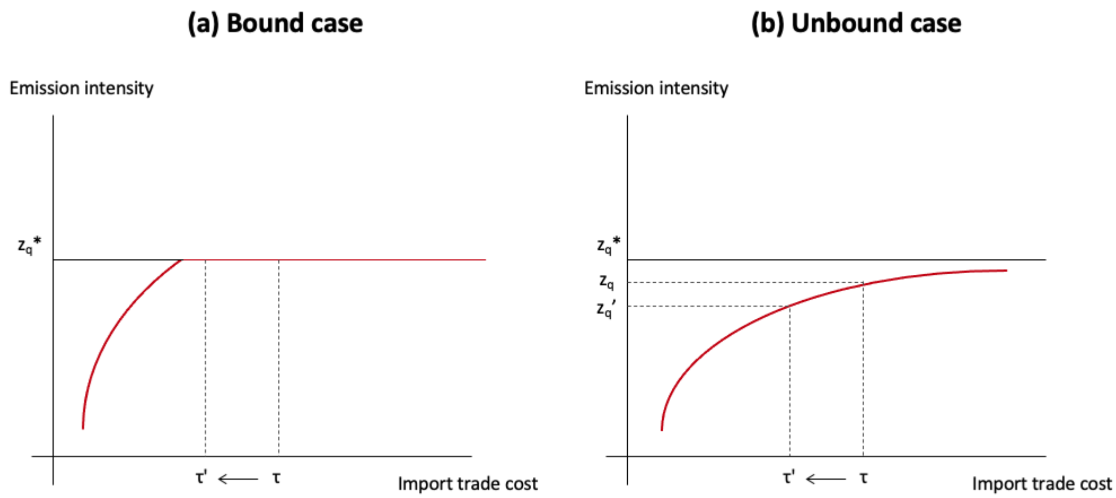
Model implications

The model mechanisms remain the same with different regulation types, as the mechanisms themselves do not depend on how emission is regulated or even whether it is regulated at all. Intermediate import cost affects emission intensity by changing energy intensity, and energy intensity changes from 1) the relative cost of energy to other inputs and 2) the adoption of technology. Lower import cost directly affects the first channel by lower intermediate input bundle price, regardless of whether emission or energy is regulated or not. Lower import cost indirectly affects the second channel by inducing firms to adopt energy-saving technology. The adoption of this technology reduces firms' overall production cost even in the absence of any environmental regulation.

Still there are some differences in result details. For example, if firms are required to produce with emission intensity (i.e. emission per output) less than or equal to some specific value, this will cause some firms to hit the bound and remain at the same emission intensity during some range of import cost changes. Figure A.4 illustrates the emission intensity of bounded and unbounded case, respectively. For example, the left can be the firm that did not install the technology, and the right can be the firm that adopted technology thus has lower emission intensity overall. Assume both firms are globally sourcing so that we can see the direct effect of intermediate import cost changes on their emission intensity.

Overall, lower import cost decreases the emission intensity as well since firm-level energy

Figure A.4: Firm emission intensity with command-and-control on emission intensity



intensity decreases with lower intermediate bundle cost. But for the firm whose emission intensity is constrained, the emission intensity remains at the upper bound level until it starts to be lower than the bound. So with command-and-control on specific emission intensity level, the effect of intermediate import liberalization can be smaller for some firms, thereby reducing the magnitude of the effect. But the overall mechanism and direction of the effect remain the same.

Another difference can be found in the presence and magnitude of government revenue. For example, the freely distributed allowance program does not generate government revenue as emission tax does. The absence (versus presence) of government revenue and how it is distributed (to either consumers or firms) would have welfare implications.

Lastly, it is worth noting the impact of intermediate trade cost changes on the price of emission permits. Lower emission intensity caused by lower intermediate import cost would weaken the demand of emission permit and decrease its price. So one may concern if the price of emission permit decreases largely enough that the improvement in emission intensity is reversed back. This depends on the responsiveness and volatility of permit market, which is affected by many other factors beyond the scope of this model. But one note that is relevant is that in my model the price of energy experiences a similar decline as the relative demand for energy declines. But this drop in energy cost was not large enough to bring reversal in the improvement of emission intensity.

Appendix B: Appendix for Chapter 2

B.1 Additional tables and figures

Table B.1: Summary statistics

	Obs	Mean	SD	Min	Max
Emission intensity	3373	-3.953	2.213	-13.066	3.094
Producer price	3373	-0.191	0.288	-1.309	3.750
Energy price	3373	-0.329	0.492	-2.112	0.506
Regulation (nonattainment)	3373	0.095	0.062	0.000	0.454
Emission factor	3373	-2.164	0.124	-2.358	-1.873
Market access cost	3373	0.007	0.005	0.000	0.053
Instrumental variables					
Import price of intermediates	3373	-0.346	0.267	-1.793	0.135
Domestic price of intermediates	3373	-0.178	0.320	-1.309	2.364
Wage	3373	-0.265	0.186	-1.023	0.258
Number of establishments	3373	6.087	1.164	1.609	10.420
Energy price (2-year lagged)	3373	-0.499	0.493	-2.159	0.359
Other statistics					
Export cost	3373	0.051	0.050	0.000	0.689
Export intensity	3373	0.165	0.100	0.042	0.462

Notes: All variables are in a natural log except for regulation. I also include the summary statistics for the (log of) export cost and export intensity, which constitute the market access cost.

Table B.2: First stage results

	(1)	(2)	(3)
Panel A. First stage on producer price			
Import price of int.	0.537***	0.239***	0.227***
	(0.031)	(0.031)	(0.031)
Domestic price of int.		0.404***	0.410***
		(0.044)	(0.043)
Energy price (t-2)	-0.028**	-0.074***	-0.077***
	(0.013)	(0.012)	(0.012)
Regulation	-0.025	0.027	0.021
	(0.159)	(0.131)	(0.132)
Emission factor	0.114*	-0.014	-0.010
	(0.066)	(0.059)	(0.059)
Market access cost	2.573***	-0.750	-0.857
	(0.876)	(0.795)	(0.781)
Wage			0.261***
			(0.054)
Number of establishments			0.033***
			(0.012)
Panel B. First stage on energy price			
Import price of int.	0.077***	0.043**	0.042**
	(0.017)	(0.018)	(0.018)
Domestic price of int.		0.046***	0.042***
		(0.008)	(0.008)
Energy price (t-2)	0.753***	0.748***	0.749***
	(0.016)	(0.016)	(0.016)
Regulation	0.000	0.006	0.015
	(0.051)	(0.050)	(0.050)
Emission factor	-0.982***	-0.996***	-1.001***
	(0.066)	(0.066)	(0.066)
Market access cost	1.819***	1.441**	1.389**
	(0.644)	(0.640)	(0.638)
Wage			-0.070***
			(0.027)
Number of establishments			0.016*
			(0.008)

Notes: All variables are in a natural log except for regulation. Robust standard errors are in brackets. $*, **, ***$ indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$.

Table B.3: Reduced-form results

	(1)	(2)	(3)
Import price of int.	0.791***	0.341*	0.343*
	(0.161)	(0.182)	(0.181)
Domestic price of int.		0.611***	0.615***
		(0.113)	(0.113)
Energy price (t-2)	0.065	-0.004	-0.005
	(0.096)	(0.097)	(0.097)
Regulation	-0.814	-0.735	-0.745
	(0.754)	(0.730)	(0.721)
Emission factor	0.652*	0.459	0.464
	(0.344)	(0.341)	(0.340)
Market access cost	7.925	2.902	2.957
	(5.470)	(5.389)	(5.386)
Wage			0.067
			(0.309)
Number of establishments			-0.017
			(0.115)

Notes: Dependent variable is the log of emission per real gross output. All variables are in a natural log except for regulation. Robust standard errors are in brackets. $*, **, ***$ indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$.

Table B.4: Summary statistics (within-industry)

	Obs	SD	Min	Max
Emission intensity	3373	0.850	-7.754	3.860
Producer price	3373	0.177	-2.059	1.816
Energy price	3373	0.463	-1.383	1.288
Regulation (nonattainment)	3373	0.045	-0.126	0.228
Emission factor	3373	0.055	-0.095	0.281
Market access cost	3373	0.003	-0.024	0.030
Instrumental variables				
Import price of intermediates	3373	0.209	-0.804	0.979
Domestic price of intermediates	3373	0.190	-1.196	1.219
Wage	3373	0.172	-0.418	0.678
Number of establishments	3373	0.177	-1.806	1.642
Energy price (2-year lagged)	3373	0.441	-1.046	1.562

Notes: This table presents the summary statistics of the variables used in the regressions after industry effects are eliminated. All variables are in a natural log except for regulation and market access cost. Mean values are all zero thus omitted in the table.

B.2 Appendix for empirical analysis

B.2.1 Derivation of Equation 2.1

First, taking logs of Equation 1.11 and approximating it around some initial point (t_0, ϵ_0) gives the following.

$$\ln Z_Q \approx \ln \epsilon\eta_e \frac{\sigma - 1}{\sigma} + \ln P - \ln r - \frac{t_0\epsilon_0}{1 + t_0\epsilon_0} \ln t - \frac{t_0\epsilon_0}{1 + t_0\epsilon_0} \ln \epsilon + \ln MAcost$$

The following steps provide the approximated expression of $lnMAcost$. Recall that $MAcost = \frac{X_d + X_f\tau_f^{1-\sigma}}{X_d + X_f\tau_f^{-\sigma}}$, and define s as the ratio of foreign sales to domestic sales, as given by

$$s = \frac{X_f\tau_f^{1-\sigma}}{X_d}$$

Then $\ln MAcost$ can be written as

$$\ln MAcost = \ln \frac{1 + s}{1 + s\tau_x^{-1}}$$

Approximating $\ln MAcost$ around free trade $(\bar{\tau_f} = 1)$ gives

$$\ln MAcost \approx \frac{X_f\tau_f^{1-\sigma}}{X_d + X_f\tau_f^{1-\sigma}} \ln \tau_f$$

since

$$\left.\frac{\partial}{\partial \ln \tau_f} \frac{1+s}{1+s\tau_f^{-1}}\right|_{\bar{\tau_f}} = \frac{s}{1+s} = \frac{X_f \tau_f^{1-\sigma}}{X_d + X_f \tau_f^{1-\sigma}}$$

$$\left.\frac{\partial}{\partial \ln s} \frac{1+s}{1+s\tau_f^{-1}}\right|_{\bar{\tau_f}} = 0$$

Thus $\ln MA$ in Equation 2.1 is measured as the multiplication of the share of foreign sales to total sales $(\frac{X_f \tau_f^{1-\sigma}}{X_d + X_f \tau_f^{1-\sigma}})$ – i.e., export intensity – and export cost $(\ln \tau_f)$.

The expression for $\ln MAcost$ in a multi-industry (i), multi-destination (c) setting is analgously given as

$$\ln MAcost_{it} \approx \text{Export intensity}_{it} \times \ln \tau_{f,it}$$

where $\ln \tau_{f,jt}$ is the average trade cost on exporting, calculated using the export value as weights.

$$\text{Export intensity}_{it} = \frac{\sum_{c'} X_{c'} \tau_{c',it}^{1-\sigma}}{X_d + \sum_{c'} X_{c'} \tau_{c',it}^{1-\sigma}}$$

$$\ln \tau_{f,it} = \sum_c \psi_{jt}^c \ln \tau_{c,it}$$

$$\psi_{it}^c = \frac{X_c \tau_{c,it}^{1-\sigma}}{\sum_{c'} X_{c'} \tau_{c',it}^{1-\sigma}}$$

B.3 Appendix for quantitative analysis

B.3.1 Robustness analyses

I test the sensitivity of the baseline results, using various parameter values. Table B.6 presents the results. It shows that the overall magnitude of the change in emission intensity is similar across calibrations. The reduction is larger with more dispersion in productivity (smaller $\theta = 4$), since it means there are more firms that are near the global sourcing and adoption cutoffs and can 'upgrade'. The reduction in total emissions is modest in this case as well due to output growth.

I also test how the impact changes with different levels of technology effectiveness. I use the larger values for β, which indicate more effective technology and larger cost savings from adoption. Both emission intensity and welfare gains from real income increase with $\beta = 5$ (by a small margin), compared to the baseline. I also try a calibration in which $\beta = 5$ and the fixed cost of adoption is lower to see whether this brings a larger reduction from increased adoption. I obtain a lower fixed cost of adoption by using a larger value for the share of establishments that installed the energy-saving equipment as the target moment.[1] But the results are similar to the baseline results, since the firms that are below the adoption cutoff are already sourcing globally, thus there is little or no additional effect. Lastly, I run the version with a higher baseline tax rate, which is calibrated by targeting Denmark's tax revenue per GDP, and show that the change on emissions is not much different from that in the baseline. This is not surprising given that there was little interaction in the effect of intermediate import cost and regulation in the main result.

I also calculate the welfare gains from the decrease in total emissions, using alternative values for the disutility paramter δ to examine how the welfare impact is sensitive to parameter assumptions. Specifically, I use the minimum and maximum value of the marginal social cost of NO_x from Heo et al. (2016). The value of the social cost used for the baseline calibration is $\$8,976$, and the minimum (lower) and maximum (higher) social cost values are $\$3,431$ and

[1] I use 33%, which is the share of establishments that participate in any energy-management activities from the 1998 MECS.

$\$12,817$ in 2000 USD.[2] The calculated welfare impact increases with social cost, but the magnitude of the wealth gains from emission reductions is still much lower than that from the real income changes.

The relatively small welfare gains from the emission-related component can be attributed to a few factors. First, the marginal social cost is estimated by monetizing the premature mortality caused by marginal emission but not other welfare losses.[3] Thus, it is highly likely that the welfare changes obtained from using the current social cost estimate are the lower bound. Second, the marginal social cost largely depends on the estimate of the value of statistical life (VSL), which itself is the subject of long-standing and ongoing discussion. Given this limitation, some papers emphasize the physical decrease of air pollution more than the welfare implication Shapiro (2021).

B.3.2 Market access vs. input import

I briefly discuss the impact of a lower export cost on emissions. Throughout the previous subsections' analyses, the import cost of intermediates was the only trade cost that changes. While increased market access from a lower export cost is not the focus of this paper, it is helpful to see its impact in comparison with a lower import cost since it is not uncommon to have trade liberalization in both directions.

One of the mechanisms through which lower export cost affects emission intensity from the literature is across-firm adjustments: reallocation toward cleaner firms and exit of the dirtiest firms. Since in my model all firms export, there is less margin for reallocation and selection than

[2] The calibrated δ are 1.9×10^{-7} and 7.3×10^{-7}, respectively.

[3] See Parry et al. (2016)for more details of the measurement of the marginal social cost of air pollutant emission.

a model in which firms decide whether or not to export. To make the change from export and import costs comparable, I disallow any changes that may occur from firms' decisions to 'enter' into global sourcing. To do so, I modify the model to a version in which all firms globally source (and export) and recalibrate it to 1998 US. There remains an entry into technology adoption.

Table B.7 shows the changes in emissions and welfare that are obtained from decreasing intermediate import and export costs by the same size I used in the main result. Two findings are notable. First, in this modified model, the decreases in emission intensity and total emissions resulting from the cut in intermediate import cost are smaller than in the baseline version (Panel A of Table 2.8). This is due to the absence of a reallocation effect that comes from those that start global sourcing, become cleaner, and gain market share. Second, a lower export cost brings an increase in both emission intensity and total emissions. Recall that emission increases with the average market access cost, which is averaged across the cost of accessing the domestic market and accessing foreign markets. On one hand, a lower export cost decreases the cost of accessing foreign markets. On the other hand, it increases the share of foreign sales within each firms' total sales – that is, export intensity. If the latter overwhelms the former, the average market access cost increases with lower export cost, which is translated into higher emissions and emission intensity. Lower export cost induces more firms to adopt energy-saving technology, but this margin is small in my calibrated model, as shown in Section 2.3.2.

As discussed earlier, an important caveat in this analysis is that it does not allow the reallocation and selection effect induced by firms' entry into exporting. Thus, the result should not be interpreted as a conclusive examination of the impact of lower export costs. Rather, it can serve as a useful comparison between the heterogeneous impact of intermediate import and export cost when the reallocation channel is restricted.

Table B.5: Calibration of parameters

	Parameters	Value	Source	Unit	
			Externally calibrated		
σ	EOS across varieties	4.76	Shapiro and Walker (2018)		
η_l	Labor cost share	0.27	Average cost shares for 19978-2014 (BEA Supply-Use Table)		
η_e	Energy input cost share	0.13	Average cost shares for 19978-2014 (BEA Supply-Use Table)		
η_m	Manufacturing input cost share	0.6	Average cost shares for 19978-2014 (BEA Supply-Use Table)		
ρ	Pareto shape parameter	5.14	Shapiro and Walker (2018)		
b	Pareto location parameter	1	Normalization		
β	Energy-saving effectiveness	1.5	Match energy cost saving of installing energy-efficient products (EPA)		
ϵ	Emission factor	1.23	Calculated using 19978 NO_x emission and 1998 energy usage (NEI and MECS)	100 US ton / tn Btu	
f_e	Fixed cost for entry	1	Normalization		
f_o	Fixed cost for operation	1	Normalization		
$\bar{I}$	Consumption expenditure	1,685,067	1998 US final expenditure on manufacturing in mn 2000 USD (WIOD)	mn 2000 USD	
$\bar{L}$	Labor supply	16,805	19978 US total employment in manufacturing in thousands persons (NBER-CES, CM)	thousands persons	
$\bar{E}^G$	Global energy supply	59,076	1998 Global mfg total consumption of non-electricity energy in tn Btu (MECS and EIA)	trillion Btu	
			Internally calibrated		
	Parameters	Value	Source	Moment	Model
f_g	Fixed cost for global sourcing	0.7	Match the ratio of the number of importer firms for 1997 (Bernard et al. (2007))	14%	14.3%
f_a	Fixed cost for technology adoption	1.6	Avdrage ratio of establishments that install equipments for improving energy efficiency (1998 MECS)	8.3%	8.2%
t	Emission tax rate	0.02	Match the air pollution tax revenue per GDP, for 1998 (OECD)	0.8%	1.2%
τ	Reference trade cost on int. goods	1.85	Match the foreign mfg input share among total mfg input for 1998 (WIOD)	15.4%	15.3%
τ^F	Reference trade cost on final goods	2.21	Match the ratio of export sales to total sales (i.e., export intensity) for 1998 (WIOD)	15.6%	15.6%

Table B.6: Change from lower intermediate import cost

(%)	Emission intensity	Total emissions	Welfare	Welfare (con)	Welfare (env)
Baseline	-1.8	-1.1	5.3	5.3	0.009
Panel A. Sensitivity with model parameters					
$\sigma = 6$	-1.9	-1.5	4.7	4.6	0.013
$\theta = 4$	-2.1	-1.0	5.7	5.7	0.008
$\theta = 6$	-1.6	-1.1	5.0	4.9	0.010
$\beta = 2$ (10% cost saving)	-1.7	-1.0	5.0	5.0	0.008
$\beta = 5$ (20% cost saving)	-1.9	-1.1	5.6	5.6	0.009
$\beta = 5$ & lower fixed cost of tech adoption	-1.7	-1.1	5.1	5.1	0.010
$t = 0.2$ (Denmark's stringency)	-1.8	-1.0	5.7	5.7	0.009
Panel B. Different values for NO_x social cost					
Lower social cost	-1.8	-1.1	5.3	5.3	0.004
Higher social cost	-1.8	-1.1	5.3	5.3	0.015

Table B.7: Change from lower intermediate trade costs

(%)	Emission intensity	Total emissions	Welfare	Welfare (con)	Welfare (env)
Import cost	-1.67	-0.84	4.28	4.27	0.007
Export cost	1.05	1.46	0.05	0.06	-0.012
Both	-0.65	0.70	4.47	4.47	-0.006

Appendix C: Appendix for Chapter 3

C.1 Additional tables and figures

Table C.1: Sample countries

AUS	Australia	IRL	Ireland
AUT	Austria	ITA	Italy
BEL	Belgium	JPN	Japan
BGR	Bulgaria	KOR	Korea
BRA	Brazil	LTU	Lithuania
CAN	Canada	LUX	Luxembourg*
CHE	Switzerland	LVA	Latvia*
CHN	China	MEX	Mexico
CYP	Cyprus	MLT	Malta*
CZE	Czech Republic	NLD	Netherlands
DEU	Germany	NOR	Norway
DNK	Denmark	POL	Poland
ESP	Spain	PRT	Portugal
EST	Estonia	ROU	Romania
FIN	Finland	ROW	Rest of the World**
FRA	France	RUS	Russia
GBR	United Kingdom	SVK	Slovak Republic*
GRC	Greece	SVN	Slovenia
HRV	Croatia*	SWE	Sweden
HUN	Hungary	TUR	Turkey
IDN	Indonesia	TWN	Taiwan**
IND	India	USA	United States

Notes: * Croatia, Luxembourg, Latvia, Malta, and Slovak Republic are included in ROW for quantitative analyses. ** Taiwan and ROW are included only in quantitative analyses but not in the empirical section.

Table C.2: Sample sectors

A	Agriculture/Forestry/Fishing
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31-C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D/E/F	Utilities/Construction
H	Transportation
Other	Other services

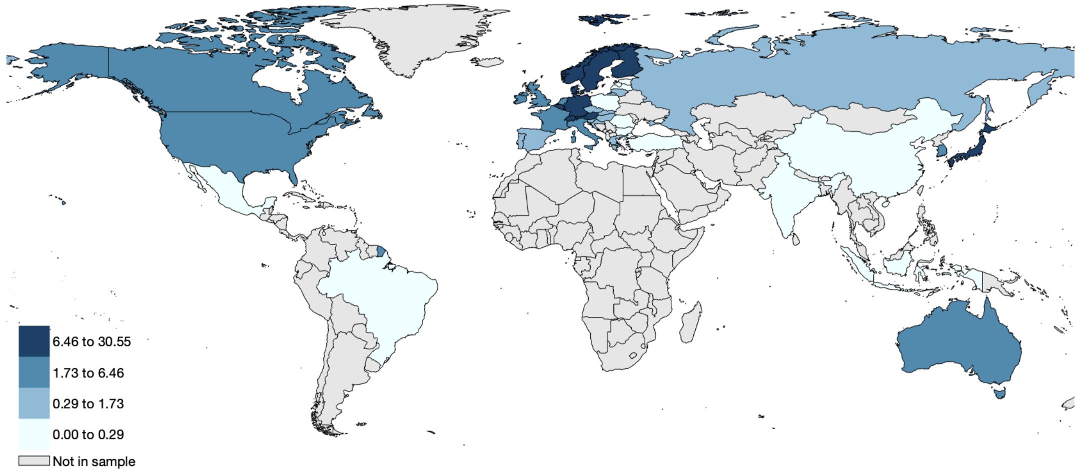
Notes: We combined A01-A03 into A and merged D, E, and F into one sector. Also, we put other service sectors than D/E/F and H as other services.

C.2 Derivations

C.2.1 Solving for the environmental disutility parameter

We solve for the μ_i^2, the square of the environmental disutility parameter μ_i, since that is how it enters the utility function anyway. And for simpler notation, I omit the subscript t, as the

Figure C.1: Number of patents on env. management (per 1000 persons)



calibration of μ_i^2 uses only 2005 information and estimates. From Equation 3.30,

$$\begin{aligned} sc_i &= \sum_{\forall k} \frac{\partial W_i}{\partial g_i} \left(\frac{\partial W_i}{\partial I_i} \right)^{-1} \frac{\partial g_i}{\partial E_k} dE_k \\ &= -\left(\frac{2 g_i I_i}{\mu_i^2 + g_i^2} \right) \times \sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k \end{aligned}$$

Since

$$\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k = \frac{\partial g_i}{\partial E_i} dE_i + \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} \tag{C.1}$$

using the functional form of $g_i(\cdot)$ and $PolTransport$

$$\begin{aligned} \ln g_i &= \hat{\psi} + \hat{\gamma}_1 \ln \left(\frac{E_i}{land_i} \right) + \hat{\gamma}_2 Meteo_i + \hat{\kappa} \ln PolTransport_i + \hat{\delta}_i + \hat{\delta}_t \\ PolTransport_i &= \sum_{i' \neq i} \frac{E_{i't}}{land_{i'}} \times \frac{1}{distance_{ii'}^2} \end{aligned}$$

From the regression estimate on own emission,

$$\hat{\gamma}_1 = \frac{\partial \ln g_i}{\partial \ln E_i} = \frac{\partial g_i}{\partial E_i}\frac{E_i}{g_i}$$

we have the first term of Equation C.1, given by

$$\frac{\partial g_i}{\partial E_i} dE_i = \hat{\gamma}_1 \frac{g_i}{E_i} dE_i \tag{C.2}$$

Also, using the estimate on the pollution transboundary term,

$$\begin{aligned}\hat{\kappa} &= \frac{\partial \ln g_i}{\partial \ln PolTransport_i} \\ &= \frac{\partial g_i}{\partial PolTransport_i}\frac{PolTransport_i}{g_i}\end{aligned}$$

so for $i' \neq i$, we have the second term of Equation C.1 as in Equation C.3.

$$\begin{aligned}\frac{\partial g_i}{\partial E_{i'}} &= \frac{\partial g_i}{\partial PolTransport_i} \times \frac{PolTransport_i}{\partial E_{i'}} \\ &= \hat{\kappa}\frac{g_i}{PolTransport_i} \times (land_{i'} d_{i'i}^2)^{-1} \\ \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} &= \hat{\kappa}\frac{g_i \sum_{i' \neq i} (land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{PolTransport_i}\end{aligned} \tag{C.3}$$

Putting Equation C.2 and Equation C.3 into Equation C.1, we get

$$\begin{aligned}
\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k &= \frac{\partial g_i}{\partial E_i} dE_i + \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} \\
&= \hat{\gamma}_1 \frac{g_i}{E_i} dE_i + \hat{\kappa} \frac{g_i \sum_{i' \neq i} (land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{PolTransport_i} \\
&= \hat{\gamma}_1 \frac{g_i}{E_i} dE_i + \hat{\kappa} \frac{g_i \sum_{i' \neq i} (land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{\sum_{i' \neq i} \frac{E_{i'}/land_{i'}}{d_{i'i}^2}}
\end{aligned}$$

Table C.3: Summary statistics for the first specification

		Unit	N	Mean	SD	Min	Max
Baseline regression							
$\ln(Emissionpc)$	$PM_{2.5}$ emissions per capita	$\ln$(metric ton per capita)	630	-5.568	0.520	-6.869	-4.390
$GDPpc$	GDP per capita	mn 2010 USD per capita	630	0.030	0.023	0.001	0.112
$GDPpc^2$	GDP per capita, squared	(mn 2010 USD per capita)^2	630	0.001	0.002	6.8×10^{-7}	0.013
$Tech$	Number of abatement-tech patents per capita	number per capita	630	.0005	0.001	0	0.006
$Trade$	Ratio of total trade flows to GDP	ratio	630	0.927	0.588	0.198	3.928
$Upstream$	Upstreamness, following Antràs and Chor (2018)	.	630	2.041	0.193	1.609	2.920
$PTAenv$	Share of trade flows with partner countries of PTAs with env. provisions	ratio	630	0.497	0.324	0	0.920
Additional regression							
$Export$	Ratio of export flows to GDP	ratio	630	0.470	0.314	0.090	2.126
$Import$	Ratio of import flows to GDP	ratio	630	0.457	0.278	0.092	1.802
$PTAenv$ (ex)	Share of export flows with partner countries of PTAs with env. provisions	ratio	630	0.508	0.336	0	0.936
$PTAenv$ (im)	Share of import flows with partner countries of PTAs with env. provisions	ratio	630	0.486	0.319	0	0.923

Table C.4: Summary statistics for the second specification

		Unit	N	Mean	SD	Min	Max
Column 1 and 2							
ln(concentration)	$PM_{2.5}$ concentration level (country ave)	$\ln$(metric ton/km^3)1 metric ton/km^3 is equivalent to 1000μg/m^3	630	-4.525	0.607	-6.502	-2.823
ln(emission/land)	$PM_{2.5}$ emissions per land area	$\ln$(metric ton/km^2)	630	-1.164	1.048	-4.015	1.417
Temp Ave	Simple average of monthly temperature	Celsius	630	10.874	6.857	-7.077	26.427
Temp SD	Standard deviation of monthly temperature	Celsius	630	7.222	2.704	0.216	16.316
Rain Ave	Simple average of monthly preciptation	mm	630	74.682	39.637	21.676	298.390
Rain SD	Standard deviation of monthly precipitation	mm	630	38.722	22.373	8.688	168.389
ln(PolTransport)	Defined as in Eq. 3.2	.	630	-10.570	1.025	-13.296	-8.713
Column 3							
ln(concentration)	$PM_{2.5}$ concentration level (country ave)	$\ln$(metric ton/km^3)	429	-4.511	0.653	-6.502	-2.823
ln(emission/land)	$PM_{2.5}$ emissions per land area	$\ln$(metric ton/km^2)	429	-1.179	1.018	-4.015	0.821
Temp Ave	Simple average of monthly temperature	Celsius	429	9.860	5.740	-7.077	25.239
Temp SD	Standard deviation of monthly temperature	Celsius	429	7.549	2.405	3.139	16.316
Rain Ave	Simple average of monthly preciptation	mm	429	70.630	27.287	27.227	173.118
Rain SD	Standard deviation of monthly precipitation	mm	429	37.705	24.133	8.688	168.389
ln(PolTransport)	Defined as in Eq. 3.2	.	429	-10.518	0.893	-12.972	-8.713
ln(pop density)	Population per km^2	$\ln$(persons/km^2)	429	4.479	1.220	0.906	6.227
Share of urban population	Ratio of population in urban agglomerates ($>$1 mn people) to the total population	ratio	429	0.242	0.139	0.044	0.635
ln(rail density)	Length of rail lines per land area	$\ln$(km/100km^2)	429	1.169	1.007	-2.188	2.511
Technology	Number of env-management patents per capita	number per capita	429	0.007	0.008	0.000	0.033

Table C.5: Determinants of $PM_{2.5}$ concentration

	(1)	(2)
ln(emission/land)	0.159***	0.196***
	(0.039)	(0.059)
Temp Ave	-0.043*	-0.034
	(0.022)	(0.029)
Temp SD	0.022	0.028
	(0.025)	(0.025)
Rain Ave	-0.003***	-0.001
	(0.001)	(0.001)
Rain SD	0.001	-0.001
	(0.001)	(0.001)
ln(PolTransport)	0.182***	0.132**
	(0.061)	(0.064)
ln(population density)		0.087
		(0.181)
Share of urban population		2.155***
		(0.775)
ln(rail density)		0.464***
		(0.099)
Technology		-3.313
		(4.253)
Observations	630	429
Within Adj. R-squared	0.117	0.152

Notes: The dependent variable is the log of $PM_{2.5}$ concentration. All columns use country fixed effects and year fixed effects. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *$<$ .1, **$<$ .05, ***$<$ .01.

Table C.6: Social cost estimates (unit: mn 2005 USD/ton)

AUS	Australia	-0.009	IDN	Indonesia	-0.008
AUT	Austria	-0.306	IND	India	-0.019
BEL	Belgium	-1.027	IRL	Ireland	-0.188
BGR	Bulgaria	-0.022	ITA	Italy	-0.499
BRA	Brazil	-0.012	JPN	Japan	-1.098
CAN	Canada	-0.011	KOR	Korea	-0.600
CHE	Switzerland	-1.071	LTU	Lithuania	-0.033
CHN	China	-0.019	MEX	Mexico	-0.029
CYP	Cyprus	-0.212	NLD	Netherlands	-1.603
CZE	Czech Republic	-0.142	NOR	Norway	-0.084
DEU	Germany	-0.630	POL	Poland	-0.072
DNK	Denmark	-0.537	PRT	Portugal	-0.159
ESP	Spain	-0.177	ROU	Romania	-0.035
EST	Estonia	-0.028	RUS	Russia	-0.004
FIN	Finland	-0.054	SVN	Slovenia	-0.138
FRA	France	-0.322	SWE	Sweden	-0.078
GBR	United Kingdom	-0.690	TUR	Turkey	-0.050
GRC	Greece	-0.153	TWN	Taiwan, China	-0.673
HUN	Hungary	-0.084	USA	United States	-0.109

Table C.7: μ_i^2 estimates (unit: $\times 10^{-4}$)

AUS	Australia	0.0031	IDN	Indonesia	0.0567
AUT	Austria	0.0073	IND	India	1.2518
BEL	Belgium	0.0019	IRL	Ireland	0.0008
BGR	Bulgaria	0.0080	ITA	Italy	0.0261
BRA	Brazil	0.1776	JPN	Japan	0.0034
CAN	Canada	0.0090	KOR	Korea	0.0035
CHE	Switzerland	0.0021	LTU	Lithuania	0.0055
CHN	China	0.3891	MEX	Mexico	0.0373
CYP	Cyprus	0.0008	NLD	Netherlands	0.0026
CZE	Czech Republic	0.0115	NOR	Norway	0.0013
DEU	Germany	0.0237	POL	Poland	0.0540
DNK	Denmark	0.0020	PRT	Portugal	0.0014
ESP	Spain	0.0091	ROU	Romania	0.0208
EST	Estonia	0.0017	RUS	Russia	0.1663
FIN	Finland	0.0061	SVN	Slovenia	0.0031
FRA	France	0.0161	SWE	Sweden	0.0031
GBR	United Kingdom	0.0060	TUR	Turkey	0.0311
GRC	Greece	0.0075	TWN	Taiwan, China	0.0007
HUN	Hungary	0.0169	USA	United States	0.0994

Table C.8: Alternative social cost estimates (unit: mn 2005 USD/ton)

		Urban	Urban+rural	Baseline
AUS	Australia	-0.168	-0.009	-0.009
AUT	Austria			-0.306
BEL	Belgium	-0.269	-1.042	-1.027
BGR	Bulgaria	-0.028	-0.022	-0.022
BRA	Brazil	-0.068	-0.012	-0.012
CAN	Canada	-0.067	-0.011	-0.011
CHE	Switzerland	-0.431	-1.134	-1.071
CHN	China	-0.022	-0.020	-0.019
CYP	Cyprus	-0.064	-0.217	-0.212
CZE	Czech Republic			-0.142
DEU	Germany	-0.293	-0.633	-0.630
DNK	Denmark	-0.231	-0.550	-0.537
ESP	Spain	-0.107	-0.180	-0.177
EST	Estonia	-0.034	-0.028	-0.028
FIN	Finland	-0.075	-0.054	-0.054
FRA	France	-0.172	-0.330	-0.322
GBR	United Kingdom	-0.249	-0.703	-0.690
GRC	Greece	-0.087	-0.153	-0.153
HUN	Hungary			-0.084
IDN	Indonesia	-0.017	-0.008	-0.008
IND	India	-0.008	-0.018	-0.019
IRL	Ireland	-0.152	-0.192	-0.188
ITA	Italy	-0.148	-0.505	-0.499
JPN	Japan	-0.347	-1.106	-1.098
KOR	Korea	-0.236	-0.598	-0.600
LTU	Lithuania	-0.032	-0.033	-0.033
MEX	Mexico	-0.046	-0.030	-0.029
NLD	Netherlands	-0.382	-1.614	-1.603
NOR	Norway	-0.128	-0.100	-0.084
POL	Poland	-0.049	-0.073	-0.072
PRT	Portugal	-0.072	-0.163	-0.159
ROU	Romania	-0.030	-0.035	-0.035
RUS	Russia	-0.031	-0.005	-0.004
SVN	Slovenia	-0.063	-0.141	-0.138
SWE	Sweden	-0.095	-0.078	-0.078
TUR	Turkey	-0.065	-0.051	-0.050
TWN	Taiwan, China			-0.673
USA	United States	-0.109	-0.109	-0.109

Table C.9: Alternative μ_i^2 estimates (unit: $\times 10^{-4}$)

		Urban	Urban+rural	Baseline
AUS	Australia	0.0002	0.0031	0.0031
AUT	Austria			0.0073
BEL	Belgium	0.0078	0.0019	0.0019
BGR	Bulgaria	0.0063	0.0079	0.0080
BRA	Brazil	0.0315	0.1744	0.1776
CAN	Canada	0.0014	0.0091	0.0090
CHE	Switzerland	0.0056	0.0020	0.0021
CHN	China	0.3374	0.3741	0.3891
CYP	Cyprus	0.0028	0.0008	0.0008
CZE	Czech Republic			0.0115
DEU	Germany	0.0512	0.0236	0.0237
DNK	Denmark	0.0048	0.0019	0.0020
ESP	Spain	0.0150	0.0089	0.0091
EST	Estonia	0.0014	0.0017	0.0017
FIN	Finland	0.0044	0.0061	0.0061
FRA	France	0.0301	0.0157	0.0161
GBR	United Kingdom	0.0169	0.0059	0.0060
GRC	Greece	0.0133	0.0075	0.0075
HUN	Hungary			0.0169
IDN	Indonesia	0.0261	0.0577	0.0567
IND	India	2.9303	1.3213	1.2518
IRL	Ireland	0.0010	0.0008	0.0008
ITA	Italy	0.0886	0.0258	0.0261
JPN	Japan	0.0109	0.0033	0.0034
KOR	Korea	0.0096	0.0035	0.0035
LTU	Lithuania	0.0056	0.0055	0.0055
MEX	Mexico	0.0235	0.0364	0.0373
NLD	Netherlands	0.0119	0.0026	0.0026
NOR	Norway	0.0008	0.0010	0.0013
POL	Poland	0.0801	0.0532	0.0540
PRT	Portugal	0.0032	0.0014	0.0014
ROU	Romania	0.0243	0.0208	0.0208
RUS	Russia	0.0236	0.1641	0.1663
SVN	Slovenia	0.0071	0.0030	0.0031
SWE	Sweden	0.0026	0.0032	0.0031
TUR	Turkey	0.0240	0.0304	0.0311
TWN	Taiwan, China			0.0007
USA	United States	0.0994	0.0994	0.0994

Table C.10: Trade elasticity

Tradable sectors		θ^j
A	Agriculture/Forestry/Fishing	9.11
B	Mining and quarrying	13.53
C10-C12	Manufacture of food products, beverages and tobacco products	2.62
C13-C15	Manufacture of textiles, wearing apparel and leather products	8.10
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	11.50
C17	Manufacture of paper and paper products	16.52
C18	Printing and reproduction of recorded media	16.52
C19	Manufacture of coke and refined petroleum products	64.85
C20	Manufacture of chemicals and chemical products	3.13
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	3.13
C22	Manufacture of rubber and plastic products	1.67
C23	Manufacture of other non-metallic mineral products	2.41
C24	Manufacture of basic metals	3.28
C25	Manufacture of fabricated metal products, except machinery and equipment	6.99
C26	Manufacture of computer, electronic and optical products	7.52
C27	Manufacture of electrical equipment	12.91
C28	Manufacture of machinery and equipment n.e.c.	1.45
C29	Manufacture of motor vehicles, trailers and semi-trailers	1.84
C30	Manufacture of other transport equipment	0.39
C31-C32	Manufacture of furniture; other manufacturing	3.98
C33	Repair and installation of machinery and equipment	1.45

Notes: The values are from Caliendo and Parro (2015)'s 99% sample estimates. We calculate the weighted average of Office, Communication, and Medical Manufacturing for the value of C26, using the global total trade flows in 2000. Service sectors are nontradable thus are omitted from the table.

Table C.11: The effects of the China shock

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	0.3075	0.3084	-0.0010	-0.0003	-0.0007	2.7492	1.2960
Austria	0.0221	0.0190	0.0031	0.0009	0.0023	-0.2372	-0.1249
Belgium	-0.0045	-0.0189	0.0143	-0.0001	0.0144	0.0037	-0.0657
Bulgaria	0.0846	0.0795	0.0051	0.0013	0.0038	-0.3029	-0.1734
Brazil	0.0338	0.0339	-0.0001	0.0000	-0.0001	0.4875	0.2956
Canada	0.0358	0.0360	-0.0001	-0.0001	0.0000	0.4382	0.0948
Switzerland	0.0218	0.0095	0.0123	0.0057	0.0066	-0.3089	-0.0955
China	3.2081	3.2106	-0.0025	-0.0021	-0.0005	13.1091	2.3286
Cyprus	0.0810	0.0774	0.0035	0.0036	0.0000	-0.5036	-0.0720
Czech Republic	0.0369	0.0311	0.0057	0.0024	0.0033	-0.3176	-0.1097
Germany	0.0338	0.0324	0.0014	0.0007	0.0007	-0.2337	-0.0683
Denmark	0.0503	0.0455	0.0048	-0.0006	0.0054	0.0387	-0.0454
Spain	0.0252	0.0249	0.0003	0.0001	0.0002	-0.1723	-0.0684
Estonia	0.0770	0.0683	0.0087	0.0034	0.0053	-0.2845	-0.1037
Finland	0.0365	0.0356	0.0009	0.0002	0.0006	-0.2110	-0.1128
France	0.0438	0.0431	0.0007	0.0004	0.0003	-0.2133	-0.0578
United Kingdom	0.0347	0.0337	0.0011	0.0002	0.0009	-0.0468	-0.0440
Greece	0.0569	0.0546	0.0023	0.0010	0.0013	-0.3899	-0.1310
Hungary	0.0752	0.0718	0.0035	0.0012	0.0022	-0.3183	-0.1279
Indonesia	0.0167	0.0176	-0.0009	-0.0003	-0.0006	3.7936	1.5681
India	0.0306	0.0316	-0.0010	-0.0006	-0.0004	7.0015	1.7023
Ireland	-0.0356	-0.0389	0.0033	0.0021	0.0012	-0.3198	-0.0720
Italy	-0.0063	-0.0072	0.0009	0.0004	0.0005	-0.3409	-0.1135
Japan	0.0186	0.0469	-0.0283	-0.0010	-0.0274	0.1834	0.7675
Korea	0.0755	0.2166	-0.1411	-0.0050	-0.1373	0.4982	2.0002
Lithuania	0.0397	0.0351	0.0046	0.0019	0.0027	-0.2993	-0.1027
Mexico	-0.0260	-0.0258	-0.0002	0.0001	-0.0002	-0.5472	0.2252
Netherlands	0.0177	0.0064	0.0113	0.0061	0.0052	-0.2053	-0.0543
Norway	-0.1030	-0.1012	-0.0017	-0.0024	0.0006	0.8885	0.0938
Poland	0.0318	0.0303	0.0015	0.0006	0.0009	-0.3153	-0.1101
Portugal	0.0558	0.0551	0.0007	0.0004	0.0003	-0.2072	-0.0555
Romania	0.1574	0.1537	0.0037	0.0023	0.0014	-0.8583	-0.1968
Russia	0.0567	0.0568	-0.0001	-0.0001	0.0000	1.0063	0.1556
Slovenia	0.0436	0.0341	0.0095	0.0033	0.0062	-0.2879	-0.1201
Sweden	0.0491	0.0483	0.0009	0.0006	0.0003	-0.4068	-0.0845
Turkey	-0.0480	-0.0489	0.0009	0.0003	0.0005	-0.4119	-0.1558
Taiwan	-0.4481	0.3547	-0.8028	-0.2546	-0.5520	3.2314	1.4725
United States	0.0340	0.0341	0.0000	0.0000	0.0000	-0.2009	0.1472

Table C.12: The effects of the China shock with additional environmental regulations

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	0.3078	0.3085	-0.0007	-0.0003	-0.0004	2.7600	0.9376
Austria	0.0221	0.0190	0.0032	0.0009	0.0023	-0.2369	-0.1275
Belgium	-0.0042	-0.0188	0.0146	-0.0002	0.0148	0.0056	-0.0670
Bulgaria	0.0850	0.0796	0.0054	0.0013	0.0041	-0.3027	-0.1818
Brazil	0.0338	0.0338	0.0000	0.0000	0.0000	0.4883	0.1718
Canada	0.0358	0.0359	-0.0001	-0.0001	0.0000	0.4395	0.0411
Switzerland	0.0223	0.0094	0.0128	0.0057	0.0071	-0.3089	-0.0994
China	3.0984	3.0981	0.0003	0.0008	-0.0005	-5.2080	-0.3016
Cyprus	0.0829	0.0775	0.0054	0.0036	0.0018	-0.5037	-0.1095
Czech Republic	0.0371	0.0311	0.0060	0.0024	0.0036	-0.3175	-0.1140
Germany	0.0338	0.0324	0.0014	0.0007	0.0007	-0.2337	-0.0693
Denmark	0.0510	0.0454	0.0056	-0.0006	0.0062	0.0388	-0.0529
Spain	0.0253	0.0249	0.0003	0.0001	0.0002	-0.1718	-0.0790
Estonia	0.0774	0.0684	0.0090	0.0034	0.0056	-0.2849	-0.1074
Finland	0.0365	0.0355	0.0009	0.0002	0.0007	-0.2101	-0.1169
France	0.0438	0.0430	0.0008	0.0004	0.0004	-0.2131	-0.0597
United Kingdom	0.0348	0.0337	0.0011	0.0002	0.0010	-0.0450	-0.0463
Greece	0.0573	0.0547	0.0026	0.0010	0.0016	-0.3902	-0.1466
Hungary	0.0753	0.0717	0.0036	0.0012	0.0023	-0.3185	-0.1321
Indonesia	0.0170	0.0177	-0.0007	-0.0003	-0.0003	3.8050	1.1596
India	0.0311	0.0318	-0.0007	-0.0006	-0.0001	7.0237	1.1477
Ireland	-0.0355	-0.0392	0.0037	0.0021	0.0016	-0.3204	-0.0806
Italy	-0.0062	-0.0072	0.0010	0.0004	0.0006	-0.3407	-0.1223
Japan	0.0352	0.0469	-0.0117	-0.0010	-0.0107	0.1863	0.3175
Korea	0.2094	0.2166	-0.0072	-0.0050	-0.0022	0.5041	0.1036
Lithuania	0.0403	0.0352	0.0051	0.0019	0.0032	-0.2997	-0.1143
Mexico	-0.0258	-0.0258	0.0000	0.0001	-0.0001	-0.5472	0.0318
Netherlands	0.0178	0.0063	0.0114	0.0061	0.0053	-0.2051	-0.0552
Norway	-0.1027	-0.1012	-0.0015	-0.0024	0.0009	0.8900	0.0816
Poland	0.0320	0.0303	0.0017	0.0006	0.0010	-0.3153	-0.1184
Portugal	0.0562	0.0552	0.0009	0.0004	0.0005	-0.2071	-0.0727
Romania	0.1574	0.1535	0.0039	0.0023	0.0016	-0.8578	-0.2072
Russia	0.0566	0.0567	-0.0001	-0.0001	0.0000	1.0095	0.1126
Slovenia	0.0441	0.0342	0.0099	0.0033	0.0066	-0.2883	-0.1244
Sweden	0.0492	0.0482	0.0010	0.0006	0.0004	-0.4063	-0.0962
Turkey	-0.0479	-0.0489	0.0010	0.0003	0.0006	-0.4119	-0.1719
Taiwan	0.1399	0.3545	-0.2146	-0.2558	0.0376	3.2459	0.3968
United States	0.0341	0.0341	0.0000	0.0000	0.0000	-0.2008	0.0424

Table C.13: The effects of the EU enlargement

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	-0.0010	-0.0010	-0.0001	0.0000	-0.0001	0.0014	0.0762
Austria*	0.1001	0.1238	-0.0237	0.0032	-0.0271	-0.8856	0.9363
Belgium*	0.0193	0.0468	-0.0275	-0.0012	-0.0263	0.0368	0.1260
Bulgaria	-0.0187	-0.0122	-0.0065	0.0001	-0.0067	-0.0286	0.2192
Brazil	-0.0011	-0.0010	-0.0001	0.0000	-0.0001	-0.0084	0.2276
Canada	-0.0004	-0.0003	-0.0001	0.0000	-0.0001	-0.0021	0.0778
Switzerland	-0.0460	-0.0024	-0.0436	0.0003	-0.0440	-0.0144	0.3366
China	-0.0011	-0.0011	0.0000	0.0000	0.0000	0.0017	0.0184
Cyprus**	1.6990	1.7676	-0.0686	-0.0620	-0.0083	8.3987	1.3744
Czech Republic**	1.5310	1.5847	-0.0536	-0.0556	0.0005	7.1331	1.0150
Germany*	0.0801	0.0830	-0.0029	0.0001	-0.0030	-0.0172	0.1432
Denmark*	0.0400	0.0938	-0.0538	-0.0048	-0.0491	0.3139	0.5056
Spain*	0.0109	0.0116	-0.0007	0.0000	-0.0006	0.0684	0.1667
Estonia**	0.5970	0.6040	-0.0070	-0.0021	-0.0049	0.1733	0.0827
Finland*	0.0233	0.0241	-0.0008	0.0000	-0.0008	-0.0155	0.1022
France*	0.0190	0.0205	-0.0015	-0.0001	-0.0014	0.0539	0.1154
United Kingdom*	0.0123	0.0149	-0.0027	-0.0001	-0.0025	0.0429	0.1108
Greece*	-0.0097	-0.0042	-0.0055	0.0004	-0.0059	-0.1383	0.3092
Hungary**	1.7182	1.7317	-0.0135	-0.0008	-0.0128	0.1992	0.4969
Indonesia	-0.0021	-0.0021	0.0000	0.0000	0.0000	-0.0181	0.0682
India	-0.0016	-0.0015	-0.0001	0.0000	-0.0001	0.0105	0.1848
Ireland*	0.0235	0.0308	-0.0073	-0.0003	-0.0070	0.0517	0.1604
Italy*	0.0264	0.0295	-0.0031	-0.0001	-0.0031	0.0461	0.3841
Japan	-0.0008	-0.0001	-0.0007	0.0000	-0.0006	0.0072	0.0182
Korea	-0.0022	-0.0009	-0.0014	0.0000	-0.0013	0.0035	0.0196
Lithuania**	0.3885	0.4054	-0.0169	-0.0030	-0.0139	0.4653	0.3748
Mexico	-0.0006	-0.0005	-0.0001	0.0000	-0.0001	0.0061	0.1789
Netherlands*	0.0233	0.0452	-0.0219	-0.0055	-0.0164	0.1838	0.1056
Norway	-0.0198	-0.0142	-0.0056	-0.0004	-0.0052	0.1440	0.3027
Poland**	0.9144	0.9242	-0.0098	-0.0001	-0.0098	0.0303	0.6943
Portugal*	0.0080	0.0104	-0.0024	0.0000	-0.0023	0.0227	0.1832
Romania	-0.0441	-0.0395	-0.0046	0.0003	-0.0049	-0.1004	0.2401
Russia	0.0015	0.0017	-0.0002	0.0000	-0.0001	0.2447	0.3345
Slovenia**	3.3775	3.4304	-0.0529	-0.0114	-0.0415	0.9940	0.6616
Sweden*	0.0910	0.0952	-0.0042	-0.0016	-0.0027	1.0210	0.4011
Turkey	-0.0135	-0.0116	-0.0019	0.0000	-0.0020	-0.0289	0.3423
Taiwan	-0.0172	-0.0018	-0.0154	-0.0011	-0.0143	0.0141	0.0285
United States	-0.0006	-0.0006	0.0000	0.0000	0.0000	0.0060	0.1677

Notes: The countries indexed with * are existing EU member countries before 2004, and the countries indexed with ** are new EU members of the 2004 enlargement.

Table C.14: The effects of the EU enlargement with additional environmental regulations

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	-0.0007	-0.0009	0.0002	0.0000	0.0002	0.0033	-0.3150
Austria*	0.2253	0.1247	0.1005	0.0027	0.0960	-0.7644	-4.1763
Belgium*	0.0991	0.0470	0.0521	-0.0023	0.0543	0.0726	-0.2396
Bulgaria	0.0284	-0.0124	0.0408	0.0001	0.0404	-0.0152	-1.3912
Brazil	-0.0008	-0.0010	0.0002	0.0000	0.0002	-0.0059	-0.9549
Canada	0.0002	-0.0002	0.0005	0.0000	0.0005	0.0001	-0.3281
Switzerland	0.1504	-0.0027	0.1531	0.0001	0.1520	-0.0048	-1.1985
China	-0.0011	-0.0012	0.0001	0.0000	0.0001	0.0021	-0.0691
Cyprus**	1.1121	0.9884	0.1237	0.0711	0.0511	-10.5771	-2.5743
Czech Republic**	0.9650	0.7846	0.1804	0.0909	0.0876	-12.8810	-3.5681
Germany*	0.0891	0.0832	0.0060	-0.0001	0.0060	0.0281	-0.2948
Denmark*	0.2761	0.0952	0.1809	-0.0052	0.1841	0.3395	-1.7351
Spain*	0.0144	0.0121	0.0024	-0.0001	0.0024	0.0920	-0.5928
Estonia**	0.3967	0.1485	0.2482	0.2038	0.0321	-18.4821	-3.0417
Finland*	0.0644	0.0243	0.0401	0.0000	0.0390	0.0030	-5.4150
France*	0.0243	0.0206	0.0037	-0.0001	0.0038	0.0740	-0.2898
United Kingdom*	0.0213	0.0150	0.0063	-0.0002	0.0065	0.0533	-0.2621
Greece*	0.0195	-0.0037	0.0232	0.0003	0.0227	-0.1252	-1.3178
Hungary**	0.9876	0.8578	0.1298	0.0688	0.0586	-19.4351	-5.0286
Indonesia	-0.0019	-0.0021	0.0002	0.0000	0.0002	-0.0161	-0.2843
India	-0.0010	-0.0015	0.0004	0.0000	0.0004	0.0122	-0.7538
Ireland*	0.0531	0.0303	0.0227	-0.0003	0.0230	0.0523	-0.4991
Italy*	0.0478	0.0301	0.0177	-0.0001	0.0176	0.0739	-2.2433
Japan	0.0022	-0.0001	0.0024	0.0000	0.0024	0.0080	-0.0644
Korea	0.0039	-0.0009	0.0048	-0.0001	0.0049	0.0051	-0.0696
Lithuania**	0.0595	-0.1921	0.2516	0.1099	0.1391	-18.6888	-5.9444
Mexico	0.0000	-0.0005	0.0006	0.0000	0.0006	0.0064	-0.7684
Netherlands*	0.0821	0.0462	0.0359	-0.0063	0.0421	0.2100	-0.1732
Norway	0.0078	-0.0132	0.0211	-0.0004	0.0214	0.1611	-1.1561
Poland**	0.3710	0.3007	0.0702	0.0349	0.0343	-19.0277	-5.2815
Portugal*	0.0191	0.0105	0.0086	-0.0001	0.0086	0.0294	-0.6775
Romania	-0.0100	-0.0394	0.0295	0.0002	0.0291	-0.0651	-1.5700
Russia	0.0027	0.0015	0.0011	0.0000	0.0012	0.2825	-2.3543
Slovenia**	2.9453	2.6064	0.3389	0.1892	0.1428	-18.1261	-4.4543
Sweden*	0.1160	0.0963	0.0196	-0.0016	0.0210	1.0586	-1.9015
Turkey	-0.0041	-0.0115	0.0074	0.0000	0.0073	-0.0231	-1.3209
Taiwan	0.0563	-0.0019	0.0582	-0.0013	0.0595	0.0173	-0.1080
United States	-0.0004	-0.0006	0.0002	0.0000	0.0002	0.0072	-0.7163

Notes: The countries indexed with * are existing EU member countries before 2004, and the countries indexed with ** are new EU members of the 2004 enlargement.

Bibliography

Abrego, Lisandro, Carlo Perroni, John Whalley, and Randall M. Wigle (2001) "Trade and Environment: Bargaining Outcomes from Linked Negotiations," *Review of International Economics*, 9 (3), 414–428, https://doi.org/10.1111/1467-9396.00289.

Akerman, Anders, Rikard Forslid, and Ossian Prane (2021) "Imports and the CO2 Emissions of Firms," Mimeograph.

Akimoto, Hajime (2003) "Global Air Quality and Pollution," *Science*, 302 (5651), 1716–1719.

Andrews, Isaiah, James H. Stock, and Liyang Sun (2019) "Weak Instruments in Instrumental Variables Regression: Theory and Practice," *Annual Review of Economics*, 11 (1), 727–753.

Antràs, Pol and Davin Chor (2018) *On the Measurement of Upstreamness and Downstreamness in Global Value Chains*, 126–194: Taylor and Francis Group.

Antràs, Pol, Teresa C. Fort, and Felix Tintelnot (2017) "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms," *American Economic Review*, 107 (9), 2514–64.

Antweiler, Werner, Brian R. Copeland, and M. Scott Taylor (2001) "Is Free Trade Good for the Environment?" *American Economic Review*, 91 (4), 877–908.

de Araujo, Inácio Fernandes, Randall W. Jackson, Amir B. Ferreira Neto, and Fernando S. Perobelli (2020) "European union membership and CO2 emissions: A structural decomposition analysis," *Structural Change and Economic Dynamics*, 55, 190–203.

Batrakova, Svetlana and Ronald B. Davies (2012) "Is there an environmental benefit to being an exporter? Evidence from firm-level data," *Review of World Economics*, 148 (3), 449–474.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott (2007) "Firms in International Trade," *Journal of Economic Perspectives*, 21 (3), 105–130.

Bockstael, N. and A. Freeman (2005) "Welfare Theory and Valuation," *Handbook of Environmental Economics*, 2, 517–570.

Boskovic, Branko (2015) "Air Pollution, Externalities, and Decentralized Environmental Regulation," Mimeograph.

Brander, James A and M Scott Taylor (1998) “Open access renewable resources: Trade and trade policy in a two-country model,” *Journal of International Economics*, 44 (2), 181–209.

Bustos, Paula (2011) “Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms,” *American Economic Review*, 101 (1), 304–40.

Caliendo, Lorenzo and Fernando Parro (2015) “Estimates of the Trade and Welfare Effects of NAFTA,” *The Review of Economic Studies*, 82 (1), 1–44.

Chay, Kenneth Y. and Michael Greenstone (2003) “The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession,” *The Quarterly Journal of Economics*, 118 (3), 1121–1167.

Chen, Shuai, Faqin Lin, Xi Yao, and Peng Zhang (2020) “WTO accession, trade expansion, and air pollution: Evidence from China’s county-level panel data,” *Review of International Economics*, 28 (4), 1020–1045.

Cherniwchan, Jevan (2017) “Trade liberalization and the environment: Evidence from NAFTA and U.S. manufacturing,” *Journal of International Economics*, 105, 130–149.

Cherniwchan, Jevan, Brian R. Copeland, and M. Scott Taylor (2017) “Trade and the Environment: New Methods, Measurements, and Results,” *Annual Review of Economics*, 9 (1), 59–85.

Chichilnisky, Graciela (1994) “North-South Trade and the Global Environment,” *The American Economic Review*, 84 (4), 851–874.

Copeland, Brian R., Joseph S. Shapiro, and M. Scott Taylor (2022) “Chapter 2 - Globalization and the environment,” in Gopinath, Gita, Elhanan Helpman, and Kenneth Rogoff eds. *Handbook of International Economics: International Trade, Volume 5*, 5 of Handbook of International Economics, 61–146: Elsevier.

Copeland, Brian R. and M. Scott Taylor (1994) “North-South Trade and the Environment,” *The Quarterly Journal of Economics*, 109 (3), 755–787.

——— (1995) “Trade and Transboundary Pollution,” *The American Economic Review*, 85 (4), 716–737.

——— (2003) *Trade and the Environment: Theory and Evidence*: Princeton University Press, Publication Title: Trade and the Environment.

——— (2004) “Trade, Growth, and the Environment,” *Journal of Economic Literature*, 42 (1), 7–71.

Costinot, Arnaud and Andrés Rodríguez-Clare (2014) “Chapter 4 - Trade Theory with Numbers: Quantifying the Consequences of Globalization,” in Gopinath, Gita, Elhanan Helpman, and Kenneth Rogoff eds. *Handbook of International Economics*, 4 of Handbook of International Economics, 197–261: Elsevier.

Crippa, Monica, Efisio Solazzo, Ganlin Huang et al. (2020) "High resolution temporal profiles in the Emissions Database for Global Atmospheric Research," *Scientific Data*, 7 (1), 121.

Cristea, Anca, David Hummels, Laura Puzzello, and Misak Avetisyan (2013) "Trade and the greenhouse gas emissions from international freight transport," *Journal of environmental economics and management*, 65 (1), 153–173.

Cui, Jingbo, Harvey Lapan, and GianCarlo Moschini (2016) "Productivity, Export, and Environmental Performance: Air Pollutants in the United States," *American Journal of Agricultural Economics*, 98 (2), 447–467.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum (2008) "Global Rebalancing with Gravity: Measuring the Burden of Adjustment," *IMF Staff Papers*, 55 (3), 511–540.

Dockery, Douglas W., C. Arden Pope, Xiping Xu, John D. Spengler, James H. Ware, Martha E. Fay, Benjamin G. Ferris, and Frank E. Speizer (1993) "An Association between Air Pollution and Mortality in Six U.S. Cities," *New England Journal of Medicine*, 329 (24), 1753–1759.

Duarte, Rosa and Ana Serrano (2021) "Environmental analysis of structural and technological change in a context of trade expansion: Lessons from the EU enlargement," *Energy Policy*, 150, 112142.

Eaton, Jonathan and Samuel Kortum (2002) "Technology, Geography, and Trade," *Econometrica*, 70 (5), 1741–1779.

EPA (2018) "Report on the Environment: Particulate Matter Emissions,"Technical report, U.S. Environmental Protection Agency.

EPA, US (2011) "Energy-Efficient Product Procurement: A Guide to Developing and Implementing Greenhouse Gas Reduction Programs,"Technical Report MSU-CSE-06-2, U.S. Environmental Protection Agency.

Farrokhi, Farid and Ahmad Lashkaripour (2021) "Can Trade Policy Mitigate Climate Change."

Forslid, Rikard, Toshihiro Okubo, and Karen Helene Ulltveit-Moe (2018) "Why are firms that export cleaner? International trade, abatement and environmental emissions," *Journal of Environmental Economics and Management*, 91, 166–183.

Frankel, Jeffrey A. and Andrew K. Rose (2005) "Is Trade Good or Bad for the Environment? Sorting Out the Causality," *The Review of Economics and Statistics*, 87 (1), 85–91.

Fu, Shihe, V. Brian Viard, and Peng Zhang (2022) "Trans-boundary air pollution spillovers: Physical transport and economic costs by distance," *Journal of Development Economics*, 155.

Greenstone, Michael (2004) "Did the Clean Air Act cause the remarkable decline in sulfur dioxide concentrations?" *Journal of Environmental Economics and Management*, 47 (3), 585–611.

Grossman, G. M. and A. B. Krueger (1993) "Environmental Impacts of a North American Free Trade Agreement.," in *The Mexico-U.S. Free Trade Agreement*: M.I.T. Press.

Hammer, Melanie S., Aaron van Donkelaar, Chi Li et al. (2020) "Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998-2018)," *Environmental Science and Technology*, 54 (13), 7879–7890.

Handley, Kyle, Fariha Kamal, and Ryan Monarch (2020) "Rising import tariffs, falling export growth: when modern supply chains meet old-style protectionism,"Technical report, National Bureau of Economic Research.

Hassler, John, Per Krusell, and Conny Olovsson (2012) "Energy-Saving Technical Change," Working Paper 18456, National Bureau of Economic Research.

He, Jie (2005) "Estimating the economic cost of China's new desulfur policy during her gradual accession to WTO: The case of industrial SO2 emission," *China Economic Review*, 16 (4), 364–402.

Heil, Mark T. and Thomas M. Selden (2001) "International Trade Intensity and Carbon Emissions: A Cross-Country Econometric Analysis," *The Journal of Environment and Development*, 10 (1), 35–49.

Heo, Jinhyok, Peter J. Adams, and H. Oliver Gao (2016) "Public Health Costs of Primary PM2.5 and Inorganic PM2.5 Precursor Emissions in the United States," *Environmental Science and Technology*, 50 (11), 6061–6070.

Hofmann, Claudia, Alberto Osnago, and Michele Ruta (2019) "The Content of Preferential Trade Agreements," *World Trade Review*, 18 (3), 365–398.

Jaffe, Dan, Theodore Anderson, Dave Covert et al. (1999) "Transport of Asian air pollution to North America," *Geophysical Research Letters*, 26 (6), 711–714.

Jia, Ruixue and Hyejin Ku (2019) "Is China's Pollution the Culprit for the Choking of South Korea? Evidence from the Asian Dust," *The Economic Journal*, 129 (624), 3154–3188.

Jung, Jaehyun, Anna Choi, and Semee Yoon (2022) "Transboundary air pollution and health: evidence from East Asia," *Environment and Development Economics*, 27 (2), 120–144.

Kim, Moon Joon (2019) "The effects of transboundary air pollution from China on ambient air quality in South Korea," *Heliyon*, 5 (12), e02953–e02953, 10.1016/j.heliyon.2019.e02953.

Kreickemeier, Udo and Philipp M. Richter (2014) "Trade and the Environment: The Role of Firm Heterogeneity," *Review of International Economics*, 22 (2), 209–225.

Lee, Hyung-Min, Rokjin J Park, Daven K Henze, Seungun Lee, Changsub Shim, Hye-Jung Shin, Kwang-Joo Moon, and Jung-Hun Woo (2017) "PM2. 5 source attribution for Seoul in May from 2009 to 2013 using GEOS-Chem and its adjoint model," *Environmental Pollution*, 221, 377–384.

Levinson, Arik (2009) "Technology, International Trade, and Pollution from US Manufacturing," *American Economic Review*, 99 (5), 2177–92.

——— (2015) "A Direct Estimate of the Technique Effect: Changes in the Pollution Intensity of US Manufacturing, 1990-2008," *Journal of the Association of Environmental and Resource Economists*, 2 (1), 43–56.

Levitt, Clinton J., Morten Saaby, and Anders Sørensen (2019) "The impact of China's trade liberalisation on the greenhouse gas emissions of WTO countries," *China Economic Review*, 54, 113–134.

Li, Quan and Rafael Reuveny (2006) "Democracy and Environmental Degradation," *International Studies Quarterly*, 50 (4), 935–956.

Limão, Nuno (2005) "Trade policy, cross-border externalities and lobbies: do linked agreements enforce more cooperative outcomes?" *Journal of International Economics*, 67 (1), 175–199, https://doi.org/10.1016/j.jinteco.2004.08.009.

Lin, Jintai, Da Pan, Steven J. Davis et al. (2014) "China's international trade and air pollution in the United States," *Proceedings of the National Academy of Sciences*, 111 (5), 1736–1741.

Liu, Junfeng, Denise L. Mauzerall, and Larry W. Horowitz (2009) "Evaluating inter-continental transport of fine aerosols:(2) Global health impact," *Atmospheric Environment*, 43 (28), 4339–4347.

Martin, L. A. (2011) "Energy efficiency gains from trade: greenhouse gas emissions and india's manufacturing sector," Mimeograph.

Melitz, Marc J. (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71 (6), 1695–1725.

Muller, Nicholas Z., Robert Mendelsohn, and William Nordhaus (2011) "Environmental Accounting for Pollution in the United States Economy," *American Economic Review*, 101 (5), 1649–75.

Nordhaus, William (2015) "Climate clubs: Overcoming free-riding in international climate policy," *American Economic Review*, 105 (4), 1339–70.

——— (2017) "Revisiting the social cost of carbon," *Proceedings of the National Academy of Sciences*, 114 (7), 1518–1523.

OECD (2012) *Mortality Risk Valuation in Environment, Health and Transport Policies*, 140.

Parry, Ian W.H., Dirk Heine, Eliza Lis, and Shanjun Li (2016) *Chapter 4. Measuring Pollution Damage from Fuel Use*, USA: International Monetary Fund.

Requia, Weeberb J. and Petros Koutrakis (2018) "Mapping distance-decay of premature mortality attributable to PM2.5-related traffic congestion," *Environmental Pollution*, 243, 9–16.

Reuther, C G (2000) "Winds of change: reducing transboundary air pollutants," *Environmental health perspectives*, 108 (4), A170–A175, `https://pubmed.ncbi.nlm.nih.gov/10753105`.

Shapiro, Joseph (2016) “Trade Costs, CO2, and the Environment,” *American Economic Journal: Economic Policy*, 8 (4), 220–54.

——— (2021) “The Environmental Bias of Trade Policy,” *The Quarterly Journal of Economics*, 136 (2), 831–886.

Shapiro, Joseph S. (2016) “Trade Costs, CO2, and the Environment,” *American Economic Journal: Economic Policy*, 8 (4), 220–54.

Shapiro, Joseph and Reed Walker (2018) “Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade,” *American Economic Review*, 108 (12), 3814–54.

Sheldon, Tamara L. and Chandini Sankaran (2017) “The Impact of Indonesian Forest Fires on Singaporean Pollution and Health,” *American Economic Review*, 107 (5), 526–29.

Taylor, M. Scott (2005) “Unbundling the Pollution Haven Hypothesis,” *Advances in Economic Analysis and Policy*, 4 (2).

Venables, Anthony (1999) *Regional Integration Agreements: A Force for Convergence or Divergence?*: The World Bank, 10.1596/1813-9450-2260.

Vennemo, Haakon, Kristin Aunan, Jianwu He, Tao Hu, Shantong Li, and Kristin Rypd3al (2008) “Environmental impacts of China’s WTO-accession,” *Ecological Economics*, 64 (4), 893–911.

Verstraeten, Willem W., Jessica L. Neu, Jason E. Williams, Kevin W. Bowman, John R. Worden, and K. Folkert Boersma (2015) “Rapid increases in tropospheric ozone production and export from China,” *Nature Geoscience*, 8 (9), 690–695.

Viscusi, W. Kip and Clayton J. Masterman (2017) “Income Elasticities and Global Values of a Statistical Life,” *Journal of Benefit-Cost Analysis*, 8 (2), 226–250.

Wang, Shaoda and Zenan Wang (2021) “The Environmental and Economic Consequences of Internalizing Border Spillovers,” Mimeograph.

Zhang, Qiang, Xujia Jiang, Dan Tong et al. (2017) “Transboundary health impacts of transported global air pollution and international trade,” *Nature*, 543 (7647), 705–709.

Zheng, Siqi, Jing Cao, Matthew E. Kahn, and Cong Sun (2014) “Real Estate Valuation and Cross-Boundary Air Pollution Externalities: Evidence from Chinese Cities,” *The Journal of Real Estate Finance and Economics*, 48 (3), 398–414.

Zhu, Xueqin and Ekko van Ierland (2006) “The enlargement of the European Union: Effects on trade and emissions of greenhouse gases,” *Ecological Economics*, 57 (1), 1–14.