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Jungho Lee
Shang-Jin Wei
Jianhuan Xu

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ABSTRACT

A current account surplus is associated with a welfare loss, according to the existing open-economy macroeconomics literature, only when there are distortions in either savings or investment. We propose a new source of welfare loss even in the absence of such distortions. In particular, a trade surplus, the largest component of a current account surplus for most countries, can alter the shipping costs and the composition of a country's imports and exports in ways that tend to raise the pollution level of the country. Thus, when a country's pollution tax is low, a trade surplus can produce a welfare loss outside the standard channels.

Jungho Lee
School of Economics
Singapore Management University
90 Stamford Road, Singapore 178903
jungholee@smu.edu.sg

Shang-Jin Wei
Graduate School of Business
Columbia University
Uris Hall 619
3022 Broadway
New York, NY 10027-6902
and NBER
shangjin.wei@columbia.edu

Jianhuan Xu
School of Economics
Singapore Management University
90 Stamford Road, Singapore
xujh03@gmail.com

1 Introduction

Current account imbalance is common in the data and sometimes a source of international frictions. Because it reflects a gap between a country's savings and investment, it is associated with a welfare loss in the standard open-economy macroeconomics only if distortions exist in either savings or investment. In this paper, we propose a new channel for such an imbalance to matter for welfare. The key idea is that a trade surplus, which is the largest component of a current account surplus for most countries, affects the unit shipping cost and alters the composition of a country's imports in a way that tends to lead to more pollution in the country, especially if its pollution tax is low. Thus, a trade surplus could produce a welfare loss even without distortions in the savings or investment level *per se.* This finding suggests a novel reason for surplus countries such as China, South Korea, Russia, and Malaysia to consider the interaction between external imbalance and a domestic environmental standard.

As a byproduct of our mechanism, we provide a new explanation for why certain countries with a large trade surplus, such as China, import so many heavy goods (i.e., goods with a high weight-to-value ratio). Whereas the weight-to-value ratio for import bundles for the world as a whole is 0.22 kg per dollar, the ratio for China is more than twice as high, at 0.46 kg per dollar. Relatively heavy products include industrial scraps and waste, such as scrap metal and discarded glass. Indeed, China was the largest importer of waste products in the world (until its government banned waste imports in 2018).[1] In 2016, waste-products imports included 45 million tons of scrap metals, used textile and fibers, waste paper, and used plastics worth over 18 billion USD.[2] Our mechanism suggests that China simultaneously running the largest trade surplus in the world and being the most voracious importer of industrial scrap is not a

[1]Incidentally, the Chinese ban on imports of many industrial waste products since early 2018 has generated a mini-crisis in many countries that had previously grown accustomed to shipping industrial scraps and waste to China.

[2]We define the waste products as HS 6-digit product lines that contain either "scrap" or "waste" in their descriptions.

coincidence.[3]

This paper proceeds in three parts. In the first part, we study how a country's trade surplus reduces the unit shipping cost of inbound trade, and how that reduction in turn alters the composition of the country's imports. We provide both a simple model and statistical evidence. A key observation is that a country's trade surplus increases the likelihood of ships returning to the country being under their full carrying capacity (De Palma et al. (2011) and De Oliveira (2014)). This imbalance reduces the unit shipping cost for the country's imports, making importing relatively heavy goods relatively cost effective. Conversely, deficit countries have a comparative advantage in exporting relatively heavy goods. These patterns hold not only across countries, but also across port cities in China. By our estimation, if a good's weight-to-value ratio is higher by 10%, its elasticity of imports to trade surplus increases by 0.12%.

In the second part of the paper, we explore some novel implications of this insight. In particular, we show that polluting industries (e.g., ceramics, cement, copper wire production) tend to use more heavy inputs (including but not restricted to recycled scrap metals and other industrial waste). As a result, by making the inputs cheaper for the polluting industries, a greater trade surplus alters a country's comparative advantage toward a more polluting production structure.

In the third part, we construct a quantitative model to evaluate the welfare effect of a trade surplus. The model features an endogenous response of the unit shipping cost to a trade surplus, which lowers the input costs of the relatively polluting industry and ultimately increases the overall consumption relative to a world in which the shipping cost does not respond to a trade surplus. The gain in utility from more consumption, however, is more than offset by a reduction in utility due to the additional pollution. The net effect of allowing the

[3]Kellenberg (2010) also relates the endogenous transport cost to Chinese waste import, but is silent about the mechanism behind the phenomenon. We provide a broader picture behind Chinese waste import, and develop a quantitative model for policy and welfare evaluation.

shipping cost to respond to a trade surplus is a welfare loss of around 4%.

We also use the quantitative model to perform policy experiments. We find that a ban on the import of foreign scraps – a policy experiment that is similar to the Chinese policy in place since 2018 – could increase welfare by making the inputs to the production of pollution more expensive, hence reducing the level of production in that sector. However, a direct increase of the pollution tax is far superior to an import ban on foreign scraps. The reason is intuitive and holds important implications for policy design: if the only market failure is a negative externality in pollution, an optimal tax on pollution can directly close the gap between the social and private costs of pollution. By contrast, banning imported scraps, such as what China does, is less effective, partly because imported industrial scrap can be substituted by both domestic industrial scrap and imported non-scrap heavy inputs.

This paper contributes to the literature in four ways. First, we suggest a novel channel for a trade surplus to be socially inefficient. In particular, a trade surplus, by altering the unit shipping costs, induces additional imports of heavy products and lowers the input costs for the polluting industries. This mechanism tends to lead to more pollution in the trade-surplus country, especially if it has a low environmental standard or weak enforcement. By contrast, the existing literature on the efficiency consequences of the trade imbalance focuses on the terms-of-trade channel (Dekle et al. (2007) and Epifani and Gancia (2017)). The welfare effect of the trade surplus comes from either frictions on the capital market or in the savings decision. By contrast, in this paper, a trade surplus magnifies a negative externality in pollution through an endogenous response of the shipping cost and the import composition to a trade surplus. Distortions in the level of saving or investment are not necessary for a trade surplus to generate a welfare loss.

The second contribution of the paper is to provide a framework to evaluate various corrective policies in this context. In particular, we find that the dramatic policy we observe in practice − a ban on imports of industrial scraps implemented by China − is inferior to increasing domestic pollution taxes. The reason for the shortcoming of the Chinese policy is also transparent in the model − not accounting for substitution between domestic and imported industrial scraps and substitution between non-scrap heavy material and imported scraps.

Third, although a large literature studies interactions between trade and environment (see surveys by Frankel (2009), Kellenberg (2009), Kellenberg (2012), and Lan et al. (2012), respectively), it does not make a connection between a trade imbalance, import composition, and the environment. We contribute by proposing a new chain of linkages from a trade imbalance to a worse environmental outcome. Those developing countries that simultaneously have a weak pollution-control regime and a trade surplus might experience especially adverse pollution effects.

Finally, our paper enriches a literature on endogenous transportation costs. Hummels and Skiba (2004) and Lashkaripour (2015) emphasize that unit weight is an important feature in international shipping, whereas Djankov et al. (2010) and Hummels and Schaur (2013) study the effect of shipping time on trade cost. However, these papers do not consider a trade imbalance a determinant of the shipping cost or a source of comparative advantage. Behrens and Picard (2011), Friedt and Wilson (2015), Jonkeren et al. (2010), Wong (2019), and Brancaccio et al. (2019) relate shipping cost to trade balance. Building on and going beyond this insight, we show, both analytically and empirically, that this change in the shipping cost disproportionately favors heavy products. In addition, as far as we know, we are the first to build a connection between the endogenous shipping-cost channel and the welfare consequences for the importing country via a new pollution channel.

The paper is hereafter structured in three parts. In the first part, we aim to establish a relationship between a country's trade imbalance and import composition. In the second part, we show that a country with a trade surplus tends to generate more pollution. In the third part, we develop a model and discuss welfare and policy implications.

2 Trade Imbalance and Import Composition

In this section, we show that if the shipping cost depends on a good's weight, a modified gravity equation predicts that the import composition systematically depends on the trade imbalance.

2.1 The logic

The reasoning can be explained via two equations. We use i to denote goods, and n and d to denote the origin and destination country, respectively. We start from the following gravity equation at the sector (or product) level:

$$X_{i,nd} = \frac{(\tau_{i,nd} p_{i,n})^{1-\sigma}}{A_n} \alpha_{i,d} E_d.$$

$X_{i,nd}$ is the amount of import of good i from country n by country d. $p_{i,n}$ is the free-on-board (FOB) price of good i from country n, and $\tau_{i,nd}$ is the corresponding trade cost per value of good i from country n to country d. Hence, $\tau_{i,nd} p_{i,n}$ is the price per unit of good i paid by a consumer in the destination country. The demand elasticity with respect to price is captured by $1 - \sigma$. E_d is the total expenditure of destination country d, and $\alpha_{i,d}$ is the share of the expenditure on good i in country d. A_n captures "capabilities" of exporters from country n as a supplier to all destinations.

The trade cost per value $\tau_{i,nd}$ is assumed to have two components: an iceberg component $g_{i,nd}$, which is the per-value cost, such as the trade tariff, and a non-iceberg cost $c_{i,nd}$, which is the per-unit cost. Then, the trade cost per value $\tau_{i,nd}$ can be written as

$$\tau_{i,nd} = g_{i,nd} + \frac{c_{i,nd}}{p_{i,n}}.$$

We assume

$$c_{i,nd} = \lambda_{nd} w_{i,n},$$

where $w_{i,n}$ is the weight per unit of good i produced by country n, and λ_{nd} is the shipping cost per unit of weight when delivering a good from n to d.[4] Notice we assume the shipping firm does not distinguish the goods it delivers but only charges a shipping fee by the weight of the goods. We then get

$$\tau_{i,nd} = g_{i,nd} + \lambda_{nd}\left(\frac{w_{i,n}}{p_{i,n}}\right). \tag{1}$$

The iceberg portion of the shipping cost is standard in the literature. The second component in the shipping cost says that the per-value shipping cost equals the per-weight shipping cost times the weight-to-value ratio. Although the last component is somewhat non-standard, it has an intuitive explanation: if the cargo is heavier, it would use more fuel in transportation, and a profit-maximizing shipping company would naturally charge a higher shipping fee.[5] We assume the weight-to-value ratio is an exogenous property of the goods. We discuss and justify this assumption when we introduce our empirical measure of the weight-to-value ratio by product.

From equation (1) and the gravity equation, we can see that if λ_{nd} decreases, the import of heavy goods (those with a high weight-to-value ratio) will increase relatively more than the import of light goods (those with a low weight-to-value ratio) because heavy goods enjoy a

[4]Hummels and Skiba (2004) point out that the shipping cost is correlated with the goods weight per unit.

[5]From speaking to firms that engage in trading in heavy goods, we learn shipping companies usually put a weight limit per container. For example, if a company ships scrap copper, which is relatively heavy, each container is only about one third full to satisfy the weight restriction. This weight restriction is approximately the same as charging a shipping fee in proportion to the weight of the cargo.

disproportionately larger decline in the trade cost. We summarize our finding in the following proposition:

Proposition 1. *If λ_{nd} decreases, the import of heavy goods will increase relatively more than the import of light goods, because the heavy goods enjoy a disproportionately larger decline in the trade cost.*

To relate Proposition 1 with the trade surplus, we make the following assumption.

Assumption 1. *A larger trade surplus tends to lead to a lower import shipping cost per weight.*

Assumption 1 is motivated by "backhaul problem," widely known in the transportation literature. Given that ships must come back after unloading their original cargo at the destination country, an opportunity cost is associated with the backhaul trip with cargo that is under capacity. To avoid this backhaul problem, a shipping company tries to balance in shipping weight (or volume) in both directions by adjusting freight rates. Behrens and Picard (2011) formalize this idea by endogenizing transportation costs through a market mechanism in a model of trade and geography. Their model predicts the growing trade surplus of China with the US will lead to a reduction in the shipping cost from the US to China.[6] Empirically, a causal effect of trade surplus on the inbound shipping cost is estimated by Jonkeren et al. (2010) (for northwestern European inland waterways) and Wong (2019) (for containerized US trade). In section 2.3.1, we additionally document a causal effect of trade surplus on the inbound shipping cost across the world.

Combining Proposition 1 with Assumption 1, we have the following proposition.

Proposition 2. *A country tends to import more heavy goods if it runs a larger trade surplus.*

[6] Related, Ishikawa and Tarui (2018) investigate the implication of asymmetric shipping cost (induced by the backhaul problem) on industrial policies such as tariff.

2.2 Data

The Weight-to-Value Ratio

We wish to extract information on the weight-to-value ratio for each HS 6-digit product from customs data. However, most countries do not report product-level weight information, making computation of the weight-to-value ratio impossible. Fortunately, the National Tax Agency of Colombia does report both the weight and FOB value of imports by product. Using these data, for each HS6 product, we compute the average weight-to-value ratio.[7] To give some concrete examples, we list the top five and bottom five products in terms of the weight-to-value ratio in Table 1.

Note we assume the weight-to-value ratio is an exogenous characteristic of the goods. To investigate the validity of this assumption, we look at the Chinese customs data. In the Chinese customs data, the weight-to-value ratio can be computed for 3,349 goods (about 60% of all HS6 goods). For these products, we find the correlation in the weight-to-value ratios computed from the Colombian and Chinese data is 0.75. Furthermore, we find the weight-to-value ratio is highly persistent over time in both datasets. For example, the auto-correlation in the weight-to-value ratio between two adjacent years is 0.98 in the Chinese customs data. Based on these findings, we believe the assumption that the weight-to-value ratio is an exogenous characteristic of goods is justified. In any case, in all subsequent regression analysis, to further enhance the credibility of the exogeneity assumption, we use the weight-to-value ratio extracted from the Colombian data but exclude from the regression sample all country pairs that involve Colombia as either an exporter or an importer.

[7] We thank Ahmad Lashkaripour for sharing these data.

Shipping Costs

We obtain port-to-port 20-foot dry-container freight rates over 2010-2017 for 128 major routes (64 country pairs in two directions) from Drewry, which is a shipping consulting firm. A 20-foot dry container has a cubic capacity of 33.2 m^3 and a payload (weight) capacity of 25,000kg per container.[8]

For all countries except three (US, China, and Canada), the Drewry covers one major port. For the US, China, and Canada, where two ports are available, we use Los Angeles, Shanghai, and Vancouver, respectively. For the shipping rate from Port A to Port B in a given year, we use the container freight rate in July of that year.[9]

Trade Data

We employ two datasets on trade. First, the bilateral trade data at the HS 6-digit level between 64 country-pairs (in both directions) from 2010-2017 are obtained from the UN Comtrade Database. Second, the data on exports and imports at the HS 6-digit product level for individual Chinese ports during 2000-2006 are obtained from the Chinese customs database.

2.3 Empirical Evidence

We test the theoretical prediction in section 2.1 in two steps. First, we check whether the data support a negative relationship between a country's trade surplus and the back-haul shipping

[8]Source: DSV Global Transport and Logistics. Although the Drewry data are a small part of our overall data, they are the most expensive part. For a detailed discussion of Drewry data, see Wong (2019).

[9]The first year for which the freight rate information is available differs across routes. The ISO country codes for the 64 country-pairs are as follows: ARE-CHN, CAN-AUS, AUS-CHN, AUS-GBR, AUS-JPN, AUS-KOR, AUS-USA, BRA-CAN, BRA-CHN, BRA-GBR, BRA-IND, BRA-JPN, BRA-KOR, BRA-USA, BRA-ZAF, CAN-CHN, CAN-GBR, CAN-IND, CAN-KOR, CAN-ZAF, CHN-CHL, CHL-GBR, CHN-COL, CHN-EGY, CHN-GBR, CHN-IND, CHN-IDN, CHN-JPN, CHN-KOR, CHN-MYS, CHN-NZL, CHN-PHL, CHN-RUS, CHN-SAU, CHN-THA, CHN-TUR, CHN-USA, CHN-VNM, CHN-ZAF, GBR-COL, CBR-IND, GBR-JPN, GBR-KOR, GBR-TUR, GBR-USA, GBR-SZF, JPN-IND, JPN-IDN, IND-KOR, IND-USA, KOR-JPN, JPN-NZL, JPN-THA, JPN-USA, KOR-USA, KOR-ZAF, MEX-USA, MYS-USA, NZL-USA, PHL-USA, RUS-USA, THA-USA, TUR-USA, USA-ZAF.

cost. Second, we check whether the elasticity of imports with respect to shipping cost is systematically bigger for products with a high weight-to-value ratio.

2.3.1 Shipping Cost and Trade Imbalance

Consider the following equation:

$$\ln(\text{Shipping cost}_{ndt}) = \alpha_0 + \alpha_1 \ln(\text{Imbalance}_{ndt}) + \Omega_{\overleftrightarrow{nd}} + \eta_{nt} + \eta_{dt} + e_{ndt}, \tag{2}$$

where n and d are the origin and destination countries, respectively. Imbalance_{ndt} is the trade surplus country d runs against country n in year t, measured by $\text{Export}_{ndt}/\text{Import}_{ndt}$ $= \text{Import}_{dnt}/\text{Import}_{ndt}$, where Import_{dnt} is country n's import from country d (or country d's export to country n) and Import_{ndt} is country d's import from country n. $\Omega_{\overleftrightarrow{nd}}$ is an origin-destination pair-specific component that affects the shipping cost for both directions, such as distance. This fixed effect does not distinguish between the two directions of the route. η_{nt} and η_{dt} are the origin-year pair and destination-year pair fixed effects, respectively, which are meant to absorb time-varying aggregate supply or demand shocks in the exporting and importing countries. e_{ndt} is an i.i.d. random component with a zero mean. The key coefficient of interest is α_1, which measures the responsiveness of the shipping cost to a trade imbalance.

Although container trade consists of the majority of international trade, some goods such as oil or ores are shipped in bulk rather than in containers. Throughout the paper, we remove non-metal ores (2 digit HS code 25), metal ores (2 digit HS code 26), and oil and gas (2 digit HS code 27) to calculate the trade imbalance.

An important challenge is that a bilateral trade imbalance may endogenously respond to the shipping cost. For example, if country d's trade surplus against country n initially causes the shipping cost from country n to country d becomes lower, country d will increase its imports from country n, causing the initial trade surplus to diminish or disappear. In addition, factors can exist that simultaneously affect both the shipping costs and bilateral trade balance. The endogeneity problem will make observing a negative relationship in an OLS regression harder. We need to have an instrumental variable approach.

To address the possible endogeneity of bilateral trade balance, we use the two countries' relative government spending as an instrumental variable. More specifically, we construct an instrumental variable for Imbalance_{ndt} by the following:

$$\Big\{\Big(\frac{\text{Import}_{nd2000}}{\text{Import}_{d2000}}\Big) \times \text{Gov}_{dt}\Big\}\Big/\Big\{\Big(\frac{\text{Import}_{dn2000}}{\text{Import}_{n2000}}\Big) \times \text{Gov}_{nt}\Big\}, \tag{3}$$

where Import_{nd2000} is country d's import from country n in 2000, Import_{d2000} is country d's aggregate import in 2000, and Gov_{dt} is county d's government expenditure in year t. Import_{dn2000}, Import_{n2000}, and Gov_{nt} are similarly defined. We interact the government expenditure with the import share of the partner country in 2000 to construct the partner-specific measure.

The idea is that a change in a country's government expenditure is likely to induce a change in its national savings. (The empirical literature on fiscal multipliers suggests the Ricardian equivalence does not hold in the data, and a change in the public-sector savings is unlikely to be offset by a change in the private-sector savings in the opposite direction.) An increase in government expenditure (or a decline in the public savings) is not only unlikely to be offset by a decline in the national investment, but is also likely to be accompanied by an increase in investment. Because a country's trade balance is its savings minus investment, a change in the two countries' government expenditure leads to a change in the two countries' savings level, and would therefore likely affect the bilateral trade balance. On the other hand, a country's government expenditure is unlikely to directly affect the bilateral trade cost. The literature on public spending provides several determinants of government expenditure (e.g., political ideology), but none of them, to our knowledge, is correlated with bilateral shipping cost (see, e.g., Facchini (2018)).

We first report the basic OLS result is reported in the first column of Table 2. Although the negative estimate of α_1, at -0.019, is consistent with Assumption 1, the estimate is not statistically significant.

In the second column of Table 2, we report the estimates from the IV regression. In the first stage, we regress the log trade imbalance on the log of government expenditure constructed in (3). The coefficient before the government expenditure is about -0.43 and significant at the 1% level, suggesting that when the government d's expenditure increases by 1%, its trade imbalance (export/import) would decrease by 0.43%. The F-statistic is around 69 in the first-stage regression. The second-stage result with the IV regression is reported in the second column of Table 2. The IV estimate of α_1 is negative and statistically significant: an increase in country d's trade surplus against country n by 10% would lead to a 1.77% decline in country d's import shipping cost.

Discussion on multi-routes arrangement

A complication is that if country A runs a surplus against country B, ships from A to B do not need to go back to A right away. Consider an extreme example: suppose A runs a surplus against B, B runs a surplus against C, and C runs a surplus against A, and each country has a balanced overall trade. In this case, a ship can travel from A to B, B to C, and C to A, while always carrying a full load in each route. This multi-routes arrangement would weaken the shipping-cost response to bilateral surplus.

We address this concern in the following way. First, we note that contracting frictions often make complicated re-routing difficult to arrange. As Brancaccio et al. (2019) document, satellite tracking of ships often finds empty ships leaving a port to go to the next port, suggesting the existence of non-trivial contracting frictions. Indeed, if multi-country rerouting could always be arranged to avoid seafaring ships below their full carrying capacity, we would not have observed a negative relationship between the shipping cost and trade imbalance as reported in the first two columns of Table 2.

Second, we zoom in on those country pairs involving one running a surplus against most trading partners and another running a deficit against most of its trading partners. These country pairs are labeled as pervasive imbalanced pairs. For an importing country in such pairs, using a multi-port route arrangement to avoid having relatively empty ships come back to its ports would be hard. Similarly, for an exporting country in such pairs, having relatively empty ships leaving its port to other countries would be hard to avoid. When such two countries are paired, the likelihood that relatively empty ships will travel from the pervasive deficit country to the pervasive surplus country is stronger. If our endogenous shipping-cost story is correct, the elasticity of the shipping cost to the trade imbalance should be greater for these country pairs.

We create a dummy ("pervasive route") for such country pairs, and add an interaction term between the dummy and the size of the bilateral imbalance. We report the result in column 3 of Table 2. The coefficient on the interaction term is negative and statistically significant. For country pairs that do not feature a pervasive imbalance, the elasticity of the shipping cost with respect to the trade imbalance is -0.007, but for country pairs involving a pervasive imbalance, the elasticity increases dramatically to -0.089 (= -0.082-0.007). These results support the interpretation that a trade surplus tends to reduce the unit shipping cost on the import side, and the effect is much stronger for countries with a pervasive trade surplus.

2.3.2 Import Elasticity with Respect to Shipping Cost

The novel prediction in Proposition 1 is that the heavy-goods imports as a share of the total imports increase when the shipping cost decreases. To test this prediction, we consider the following equation:

$$\ln(\text{Import}_{i,ndt}) = \beta_0 \ln(\text{Shipping cost}_{ndt}) + \beta_1 \ln(\text{Shipping cost}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right) + \eta_{i,nt} + \eta_{i,dt} + \epsilon_{i,ndt}, \tag{4}$$

where n and d are the origin and destination countries, respectively, i refers to a HS 6-digit product, $\frac{w_i}{p_i}$ is the weight-to-value ratio of good i, $\eta_{i,nt}$ ($\eta_{i,dt}$) is the origin-good-year (destination-good-year) fixed effect, and $\varepsilon_{i,ndt}$ is an random component with a zero mean.[10] We allow $\varepsilon_{i,ndt}$ to be correlated among the same good across countries, different goods in the same destination country, and different goods in the same origin country.

The first column of Table 3 reports the benchmark result for equation (4). β_0 is -0.711 and statistically significant at the 1% level, which means the import of good i from country A would be 7.11% larger than from country B if the shipping cost from country A is 10% lower than from country B. More importantly, β_1 is -0.062 and statistically significant at the 1% level. This finding suggests shipment of relatively heavy goods is more responsive to a given decline in the unit shipping cost than that of relatively light goods. The import elasticity with respect to the shipping cost is 0.62% higher for good i than for good j if the weight per value of good i is 10% greater than good j.

If importation of a good requires a fixed cost, a more permanent reduction in the shipping cost may elicit a stronger response in the import pattern than a transitory change in the shipping cost. To investigate this possibility, we create a dummy variable, "Persist," for country pairs whose bilateral trade imbalance takes on the same sign (e.g., the importing country always runs a bilateral surplus) at least during the three years from 2015 to 2017. In the second column of Table 3, we add a triple-interaction term among the "persist" dummy

[10] We assume the weight-to-value ratio is a physical feature of a product and does not depend on the origin or destination country. In the data section, we provide evidence that this assumption is reasonable. Nonetheless, in the regression table, we present results when this assumption is relaxed.

(for the country pair), the shipping cost (for the bilateral route), and the log weight-to-value ratio (for the imported product). The coefficient on the triple interaction is negative and statistically significant. This finding suggests the effect of a change in shipping costs on the composition of imports is indeed more pronounced for country pairs that feature an importing country running a persistent surplus against the exporting country.

The regressions so far already control for origin-good-year fixed effects and destination-good-year fixed effects. Still, some trade costs such as tariff rates can potentially vary by origin-destination pair or by time. Also, the weight-to-value ratio of the good could depend on the characteristics of the importing countries. For example, richer countries may import higher-quality varieties for a given HS 6-digit product. Assume the weight-to-value ratio has two components: the first one is a physical feature that depends on the product but not on country identity, and the second one depends on the importing country's income (and other features). Then, we also need to control for origin-destination-year variations.

We show the result of the ambitious set of control variables, including origin-destination-year fixed effects, in the third column of Table 3. Such an extension would not allow us to identify the coefficient before the shipping-cost variable, because it is absorbed by the newly added fixed effects. Importantly for us, we find that with this additional and demanding set of controls, the key coefficient for the interaction term between a product's weight-to-value ratio and the shipping cost remains negative and statistically significant. This finding suggests the notion that a given decline in the shipping costs favors the shipment of relatively heavy goods is a robust feature of the data.

By controlling for origin-destination-year fixed effects, we also address possible endogeneity of the shipping cost. Once we control for origin-destination-year fixed effects, a sufficient condition for the consistent estimate for β_1 is that $\ln\left(\frac{w_i}{p_i}\right)$ and $\epsilon_{j,ndt}$ are independent for all i and j. Given that we use the weight-to-value ratio from Colombian data and exclude any country pairs that involve Colombia as either an exporter or an importer, we believe the identifying assumption is reasonable. Note that under our identifying assumption, the estimate for β_1 is significantly negative.

In the fourth column of Table 3, we use log imbalance as a proxy for log shipping cost to test the prediction of Proposition 2. The coefficient estimate for $\ln(\text{imbalance}) \times \ln\left(\frac{w}{p}\right)$ is 0.012 and significant at the 1% level. This result is consistent with the prediction of the Proposition 3. A greater trade surplus tends to alter the composition of imports toward heavier goods.

By combining the estimates in equations (2) and (4) ($\hat{\alpha}_1 \times \hat{\beta}_1$), we see the trade-imbalance and shipping-cost channel explains a substantial portion of the variations in the relative import value of heavy versus light goods.[11]

To summarize, the shipping cost is indeed negatively related to the trade imbalance. Moreover, a given reduction in the shipping cost benefits the heavy goods more than the light goods as predicted by Proposition 1. This conclusion holds after controlling for a large number of fixed effects, and accounting for possible endogeneity of the trade imbalance. Finally, the trade imbalance affects the composition of imports mostly through its impact on the shipping cost of the importers.

2.3.3 Port-level Evidence

In the cross-country evidence reported above, unmeasured time-varying country-pair features can, in principle, be correlated with unit shipping costs. In this subsection, we explore variations across ports within a country. Specifically, we use port-level trade data of the Chinese customs from 2000-2006 as a robustness check. Under the assumption that the comparative advantage is similar across different ports within a country, this exercise should help alleviate concerns of a possible correlation between bilateral shipping costs and unobserved country-level

[11]For instance, take the estimates of the second columns in the Table 2 and Table 3, $\hat{\alpha}_1 \times \hat{\beta}_1 = -0.177 \times -0.06 = 0.011$. It is approximately the same magnitude as column 4 of Table 3.

comparative advantage.

In the Chinese customs data, for a given pair of port and HS6 good and a given trading partner, we sum up all bilateral imports and bilateral exports in a year, respectively. For example, we know Shanghai port's total exports to the US by product, and the same port's total imports from the US by product.[12]

The gravity equation to be estimated is as follows:

$$\begin{aligned}\ln(\text{Import}_{i,mnt}) =& \beta_0 \ln(\text{Imbalance}_{mnt}) + \beta_1 \ln(\text{Imbalance}_{mnt}) \times \ln\left(\frac{w_i}{p_i}\right) \\ &+ \eta_{i,mt} + \eta_{i,nt} + \varepsilon_{i,mnt}, \qquad (5)\end{aligned}$$

where m denotes a port in China, and $\text{Import}_{i,mnt}$ is the dollar value of good i's import into port m from country n. Imbalance_{mnt} is the ratio of total exports from port m to country n to the total imports into port m from country n. $\eta_{i,mt}$ and $\eta_{i,nt}$ are port-product-year and origin-product-year fixed effects, respectively. The key parameter of interest is β_1. If a greater port-level trade surplus leads to relatively more port-level imports of heavy products, we expect $\beta_1 > 0$.

Table 4 reports the estimation results. In the first column, where we control for both product-port-year triplet fixed effects and product-exporter-year triplet fixed effects, β_1 is estimated to be 0.0095 and statistically significant at the 1% level. That is, the import elasticity with respect to the trade imbalance is higher for heavier products. In the second column, where we also control for port-exporter-pair fixed effects, β_1 is estimated to be 0.0064 and statistically significant. These estimates provide confirmation of our mechanism at the level of ports within a country even after we control for a large number of relatively demanding fixed effects.

[12]More details of the port trade data are provided in Appendix B.

3 Application: Trade Surplus and Pollution

In this section, we investigate the relationship between the trade imbalance and pollution. First, we show a connection between pollution intensity of the industries and their relative dependence on heavy goods as inputs. Next, we show the relative size of polluting industries in an economy tends to expand in times of a larger trade surplus. This finding is consistent with the first data pattern, because the inputs used more intensively in the polluting industries (i.e., relatively heavy inputs) tend to be cheaper in times of a larger trade surplus. We use variations within China and over time to investigate these data patterns.

3.1 Heavy Inputs and Polluting Output

We measure each sector's input heaviness via a two-step procedure. First, we map every 6-digit HS commodity to industrial sector classification in China's 2012 input-output table. Second, we estimate the weight-to-value ratio of the intermediate input bundle for each industry by combining sector-level weights on each input implied by the input-output table and the product-level weight-to-value ratio extracted from the Colombian customs data. The details of the estimation are reported in Appendix C.

We measure each Chinese industry's output pollution intensity based on the data from the World Bank's Industrial Pollution Projection System (IPPS), which covers emissions of three main pollutants, namely, SO2, NO2, and total suspended particles (TSP). In particular, for each sector, we compute ratios of SO2, NO2, and total suspended particles (TSP) emission per dollar value of output, respectively.[13]

Table 5 reports the correlation between sector-level output-pollution-intensity measures and the sector-level weight-to-value ratio of the intermediate input bundle. The correlation is

[13] These data were assembled by the World Bank using the data from the US Environmental Protection Agency (EPA) emissions database and manufacturing census. See Bombardini and Li (2016) for more details of this dataset.

positive and statistically significantly different from zero for each of the three pollutants. This finding suggests industries using heavier inputs tend to be more polluting in their output.

An example of a polluting sector is one that uses industrial wastes. Most industrial waste goods have a relatively high weight-to-value ratio. Figure 1 plots the density of the weight (kg)/value (US dollar) ratio for waste goods (the solid line) and for other goods (the dashed line). On average, the weight-to-value ratio of non-waste goods is much lower, about 0.1 kg/USD. By contrast, waste goods are much heavier, with the peak of its density at about 1 kg/USD. Recycling of waste and scrap products often involves more pollution and more unhealthy consequences than other imports. For example, imported waste products are often dirty, poorly sorted, or contaminated with hazardous substances. The problem is worse if the importer is a developing country. A film, "Plastic China," shows the environmental damage caused by the country's plastic-recycling industry, which is dominated by many small-scale outfits that often lack proper pollution controls.[14]

3.2 Trade Surplus and Expansion of Polluting Industries

If a greater trade surplus leads to lower prices of relatively heavy inputs, which favor polluting industries, the previous insight would imply an expansion of the relative size of the polluting industries in times of a greater trade surplus. We now investigate this prediction using Chinese data. In particular, we estimate the following equation:

$$\ln(\text{Output}_{i,t}) = \beta_1 \ln(\text{Imbalance}_t) \times \text{Polluting-sector}_i + \eta_i + \eta_t + \epsilon_{i,t}. \tag{6}$$

$\text{Output}_{i,t}$ is industry i's total sales in year t. Imbalance_t is China's trade imbalance in year t measured by the ratio of China's exports to imports. $\text{Polluting-sector}_i$ is an indicator variable

[14]The negative health effect of waste management has been pointed out in the medical research, such as Rushton (2003).

that equals 1 if the industry's pollution intensity in terms of SO2 emission is above the median level, and 0 otherwise. (We have conducted similar exercises with NO2 and TSP pollution measures, and find similar results. We omit these results to save space.)

In all specifications, we control for the industry fixed effects and year fixed effects. We use the industry output data from year 1999-2017. Each industry i is a 4-digit CSIC industry. All standard errors are clustered at the industry level.

In the first column in Table 6, the coefficient on the interaction term is 0.905 and statistically significant. Therefore, an increase in the trade imbalance tends to be associated with an expansion of the more polluting industries relative to other industries. In the second column, we add $\ln(\text{Imbalance}_t) \times \text{Heavy-sector}_i$ as an additional regressor, where Heavy-sector_i is an indicator variable for industries whose input bundles are heavier than the median value across industries. In this case, the coefficient for the new regressor is 0.921 and statistically significant, whereas the point estimate for $\ln(\text{Imbalance}_t) \times \text{Polluting-sector}_i$ becomes smaller and loses statistical significance. In other words, the effect of a larger trade surplus on the sector composition of the aggregate output comes primarily through favoring those industries with heavy inputs.

One may be concerned with possible endogeneity of the trade imbalance. For example, common missing factors may exist that simultaneously affect the size of the trade balance and the relative size of the pollution-intensive sectors. Given that we control for the year fixed effects, a sufficient condition for the identification of β_1 is that $\text{Polluting-sector}_i$ and $\epsilon_{j,t}$ are independent for all i and j. Note we use the World Bank data, which is based on the US emission database, to construct the polluting-sector dummy. One might worry that pollution intensity in the US may be correlated with China's domestic output through specialization between the US and China. To address this concern, we check the correlation for the industry-level pollution intensity of each pollutant between 1990 and 2000. The correlation for SO2, NO2, and TSP are 0.98, 0.94, and 0.90, respectively. In other words, the industry-level pollution intensity rarely changed over a 10-year period. This finding suggests the pollution intensity of an industry is a rather fixed characteristic. Given that the pollution intensity of an industry is likely to be exogenous, we consider our identifying assumption reasonable.

3.3 Welfare Loss from Trade Surplus

In the previous section, we show that an increase in the trade surplus leads to an increase in the imports of heavy goods and a relative output expansion of pollution-intensive sectors. Strong environmental regulation can potentially mitigate the pollution consequence of a larger trade surplus. However, in Appendix D, we find the extra pollution induced by heavy-goods (or waste-goods) processing does not seem to be met by a tougher environmental regulation in those countries. In general, the strength of environmental regulation is not correlated with the share of heavy-goods imports or the level of the trade imbalance across countries. In such a setting, a trade surplus may bring on a welfare loss via additional imports of heavy goods and additional pollution.

Perhaps seeing a connection between imports of industrial waste and pollution, the Chinese government began in 2018 to ban imports of certain industrial scraps with a plan to eventually ban more scrap imports. Is such a ban socially efficient? Can the problem be addressed in a better way? We address these questions through the lens of a quantitative model in the next section.

4 A Quantitative Model and Policy Evaluations

We now use a model to evaluate the welfare effects of various policies including a ban on imports of industrial waste, which is motivated by a relatively new policy introduced by China in 2018. Unlike the empirical analysis, the model allows us to conduct counterfactual thought experiments that take into account possible endogenous responses by both the quantity of domestically generated scrap goods and imports of non-scrap heavy goods. In addition, the model allows us to make welfare statements about various policies.

The model economy features three types of intermediate inputs in production: (recycled) scrap goods, (non-scrap) heavy material, and light material. The light material represents all intermediate inputs that would not generate pollution in the production process. Both (recycled) scraps and (non-scrap) heavy material can generate pollution when used as intermediate inputs. We separate heavy material from scraps for two reasons. First, not all pollution-generating intermediate inputs in the data are (recycled) industrial scraps. Second, because China has introduced a ban on the imports of industrial scraps but not other pollution-generating material, we would like to allow for substitution between industrial scraps and other pollution-generating material in the policy simulations. For concreteness, we calibrate the model to certain features of the Chinese economy, and, for simplicity, assume all international variables are exogenous to the home economy.

4.1 Consumer problem

The home country is populated by identical consumers of measure L. The agent can live two periods $t = 1, 2$ (young and old). In the first period, the agent supplies one unit of labor inelastically and can save through the international capital market with an exogenous interest rate R. In the second period, the agent retires and uses the savings to consume.

The representative consumer's utility is $\ln c_1 + \rho \ln c_2 - \eta x_1$. c_1 and c_2 are the consumption levels in the two periods, and ρ is the discount factor. x_1 is the pollution in the first period and η measures disutility per unit of the pollution. Because the agent does not supply any labor in the second period, no domestic production exists, and hence the pollution in the second period is 0.

In the consumption process, some scrapped goods will be generated. The scrapped goods are assumed to be a fixed proportion $\phi > 0$ of the final consumption goods. The scrapped goods can be recycled into intermediate inputs for the production of other goods domestically or exported to the rest of the world (ROW). The amounts of domestic usage and exports are denoted as k_t and $E_{k,t}$, respectively, and the domestic and international prices are $P_{k,t}$ and $P^*_{k,t}$, respectively. To export one unit of scrap goods, an iceberg cost $\tau_{k,t} > 1$ should be paid. To simplify the model, we assume that for ROW firms, the domestic and foreign goods are perfect substitutes. The no-arbitrage condition implies $\tau_{k,t}P_{k,t} = P^*_{k,t}$ and the resource constraint of the scrap goods implies

$$k_t + \tau_{k,t}E_{k,t} = \phi c_t.$$

The revenue from selling the scrap goods (domestic sales + export) is $P_{k,t}k_t + P^*_{k,t}E_{k,t} = P_{k,t}\phi c_t$.

The consumer in each period is endowed with heavy material H (such as copper) and light material M (such as fabrics). Both material goods can be used in the production or can be traded. The domestic and international prices of the light material are denoted as $P_{m,t}$ and $P^*_{m,t}$, respectively. Similarly, the domestic and international prices of the heavy material are denoted as $P_{h,t}$ and $P^*_{h,t}$, respectively. The no-arbitrage condition ensures $\bar{\tau}_{m,t}P_{m,t} = P^*_{m,t}$ and $\tau_{h,t}P_{h,t} = P^*_{h,t}$, where $\bar{\tau}_{m,t}$ $(\tau_{h,t})$ is the export trade cost for the light (heavy) material. The unit trading costs may respond to the size of the trade imbalance, as we explain below. The total revenue from selling the light and heavy goods is $P_{m,t}M + P_{h,t}H$.

The consumer's problem is as follows:

$$\max_{\{c_t,S_t\}} \ln c_1 + \rho \ln c_2 - \eta x_1$$

$$\text{subject to} \quad P_{c,1}c_1 + S_1 = w_1 L + P_{k,1}\phi c_1 + P_{m,1}M + P_{h,1}H + \Pi_1 \tag{7}$$

$$P_{c,2}c_2 = (1+R)\, S_1 + P_{k,2}\phi c_2 + P_{m,2}M + P_{h,2}H + \Pi_2.$$

The two equalities denote the budget constraints in the two periods, respectively. $P_{c,t}$ is the price of the final consumption goods. w_t is the wage per unit of labor in the home country. S_t is the saving of the country or the current account surplus. Π_t is the lump-sum transfer from the government, which we explain later. The right-hand side of the first-period budget is the income of the household, including labor income, and the three incomes from selling the scrap goods, light material, and heavy materials, respectively. The left-hand side denotes the first-period expenditure including the consumption and the saving. In the second-period budget, the income comes from the gross returns on the first-period saving, the three revenues from selling the scrap goods, light material, and heavy material, and a transfer from the government.

The final-goods consumption is tradeable. Without loss of generality, we assume the trade cost of final goods is 0 and denote its international price as $P^*_{c,t}$. Hence, $P_{c,t} = P^*_{c,t}$. The domestic final-goods producer combines output from the polluting sector q_t and output from the non-polluting (green) sector y_t to produce C_t:

$$C_t = \Omega_c y_t^{\alpha} q_t^{1-\alpha},$$

where $\Omega_c = \alpha^{-\alpha} (1-\alpha)^{-(1-\alpha)}$ and α is the share of the final expenditure on the green sector's output. We denote the prices of y_t and q_t as $P_{y,t}$ and $P_{q,t}$ respectively. The optimality condition yields

$$P^*_{c,t} = P^{\alpha}_{y,t} P^{1-\alpha}_{q,t}, \;\; y_t = \alpha \frac{P^*_{c,t} C_t}{P_{y,t}}, \;\; q_t = (1-\alpha) \frac{P^*_{c,t} C_t}{P_{q,t}}.$$

Now, we specify the export trade cost for heavy materials and scrap goods. We assume the export trade costs for heavy materials and scrap goods are affected by the trade imbalance, measured by total export divided by total import. More specifically,

$$\tau_{h,t} = \bar{\tau}_{h,t} \left(\frac{Export}{Import} \right)^{v}, \tag{8}$$

$$\tau_{k,t} = \bar{\tau}_{k,t} \left(\frac{Export}{Import} \right)^{\upsilon}, \tag{9}$$

where $\upsilon > 0$ and $\bar{\tau}_{h,t}$ and $\bar{\tau}_{k,t}$ are the exogenous part of the trade costs if total export = total import ($S_t = 0$). υ measures the elasticity of export trade costs with respect to the trade imbalance. Its value in subsequent simulations will be guided by the empirical estimates in the earlier section. The above two equations suggest that for a deficit country, the heavy and scrap goods' export cost becomes cheaper when the deficit increases. For the import costs of the heavy and scrap goods, we later specify two similar equations.

Both the polluting and green sectors have a representative firm. The output of these two sectors cannot be traded. However, the materials they use are tradeable. Both sectors combine materials and labor to produce. Because the second period has no labor supply, the domestic output in both sectors will be zero, and the final good in the second-period consumption will be imported.

4.2 Non-polluting (Green) Sector

The representative firm in the non-polluting sector uses light material and labor to produce. The light material comes from either domestic supply or imports. We use m_t and m_t^* to denote the domestic and foreign imported light material goods.[15] The production function of the non-polluting sector is

$$y_t = \Omega_y \left(m_t^{\omega} m_t^{*(1-\omega)} \right)^{\theta} L_{y,t}^{1-\theta},$$

where $\Omega_y = (\omega\theta)^{-\omega\theta}((1-\omega)\theta)^{-(1-\omega)\theta}(1-\theta)^{-(1-\theta)}$ and $L_{y,t}$ is the labor employed by this sector. ω measures the share of the domestic light material in the total amount of light material used, and $1-\theta$ measures the labor share in the production.

[15]For simplicity, we assume the foreign producer takes the domestic light material and foreign light material as perfect substitutes so that $\bar{\tau}_m P_m = P_m^*$, whereas the domestic producer's technology takes m and m^* as imperfect substitutes. Similar assumptions also apply to heavy material and scraps.

We use $\bar{\tau}^*_{m,t}$ to denote the import trade cost of the light materials, which, for simplicity, is assumed to be exogenous. The optimality conditions yield

$$P_{y,t} = w_t^{1-\theta} P_{m,t}^{\omega\theta} \left(\bar{\tau}^*_{m,t} P^*_{m,t}\right)^{(1-\omega)\theta},$$

and the demands for each production input are derived, respectively, as follows:

$$m_t = \omega\theta \frac{P_{y,t}y_t}{P_{m,t}}, m^*_t = (1-\omega)\,\theta \frac{P_{y,t}y_t}{\bar{\tau}^*_{m,t}P^*_{m,t}}, L_{y,t} = (1-\theta)\,\frac{P_{y,t}y_t}{w_t}.$$

4.3 Polluting Sector

The representative firm in the polluting sector uses heavy material, scrap goods, and labor to produce q_t. The production function is

$$q_t = \Omega_q \left(h_t^{\beta} h_t^{*(1-\beta)}\right)^{\sigma} \left(\gamma k_t^{\frac{\omega_k-1}{\omega_k}} + (1-\gamma)\, k_t^{*\frac{\omega_k-1}{\omega_k}}\right)^{\frac{\lambda\omega_k}{\omega_k-1}} L_{q,t}^{1-\sigma-\lambda}, \tag{10}$$

where $\Omega_q = (\beta\sigma)^{-\beta\sigma}((1-\beta)\sigma)^{-(1-\beta)\sigma}(1-\sigma-\lambda)^{\sigma+\lambda-1}$. h_t and h^*_t are the domestic and imported heavy materials. k_t and k^*_t are the domestic and foreign scrap goods. $L_{q,t}$ are the labor hired in this sector. β and γ measure the share of domestic heavy and scrap materials relative to the imported counterparts. $\sigma$and λ measure the share of heavy materials and scrap goods in the total production. ω_k is the elasticity of substitution between the domestic and foreign scraps. We distinguish ω_k away from 1 because the substitution between domestic and foreign scraps may be higher than that of other materials. Because we wish to explore later the sensitivity of the policy experiments to different degrees of substitution between domestic and imported scraps, we use a more general functional form to describe this particular substitution than that between domestic and imported heavy material.

We use $\tau^*_{h,t}$ and $\tau^*_{k,t}$ to denote the import costs of heavy material and scraps, respectively.

Specifically,

$$\tau_{h,t}^{*} = \bar{\tau}_{h,t}^{*} \left(\frac{Export}{Import} \right)^{-v}, \tag{11}$$

$$\tau_{k,t}^{*} = \bar{\tau}_{k,t}^{*} \left(\frac{Export}{Import} \right)^{-v}, \tag{12}$$

where $\bar{\tau}_{h,t}^{*}$ and $\bar{\tau}_{k,t}^{*}$ are some constants. These two equations say that when the surplus increases, the import cost will decrease. The exact magnitude of the elasticity is guided by the empirical estimates in the early section.

From the production process, if the polluting sector's output is q_t, the firm emits $x_t = (b - \delta_t) q_t$ amount of pollution, where b is the amount of pollutant produced per unit of output, and δ_t is the amount of pollution abatement per unit of output. Pollution abatement is costly because the firm may need to purchase and install new equipment, or to adopt more costly production technique. To reduce $\delta_t q_t$ amount of pollution, we assume the abatement cost is $w_t \psi(\delta_t) q_t$, where ψ is an increasing and convex function with $\psi(0) = 0$. We assume the government imposes a penalty of T_t for each unit of emission and the tax is transferred to the consumer in a lump-sum amount of Π_t.

The firm's problem is

$$\max_{\{h_t, h_t^*, k_t, k_t^*, L_{q,t}, \delta_t\}} \left\{ \begin{array}{c} P_{q,t} q_t - w_t L_{q,t} - P_{h,t} h_t - P_{h,t}^{*} \tau_{h,t}^{*} h_t^{*} - P_{k,t} k_t - P_{k,t}^{*} \tau_{k,t}^{*} k_t^{*} \\ -w_t \psi(\delta_t) q_t - T_t (b - \delta_t) q_t \end{array} \right\}$$

$$\text{subject to} \quad \delta_t \leq b, \quad \text{and equations (10), (11), and (12).}$$

The firm's problem implies

$$P_{q,t} = \Delta_{q,t} + w_t \psi(\delta_t) + T_t (b - \delta_t),$$

where $\Delta_{q,t} = w_t^{(1-\sigma-\lambda)} P_{h,t}^{\beta\sigma} \left(P_{h,t}^* \tau_{h,t}^*\right)^{(1-\beta)\sigma} \left(\gamma^{\omega_k} P_{k,t}^{1-\omega_k} + (1-\gamma)^{\omega_k} \left(P_{k,t}^* \tau_{k,t}^*\right)^{1-\omega_k}\right)^{\frac{\lambda}{1-\omega_k}}$, which is the per-unit cost of production. The abatement cost is derived:

$$\delta_t = \min[b, \psi'^{-1}\left(\frac{T_t}{w_t}\right)].$$

If $T_t = 0$, the total pollution reduction is $\delta_t = 0$ and the marginal cost of production $\Delta_{q,t} = P_{q,t}$.

Finally, the demands for each input are derived as

$$\begin{aligned}
h_t &= \beta\sigma \frac{\Delta_{q,t} q_t}{P_{h,t}}, \quad h_t^* = (1-\beta)\,\sigma \frac{\Delta_{q,t} q_t}{P_{h,t}^* \tau_{h,t}^*}, \; L_{q,t} = (1-\sigma-\lambda)\,\frac{\Delta_{q,t} q_t}{w_t} \\
k_t &= \frac{\lambda \gamma^{\omega_k} P_k^{-\omega_k} \Delta_{q,t}}{\left(\gamma^{\omega_k} P_{k,t}^{1-\omega_k} + (1-\gamma)^{\omega_k} \left(P_{k,t}^* \tau_{k,t}^*\right)^{1-\omega_k}\right)^{\lambda}} q_t, \\
k_t^* &= \frac{\lambda\,(1-\gamma)^{\omega_k} \left(P_{k,t}^* \tau_{k,t}^*\right)^{-\omega_k} \Delta_{q,t}}{\left(\gamma^{\omega_k} P_{k,t}^{1-\omega_k} + (1-\gamma)^{\omega_k} \left(P_{k,t}^* \tau_{k,t}^*\right)^{1-\omega_k}\right)^{\lambda}} q_t.
\end{aligned}$$

4.4 Equilibrium

The lump-sum transfer Π_t in the budget constraint (7) comes from the government's pollution tax, which is defined as $T_t\,(b-\delta_t)\,q_t$. Notice that in the second period, the lump-sum transfer will be 0 because no domestic production exists.

A competitive equilibrium is defined as the lump-sum transfer Π_t, the prices, final-goods consumption and saving $\{c_t, S_t\}$, labor demand $\{L_{y,t}, L_{q,t}\}$, and the amount of pollution abated δ_t, such that (i) given the prices, all individual optimality conditions are satisfied, (ii) all markets clear, including the scrap market, and (iii) the lump-sum transfer is consistent with the government's budget constraint.

4.5 Calibration

The pollution-abatement technology is assumed to be $\psi(\delta) = \frac{\xi}{2}\delta^2$. We assume all parameters, such as international material prices, remain the same for the two periods. We calibrate the model economy to match the model moments of period 1 with the Chinese economy in 2012 (as indicated by a corresponding input-output table for China in that year). We normalize the labor supply L to be 1 and the wage per person to be 1.[16]

To calibrate the parameters in the production function, we set $\alpha = 0.6$ to match the expenditure share of the polluting sector (60%).[17] We set $\theta = 0.45$ to match the labor share in the non-polluting sector (55%), and choose ω to match the import share of the light material in the total expenditure (9.2%). We assume $\beta = \gamma$ and calibrate σ, λ, β, and γ to match the labor share in the polluting sector (52%), the import share of heavy goods (12.3%), and the import share of scraps in the total expenditure (0.5%). In the baseline calibration, we set $\omega_k = 5$ following Broda and Weinstein (2006).

For international prices P_m^*, P_h^*, and P_k^*, we use information in China's customs data and the 2012 input-output data. We classify all goods into four categories. First, we assign each HS6 good to either the final-consumption-goods basket or the intermediate-inputs basket.[18] Among the intermediate inputs, a good is placed in the scrap basket if its name description includes either scrap or waste. For the remaining intermediate inputs, they are placed in the heavy-material basket if their weight-to-value ratios are above the median value across all non-scrap goods, and in the light-material basket otherwise. In terms of the average prices of each type of goods, by normalizing $P_c^* = 1$, we infer that $P_h^* = 1.3, P_m^* = 0.98$, and $P_k^* = 0.1$.

For the unit-trade-cost functions, we assume all exogenous trade costs $\bar{\tau}$ the same, and

[16] This normalization implies that the value of one unit in our model is around 24,000 RMB or 3,500 USD.

[17] The polluting sector in the model corresponds to an aggregation of the Chinese industries whose SO2 pollution intensities are above the median across all industries.

[18] The classification is based on https://unstats.un.org/unsd/tradekb/Knowledgebase/50090/Intermediate-Goods-in-Trade-Statistics.

calibrate it to match the total transportation cost to be around 20% of the trade prices when running a trade balance. This assumption is consistent with the estimates in Anderson and Van Wincoop (2004).[19] Because China is a persistent trade-surplus country, we set the elasticity of the unit trade cost for scraps with respect to a trade surplus, υ, to 0.089, based on the empirical estimates in column 3 of Table 2.

For the parameters related to the pollution, we assume the pollution tax is zero in the benchmark case.[20] In our model, we choose one unit of x as one ton of emission. We then set the pollution generated per unit of output, b, to match the tons of pollutant emission per value.[21] For pollution-abatement cost ξ, we use the information on the price of tradeable permits on SO2 emission in the US, which is about 1,600 USD per ton (Burtraw and Szambelan (2009)), or 0.46 model unit value. This value should equal to the marginal cost of the abatement $w\xi q$, and allows us to back out ξ.[22]

For parameters related to the intermediate inputs, we calibrate ϕ so that the model economy does not export scrap in equilibrium. The endowments of light material M and heavy material H are calibrated to match the shares of their exports in total expenditure (13.0% and 11.7%, respectively).

For the remaining parameters (mostly in the consumer problem), we calibrate ρ to generate a trade surplus/GDP ratio of 5% (roughly the level for China in the recent past). We set the foreign real return $R = 10\%$. (If the model period is five years, the annual real interest rate

[19] Another way to think about the transportation cost in our model is to explain it as the ratio between cost of insurance/freight (CIF) and the free-on-board cost (FOB). According to Gaulier et al. (2008), the China's CIF/FOB ratio is around 3% to 7%. In the Appendix E, we show the results of the calibration under $\bar{\tau} = 1.05$ and find our model prediction is robust to this change.

[20] China does not have a pollution tax, but had a pollution discharge fee until 2018. However, the fee was too low to deter the pollution, and the enforcement was not strong enough (Li and Chen (2018)).

[21] From the China city statistical yearbook, we aggregate all pollutants including air, solid, and water pollutants, and then divide the sum by total GDP.

[22] In reality, ξ may be different across various pollutants, or in different countries. Given that we do not have relevant information on China, we use information from the US. Note that as long as the environmental tax is 0, the abatement technology ξ does not matter for the benchmark calibration, because no one will choose to reduce the emission. ξ will affect the counterfactual simulation, especially when the optimal tax is imposed.

would be 2%.)

The last one, maybe one of the most important parameters, is η, which measures the percentage reduction in consumption necessary to reduce pollution emission by one ton. A few challenges arise when calibrating η. First, we need to decide which pollutants to include. In our exercise, we include three air pollutants, PM10, SO2, and the ozone, all of which are considered to have great adverse health consequences. However, by ignoring other pollutants, we may underestimate η.

Second, most papers that estimate the willingness to pay (WTP) of pollution focus on the concentration of a particular pollutant. We need to convert the tons of emission in our model to the concentration. For a given pollutant, we regress the annual total emission (in tons) in the US on the nationwide average concentration of that pollutant. We can infer the change in concentration when increasing one ton of emission for various pollutants. The concentration and total pollution emissions data are from the EPA. Using 1990-2018 data, we find that one ton of PM10, SO2, and VOC+NOX emissions increase the concentration of PM10, SO2, and the ozone by $2.46\mu g/m^3$, 4.56 ppb, and 0.99 ppb, respectively.

Third, the estimates of WTP are very different in the literature.[23] One of the most cited estimates is from Bajari et al. (2012), which uses a hedonic price-regression approach and handles the time-varying correlated unobservables. Their estimates (Table 6 in their paper) suggest the WTP of PM10 ($1\mu g/m^3$), SO2 (1 ppb), and the ozone (1ppb) are 103, 178, and 180 USD (in 2003 dollar), respectively. Hence, the monetary costs of one ton of emission of PM10, SO2, and the ozone are 253.38 (103×2.46), 811.68 (178×4.56), and 178.2 (180×0.99), respectively. We take the WTP of one ton of emission as the max of these three numbers (811.68), which implies $\eta = 0.03$.[24]

[23]For instance, Smith and Huang (1995) survey the WTP of the TSP emission, and find the number varies from -239.8 USD to 1807 USD. Sieg et al. (2004) survey the WTP of the ozone emission, and it varies from 8 USD to 181 USD.

[24]The US consumption per capital is about 28,000 USD in 2012 (in 2003 dollar). Therefore, one ton of emission is equivalent to about a 3% (811.68/28,000) consumption reduction.

The last challenge is that we need to assume China and the US have the same η. Bayer et al. (2016) show the WTP of pollution is low for low income-groups. Thus, we may overestimate η in the Chinese economy. The η is underestimated due to the first concern and overestimated due to the last concern. Overall, the bias of η is not clear. In any case, we conduct a robustness check regarding η in Figure 3, which we explain below.

We provide additional details of the calibration in Appendix E.

4.6 Welfare and Policy Analysis

Welfare Cost of Trade Surplus

The baseline results are recorded in the first column of Table 7, where we normalize the pollutant emission (in the first row), imports of scrap and heavy material in the first period (in the second and third rows, respectively), the total export value of heavy goods and scrap (the fourth row), and the wage per capita (the fifth row) to be 100. The trade surplus in this case is about 5% of GDP (the sixth row). For subsequent calculations of the welfare effect of a given thought experiment, we report the percentage change in the part of the utility $\ln(c_1) + \rho \ln(c_2)$ from a change in consumption relative to the benchmark case while ignoring any disutility of pollution (second to the last row), and the percentage change in total utility due to the thought experiment that also takes into account any change in disutility from a change in the pollution level (the last row). By construction, the last two numbers are zero in the baseline case.

We next quantify the welfare cost of a trade surplus through our endogenous shipping cost channel when the environmental regulation is weak (i.e., $T = 0$). To this end, we set $v = 0$, thereby making the shipping cost independent of the trade surplus. (Relative to the case of endogenous shipping costs, the import shipping cost becomes higher and the export shipping cost becomes lower.) The results are presented in the second column of the table.

With exogenous shipping costs, the welfare is affected in four ways: two working through consumption and two through pollution. First, a higher unit shipping cost on the import side increases the input costs of the polluting industry, which reduces pollution. Second, a lower unit shipping cost on the export side leads to more exports of scraps and heavy material, which further increases the input costs to the polluting industry and augments the reduction in pollution. The combined consequence of the first two effects is a total reduction of pollution by 0.83% and an increase in utility by about 0.32%. Third, the higher input costs to the polluting industry lowers the sector's production and lowers the wage rate, which in turn lowers the lifetime income. Fourth, the additional exports of domestic scraps and heavy material increase total revenue and boost export revenue, resulting in an increase in the lifetime income. We find the fourth effect numerically dominates the third effect, and the combined consequence of the third and fourth effects is an additional increase in consumption, leading to a 0.09% increase in utility. Overall, the total consequence of all four effects is a 0.41% welfare increase.

We can also summarize the results in the reverse direction − by going from column 2 (with no response of the shipping cost to a trade surplus) to column 1 (with an endogenous reduction in the shipping cost to a trade surplus). Four channels exist. First, because a trade surplus can endogenously reduce the unit shipping cost, the country imports more scraps and more heavy material than it would in the absence of a trade surplus. Second, the endogenous change in the shipping cost on the export side implies a reduction in the exports of the scrap goods and heavy material. Both channels lead to a reduction in the input costs of the polluting industry, leading to more pollution and a lower utility. Third, due to a lower price of the polluting industry's output along with a higher wage rate, the consumption increases. Fourth, the higher shipping cost on the export side implies a reduction in the total export revenue, which by itself would depress consumption. The net effect of all four channels is a 0.41% reduction in welfare.

With an endogenous response of the shipping cost to the trade imbalance, an increase or decrease in the trade imbalance may have systematically different welfare consequences. To illustrate, we impose a credit market constraint on the household problem $S \leq \bar{S}$. Then, variations in $\bar{S}$ generate variations in the level of the trade imbalance. The results from varying $\bar{S}$ are plotted in Figure 2. On the x-axis, the saving/GDP ratio increases from a deficit -5% to a surplus 5%. For a given trade imbalance, we plot the difference with and without endogenous responses of the shipping cost. This difference is the total effect on welfare that incorporates the changes in welfare due to changes in both pollution and consumption (solid line). To isolate the importance of the pollution channel, we also report the partial utility change resulting from a change in consumption without a change in pollution (dashed line). As we can see, when the trade surplus increases from 0% to 5%, the welfare level in a world in which the shipping costs responds to the trade balance relative to one with an exogenous shipping cost declines monotonically from 0% to 0.4%. The utility change excluding pollution is much smaller, suggesting the pollution channel is a quantitatively important part of the story. Conversely, a country with a trade deficit tends to enjoy a utility gain in a world with an endogenous shipping cost relative to one with an exogenous shipping cost. Much of the gain comes from the fact that the endogenous shipping channel lowers the pollution level in the trade-deficit country.

Banning Scrap Imports

We now examine the effects of some public policies that aim to improve upon the outcomes. In particular, we analyze a ban of imports of all scraps, which is motivated by a similar policy that China has implemented since early 2018. We then compare it with a policy of increasing the pollution tax.

We summarize the results in Table 8. For ease of comparison, we copy the baseline results of Table 7 and paste them into the first column of the current table. The result on banning scrap imports is shown in the second column of Table 8. Banning scrap imports raises the input cost of the polluting sector higher, which in turn generates several effects. First, the output in the polluting sector decreases, and the pollution in turn decreases by 1.36%. The import of heavy goods decreases by 0.75%, because the polluting sector shrinks. Second, the contraction of the polluting sector results in a decline of the final good production at home and a decline of the export revenue of the final goods. Because this effect dominates the decrease in imports, the trade surplus reduces by 4.83%. While the reduction in the trade surplus pushes up the unit shipping cost of importing heavy goods and scraps, it pushes down the unit shipping costs on the export side. In response to a lower export shipping cost, the exports of heavy material and scraps increase by 0.57%. Third, the reduced output in the polluting sector pushes down the labor demand (so that the wage declines by 0.75%). Hence, the lifetime income decreases and the utility from consumption declines by 0.27%. Finally, the utility loss from a lower consumption is more than offset by a utility gain from lower pollution. The net change in welfare is a gain of 0.26% relative to the benchmark case.

We now consider some sensitivity analyses. Would the result be different if using recycled scrap is less polluting than using the heavy materials? For instance, recycling scrap copper may be less polluting than extracting copper ore from the ground and processing them into copper inputs. Indeed, the pollution effect of using raw copper ore may even become stronger as one hunts for increasingly scarce raw ores or has to smelt increasingly impure ores. For this exercise, we consider (non-scrap) heavy material as a substitute for scrap. In the copper example, the heavy material can be thought of as the copper processed from the raw copper ore. Instead of assuming the pollution intensity b from heavy material is a constant, we now assume its pollution intensity is an increasing function in its usage relative to that of the scrap:

$$b = b_0 \left[\frac{h_t^{\beta} h_t^{*(1-\beta)}}{\left(\gamma k_t^{\frac{\omega_k - 1}{\omega_k}} + (1-\gamma)\, k_t^{*\frac{\omega_k - 1}{\omega_k}} \right)^{\frac{\omega_k}{\omega_k - 1}}} \right]^{b_1},$$

where b_0 and b_1 are two positive parameters. This equation suggests the pollution intensity is increasing when the firm uses more heavy material relative to the scrap. We choose $b_1 = 0.1$ and calibrate b_0 to match the tons of pollutant emission per value. The results in column 3 are intuitive. First, because no pollution tax exists, the effect of pollution is not internalized, and all variables except for the pollution emission (reported in the first row) and the utility change (the last row) are the same as in column 2. Second, because the heavy material is more polluting, the pollution level is 4% higher than in the baseline case, and the overall utility is 1.86% lower. In other words, banning scrap imports can lower the overall welfare when the heavy material is more polluting than the scrap itself.

The second sensitivity exercise investigates the consequence of a higher degree of elasticity of substitution between foreign and domestic scraps. Whereas the elasticity in the baseline case is set at 5, which follows Broda and Weinstein (2006), we now increase it dramatically to $\omega_k = 200$. In other words, we assume they are close to perfect substitutes. The results are shown in column 4. Compared to the second column, both the reduction in consumption and the reduction in pollution become much smaller. The reason is intuitive: because the firm can more easily substitute the imported scrap with domestic scrap, a given increase in the cost of the imported scraps would not alter the production by as much. As a result, the impacts on consumption and pollution also become smaller. Relative to the baseline case in column 1, the net welfare effect is a 0.13% increase, which is smaller than the case in column 2 when the elasticity is substantially smaller. Because the elasticity of substitution increases substantially from column 2 to column 4 without dramatically altering the end result, one may also conclude the welfare analysis of banning scrap imports is not sensitive to the assumption on elasticity of substitution between foreign and domestic scraps.

Finally, we check the sensitivity of our result to η. In Figure 3, we plot the welfare change after banning the scrap import under different values of η. Similar to Figure 2, the solid line and dashed line denote the net utility change and utility change excluding pollution. When $\eta = 0.03$, the numbers are the same as those in the last two rows of column 2 of Table 8. Not surprisingly, the change in η will not affect the utility change excluding pollution, because individuals do not take into account the externality. This number is always negative because the import ban increases the cost of production. After including pollution, the net welfare is positive as long as $\eta \geq 0.015$. In other words, the ban of scrap import can bring a welfare gain if the Chinese WTP to pollution is more than half of American's WTP.

Optimal Regulation

We now consider the optimal tax on pollution. Specifically, we do a grid search over the value of T that maximizes the consumer's welfare. We find the optimal tax is $T = 0.0589$, which is about 1,414 RMB (202 USD) per ton of pollution emission. We should note at the outset that the welfare is maximized when the optimal pollution tax is imposed, because pollution externality is the only source of market failure in our model. This qualitative conclusion can be reached even without looking at the numbers. One purpose of the calibration exercise is to study how close other policies − such as a ban on imports of scraps − can approximate the optimal pollution tax in terms of the welfare changes.

After imposing this pollution tax, the representative firm in the polluting sector responds by cutting emissions, which leads to smaller production in the polluting sector, a reduced demand for scraps and heavy material, and a higher cost of the output from the polluting sector. As a result, the pollution emission declines by 76.99%. The consumption also declines given the higher cost of production. However, a utility loss from a lower level of consumption (a utility loss of 11.74% as reported in the second to the last row in column 5) is more than offset by a utility gain from a lower level of pollution. On net, the welfare gain is 18.56% (the last row in column 5) higher than in the benchmark case.

The most important reason for the relatively big welfare gain is that a higher pollution cost has reduced the demand for both scrap and heavy material, whether they are imported or domestically sourced. From the second and third rows, the scrap- and heavy-goods imports decline by 85.57%. Meanwhile, because the demand for domestic scrap and heavy material declines, the household would choose to sell them abroad. As a result, the revenue from exporting scrap and heavy goods increases by 52.43%.

Compared to an optimal tax on pollution (column 5), a ban on scrap imports (column 2) seems far inferior. In other words, although banning imports of scrap can increase welfare given the structure of the model and the parameter values, one can do far better by switching to an optimal tax on pollution (without banning imports). Banning scrap imports (as China has done) is a poor substitute for an optimal tax on pollution. The effect of increasing the cost of importing scraps on closing the gap between the private and social costs of pollution is indirect and imprecise, in part because foreign scraps can be substituted by both imported heavy material and domestic scraps.

5 Conclusion

This paper provides a new channel for the trade imbalance to have welfare consequences. We go beyond the existing insight that the shipping cost responds endogenously to the trade imbalance, and study how a trade imbalance can affect the composition imports and the welfare of the importing country. Consistent with our theory, we find trade-surplus countries import more heavy goods, including scrap metals and other industrial waste. With nearly 2 million observations, we show strong and robust evidence that the composition of trade is affected by shipping costs, and shipping costs in turn are affected by the trade imbalance.

This theory helps explain why China imports so much scraps and industrial waste: China being a country with a very large trade surplus while being a very large importer of scraps and waste (and other heavy goods) is not a coincidence. Because the recycling of scraps and waste (to produce intermediate inputs) generates pollution, the mechanism we study suggests a concrete channel for a trade surplus to generate a welfare loss, especially in countries with low environmental standards or weak enforcement. In other words, even in the absence of distortions in savings or investment, a trade surplus can reduce welfare.

With the help of a quantitative model, we can perform counterfactual policy experiments. We find that a ban on imports of scraps, a policy that China has implemented since 2018, is able to increase welfare − by raising the cost of pollution indirectly. However, the model also makes clear that such a policy is inferior to a direct increase in a pollution tax. A ban on imports of scraps is not as effective, partly because domestic scraps and imported (non-scrap) heavy material are substitutes for foreign scraps.

References

J. E. Anderson and E. Van Wincoop. Trade costs. *Journal of Economic literature*, 42(3): 691–751, 2004.

P. Bajari, J. C. Fruehwirth, C. Timmins, et al. A rational expectations approach to hedonic price regressions with time-varying unobserved product attributes: The price of pollution. *American Economic Review*, 102(5):1898–1926, 2012.

P. Bayer, R. McMillan, A. Murphy, and C. Timmins. A dynamic model of demand for houses and neighborhoods. *Econometrica*, 84(3):893–942, 2016.

K. Behrens and P. M. Picard. Transportation, freight rates, and economic geography. *Journal of International Economics*, 85(2):280–291, 2011.

M. Bombardini and B. Li. Trade, pollution and mortality in China. Technical report, National Bureau of economic research, 2016.

G. Brancaccio, M. Kalouptsidi, and T. Papageorgiou. Geography, transportation and endogenous trade costs. *Econometrica, Forthcoming*, 2019.

L. Brandt, J. Van Biesebroeck, L. Wang, and Y. Zhang. WTO accession and performance of chinese manufacturing firms. *American Economic Review*, 107(9):2784–2820, 2017.

C. Broda and D. E. Weinstein. Globalization and the gains from variety. *The Quarterly journal of economics*, 121(2):541–585, 2006.

D. Burtraw and S. J. Szambelan. US emissions trading markets for SO2 and NOx. *Permit Trading in Different Applications*, pages 15–45, 2009.

G. F. De Oliveira. Determinants of european freight rates: The role of market power and trade imbalance. *Transportation Research Part E: Logistics and Transportation Review*, 62:23–33, 2014.

A. De Palma, R. Lindsey, E. Quinet, and R. Vickerman. *A handbook of transport economics*. Edward Elgar Publishing, 2011.

R. Dekle, J. Eaton, and S. Kortum. Unbalanced trade. *The American Economic Review*, 97 (2):351–355, 2007.

S. Djankov, C. Freund, and C. S. Pham. Trading on time. *The Review of Economics and Statistics*, 92(1):166–173, 2010.

P. Epifani and G. Gancia. Global imbalances revisited: The transfer problem and transport costs in monopolistic competition. *Journal of Journal of International Economics*, 108(5): 99–116, 2017.

F. Facchini. What are the determinants of public spending? an overview of the literature. *Atlantic Economic Journal*, 46(4):419–439, 2018.

J. A. Frankel. Environmental effects of international trade. *Working Paper*, 2009.

F. Friedt and W. W. Wilson. Trade, transportation and trade imbalances: An empirical examination of international markets and backhauls. *Working Paper*, 2015.

G. Gaulier, D. Mirza, S. Turban, and S. Zignago. International transportation costs around the world: A new CIF/FOB rates dataset. *CEPII. March*, pages 304–24, 2008.

D. Hummels and A. Skiba. Shipping the good apples out? an empirical confirmation of the Alchian-Allen conjecture. *Journal of Political Economy*, 112(6):1384–1402, 2004.

D. L. Hummels and G. Schaur. Time as a trade barrier. *The American Economic Review*, 103 (7):2935–2959, 2013.

J. Ishikawa and N. Tarui. Backfiring with backhaul problems: Trade and industrial policies with endogenous transport costs. *Journal of International Economics*, 111:81–98, 2018.

O. Jonkeren, E. Demirel, J. van Ommeren, and P. Rietveld. Endogenous transport prices and trade imbalances. *Journal of Economic Geography*, 11(3):509–527, 2010.

D. Kellenberg. Consumer waste, backhauling, and pollution havens. *Journal of Applied Economics*, 13(2):283–304, 2010.

D. Kellenberg. Trading wastes. *Journal of Environmental Economics and Management*, 64(1): 68–87, 2012.

D. K. Kellenberg. An empirical investigation of the pollution haven effect with strategic environment and trade policy. *Journal of international economics*, 78(2):242–255, 2009.

J. Lan, M. Kakinaka, and X. Huang. Foreign direct investment, human capital and environmental pollution in China. *Environmental and Resource Economics*, 51(2):255–275, 2012.

A. Lashkaripour. Worth its weight in gold: Product weight, international shipping and patterns of trade. *Working Paper*, 2015.

Y. Li and K. Chen. A review of air pollution control policy development and effectiveness in china. *Energy Management for Sustainable Development*, page 1, 2018.

L. Rushton. Health hazards and waste management. *British medical bulletin*, 68(1):183–197, 2003.

H. Sieg, V. K. Smith, H. S. Banzhaf, and R. Walsh. Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review*, 45(4): 1047–1077, 2004.

V. K. Smith and J.-C. Huang. Can markets value air quality? a meta-analysis of hedonic property value models. *Journal of political economy*, 103(1):209–227, 1995.

W. F. Wong. The round trip effect: Endogenous transport costs and international trade. *Working Paper*, 2019.

Tables and Figures

Table 1: Top and Bottom 5 Goods in Terms of Weight-to-Value Ratio

Highest Weight-to-Value Ratio	Lowest Weight-to-Value Ratio
Bitumen and asphalt	Diamond
Limestone	Precious metal
Wasted granulated slag from iron	Gold
Ceramic building bricks	Halogenated derivatives
Scrap glass	Watch

NOTE: This table shows the top and bottom 5 goods in terms of the weight-to-value ratio, estimated from transaction-level data on Colombian imports, averaged over 2007-2013.

Table 2: Bilateral Trade Imbalance and Shipping Costs across International Shipping Routes

	(1)	(2)	(3)
	$\ln \lambda_{ndt}$	$\ln \lambda_{ndt}$	$\ln \lambda_{ndt}$
ln(Imbalance$_{ndt}$)	-0.019	-0.177***	-0.007
	(0.022)	(0.062)	(0.022)
ln(Imbalance$_{ndt}$) $\times$ Pervasive-route			-0.082*
			(0.042)
Country-pair FE	Y	Y	Y
Destination-year FE	Y	Y	Y
Origin-year FE	Y	Y	Y
IV		Y	
Obs.	728	728	728
R-squared	0.93	0.93	0.93

Notes: This table shows the estimation results of equation (2). λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance$_{ndt}$ is the bilateral trade imbalance between a country-pair (n and d) in a year, measured by the total export of d to n divided by the total import of d from n. Pervasive route=1 if the destination country runs an aggregate trade surplus and the origin country runs an aggregate trade deficit. We use the log value of equation (3) for an instrumental variable for Imbalance$_{ndt}$ *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Shipping Cost and Heavy Goods Imports – International Evidence

	(1) $\ln(\text{Imp}_{i,ndt})$	(2) $\ln(\text{Imp}_{i,ndt})$	(3) $\ln(\text{Imp}_{i,ndt})$	(4) $\ln(\text{Imp}_{i,ndt})$
$\ln \lambda_{ndt}$	-0.711***	-0.714***		
	(0.017)	(0.017)		
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$	-0.062***	-0.051***	-0.06***	
	(0.007)	(0.007)	(0.007)	
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right) \times \text{Persist}$		-0.017***		
		(0.001)		
$\ln(\text{Imbalance}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right)$				0.012***
				(0.004)
Origin-good-year FE	Y	Y	Y	Y
Destination-good-year FE	Y	Y	Y	Y
Destination-origin-year FE			Y	Y
Obs.	1,836,440	1,836,440	1,836,440	1,976,537
R-squared	0.80	0.80	0.83	0.83

Notes: This table shows the estimation results of equation (4). $\text{Imp}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} is the bilateral trade imbalance between a country pair (n and d) in year t, measured by the total export of d to n divided by the total import of d from n. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. "Persist" is the dummy variable indicating one partner within a pair (n and d) runs a persistent trade surplus to the other partner. Standard errors are clustered at the goods, destination, and origin level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Trade Imbalance and Import Composition across Chinese Ports

	(1)	(2)
	$\ln(\text{Import}_{i,nmt})$	$\ln(\text{Import}_{i,nmt})$
$\ln(\text{Imbalance}_{nmt})$	0.065***	0.003*
	(0.002)	(0.001)
$\ln(\text{Imbalance}_{nmt}) \times \ln\left(\frac{w_i}{p_i}\right)$	0.0095***	0.0064***
	(0.001)	(0.001)
Port-good-year FE	Y	Y
Origin-good-year FE	Y	Y
Port-origin FE		Y
Obs.	4,917,896	4,917,336
R-squared	0.79	0.81

Notes: This table shows the estimation results of equation (5). $\text{Import}_{i,nmt}$ is the import of good i from an origin country (n) to a Chinese port (m) in year t. Imbalance_{nmt} is the bilateral trade imbalance between an origin (n)-port (m) pair in year t, measured by the total export of m to n divided by the total import of m from n. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. Standard errors are clustered at goods, origin level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Correlations between Output Pollution Intensities and Input Weight/Value Ratio across Chinese Industries

	weight-per-value for inputs	ln(SO2)	ln(NO2)
ln(SO2)	0.219***		
	(0.061)		
ln(NO2)	0.189*	0.980***	
	(0.106)	(0.000)	
ln(TSP)	0.194*	0.929***	0.944***
	(0.098)	(0.000)	(0.000)

Notes: This table shows the correlations between output pollution intensities and input weight-per-value across Chinese industries. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Trade Imbalance and the Relative Expansion of the Polluting Industries

	(1)	(2)
	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$
$\ln(\text{Imbalance}_t) \times \text{Heavy-sector}_i$		0.921**
		(0.374)
$\ln(\text{Imbalance}_t) \times \text{Polluting-sector}_i$	0.905***	0.666
	(0.421)	(0.410)
Year FE	Y	Y
Industry FE	Y	Y
Obs.	6,630	6,630
R-square	0.98	0.98

Notes: This table shows the estimation results of equation (6). The dependent variable, Output_{it}, is the output of industry i in year t. Imbalance_t = Chinese exports/Chinese imports in year t. Heavy-sector_i and $\text{Polluting-sector}_i$ are dummy variables defined in section 3.2. Standard errors are clustered at industry levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Welfare Effect of Endogenous Shipping Cost

	(1) Baseline	(2) Exog. shipping cost
Pollution	100	99.17
Scrap import	100	99.30
Heavy goods import	100	99.30
Heavy goods+scrap export	100	101.93
Wage	100	99.30
Surplus/GDP (%)	5.03	5.14
Utility change from c (%)	0	0.09
Utility change (%)	0	0.41

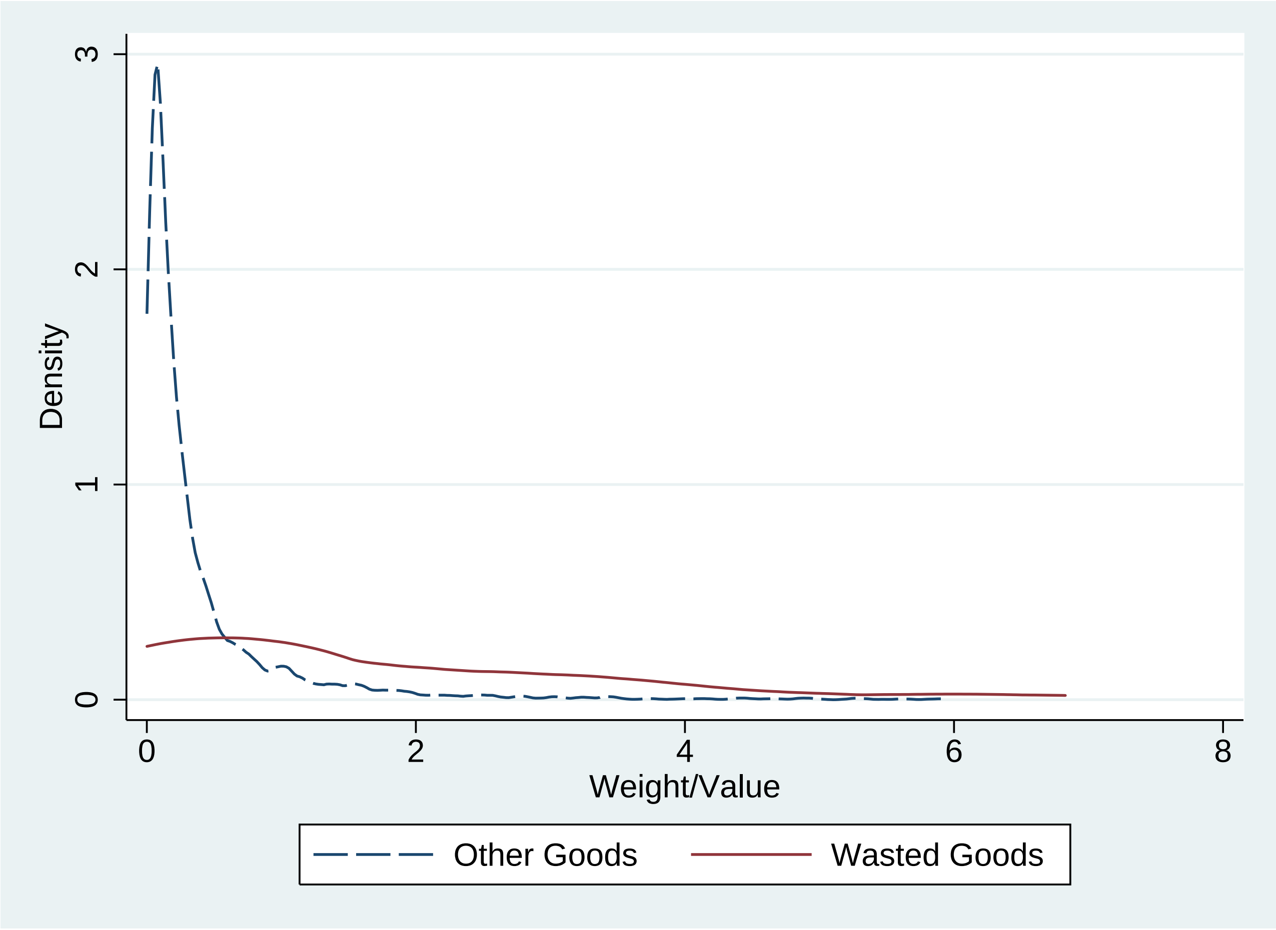
Notes: This table presents the welfare effect of the endogenous shipping cost. In column (1), the baseline results are shown where pollution, scrap imports/exports, (non-scrap) heavy material imports/export, and wage are all normalized to be 100. In column (2), we assume the shipping cost does not respond to the trade imbalance ($v = 0$).

Table 8: Welfare Comparisons of Counterfactual Policy Experiments

	(1) Baseline	(2) Ban scrap imports	(3) Dif pollution Intensity	(4) High elasticity	(5) Optimal tax
Pollution	100	98.64	104.05	99.34	23.01
Scrap import	100	0	0	0	14.43
Heavy goods import	100	99.25	99.25	99.64	14.43
Heavy goods+scrap export	100	100.57	100.57	100.34	152.43
Wage	100	99.25	99.25	99.64	37.60
Surplus/GDP (%)	5.04	4.83	4.83	4.93	-0.13
Utility change from c (%)	0	-0.27	-0.27	-0.14	-11.74
Utility change (%)	0	0.26	-1.86	0.13	18.56

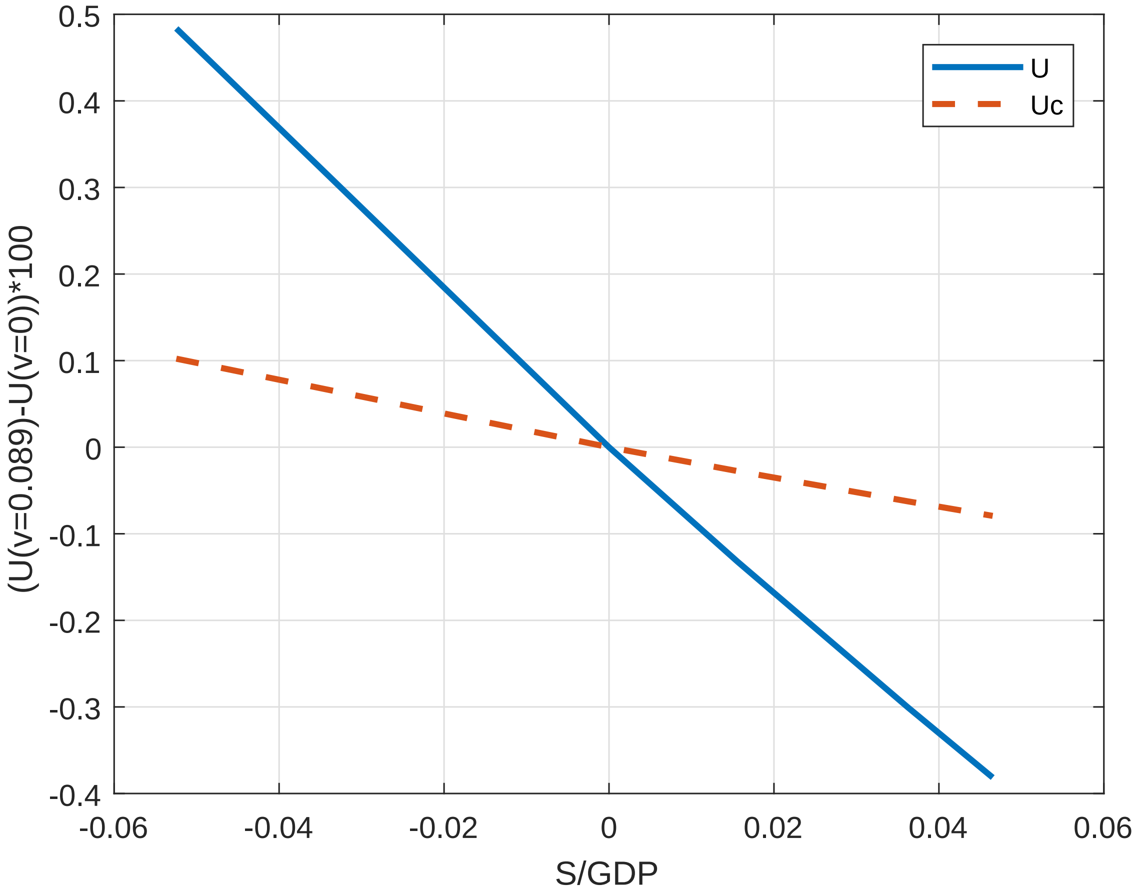
Notes: This table presents the model predictions for different counterfactual experiments. In column (1), the baseline results are shown where pollution, scrap imports/exports, (non-scrap) heavy material imports/export, and wage are all normalized to be 100. In column (2), a ban on scrap imports is imposed. In column (3), a ban on scrap imports + low pollution intensity of recycling scraps is imposed. In column (4), a ban on scrap imports is imposed, but the elasticity of substitution between domestic and imported scraps is increased ($\omega_k = 200$). In column (5), the optimal tax on pollution is imposed.

Figure 1: The Weight-to-Value Ratio (kg/US$) for Industrial Waste Goods versus Other Goods



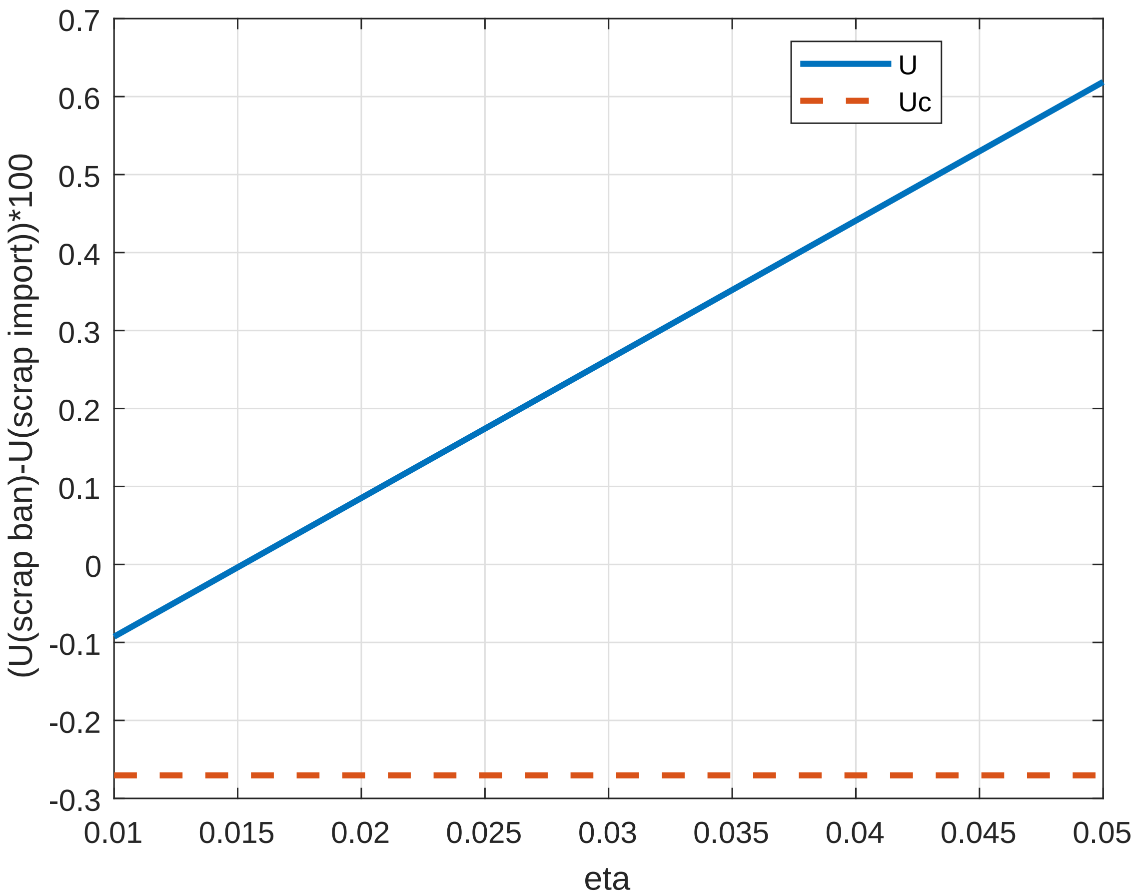
NOTE: This figure shows the density of the weight-to-value ratio. We define the waste products as HS 6-digit product lines that contain either “scrap” or “waste” in their descriptions.

Figure 2: The Welfare Cost of Trade Surplus



NOTE: This figure shows the utility difference when $v = 0.089$ and $v = 0$ under different trade-surplus values. U refers to the net utility change. U_c refers to the partial change in welfare ignoring pollution.

Figure 3: The Welfare Change of Banning Scrap Import



NOTE: This figure shows the utility change when banning the scrap import under different η values. U refers to the net utility change. U_c refers to the partial change in welfare ignoring pollution.

Online Appendix (not for publication in print)

A Alternative Equilibrium Restriction

In our theory (section 2), we impose an equilibrium restriction whereby the total weight is balanced for bilateral trade between two countries. In this section, we consider an alternative equilibrium restriction: the total volume (or the number of shipping containers) is balanced for bilateral trade between two countries.

First, we redefine the per-unit shipping cost $c_{i,nd}$ as

$$c_{i,nd} = \lambda_{nd} v_{i,nd},$$

where λ_{nd} is the shipping cost per container and $v_{i,nd}$ is the number of containers per unit of good i. Then, the per-value trade cost is

$$\tau_{i,nd} = t_{i,nd} + \lambda_{nd} \left(\frac{v_{i,nd}}{p_{i,nd}} \right),$$

where $\frac{v_{i,nd}}{p_{i,nd}}$ is the number of containers per dollar.

With the same argument in section 2, λ_{nd} is decreasing in the trade surplus. Therefore, a country that runs a trade surplus imports goods that have a high container-per-value ratio. We can rewrite the above equation as

$$\tau_{i,nd} = t_{i,nd} + \lambda_{nd} \left(\frac{w_{i,nd}}{p_{i,nd}} \frac{v_{i,nd}}{w_{i,nd}} \right),$$

where $\frac{w_{i,nd}}{p_{i,nd}}$ is the weight-per-value ratio and $\frac{v_{i,nd}}{w_{i,nd}}$ is the number of containers per unit of weight. Note that although we do not observe $\frac{v_{i,nd}}{p_{i,nd}}$, if the container-per-weight ratio is similar across goods, our main proposition that a trade surplus country tends to import more heavy goods still holds.

Under the assumption that the container-per-weight ratio is the same within a 2-digit HS code, we re-test whether the trade-surplus country imports more heavy goods. Note we control the destination-origin-year-2-digit HS code dummies. The results are reported in Table 9.

Table 9: Estimates for the Log Import Value Regressions

	(1) $\ln(\text{Imp}_{i,ndt})$
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$	-0.011
	(0.009)
Origin-good-year FE	Y
Destination-good-year FE	Y
Destination-origin-year-HS2 FE	Y
Obs.	1,830,158
R-squared	0.85

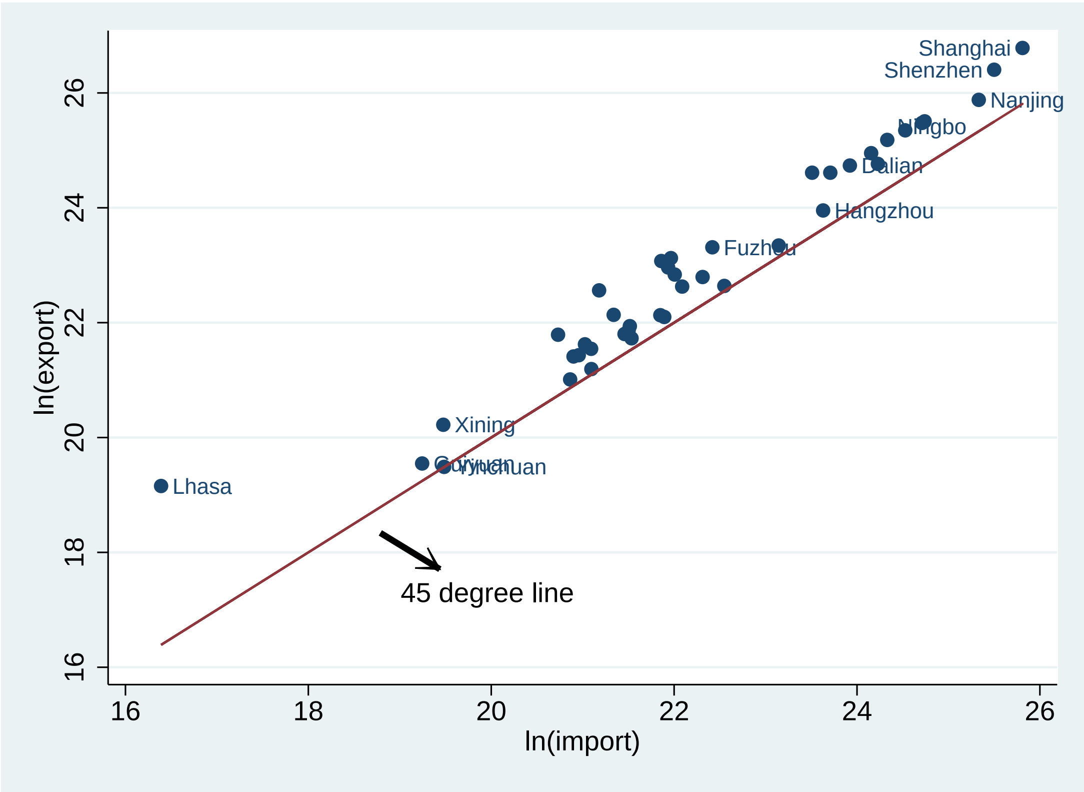
Notes: This table shows the estimation results of equation (4) while additionally controlling for Destination-origin-year-HS2 fixed effect. $\text{Imp}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} is the bilateral trade imbalance between a country pair (n and d) in year t, measured by the total export of d to n divided by the total import of d from n. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. Standard errors are clustered at the goods, destination, and origin level. *** p<0.01, ** p<0.05, * p<0.1.

With a finer level of fixed effect, the coefficient becomes smaller. Nevertheless, we have the consistent result: the elasticity of the import value with respect to the shipping cost is higher for goods with a higher weight per value.

B The Chinese Port-Level Data

To show more about the Chinese port-level data, we plot the export and import of each port in year 2006. Figure 4 shows the results. Notice that although we use the word port, we actually mean a city in customs data. For instance, even though Xining is not a coastal city, customs data are recorded for Xining. Because our story does not only hold for maritime trade, we include those inland cities in the analysis. The x-axis and y-axis are the export and import in log values, respectively.

Figure 4: The Export and Import of Chinese Ports



NOTE: This figure shows the ln(export) and ln(import) of each Chinese port in year 2006.

We observe a large variation in the export and import values across Chinese ports. For example, Shanghai, the largest port in China, is 10 times larger in trading volume, than the smallest port in terms of either imports or exports.

C The Weight-per-Input Value across Industries

To construct the weight-to-value ratio of intermediate inputs for an industry, we first map each HS6 product to an Chinese 4-digit industry (CSIC).[25] We then map each CSIC code to an input-output table industry. By combining the usage table of the 2012 Chinese input-output table and the weight-to-value ratio from the Colombian data, we compute the average weight-to-value ratio of each industry's input. We list all the ratios in Table 10.

Table 10: The Weight-to-Value Ratio of Intermediate Inputs of Each Industry

Industry Name	Weight-per-input-value
Asbestos cement products manufacturing	1.78
Building ceramics manufacturing	0.81
Cement manufacturing	0.69
Frozen food manufacturing	0.69
Compound fertilizer manufacturing	0.55
Candied production	0.49
Steel rolling	0.43
Daily glass products and glass packaging containers	0.40
Manufacture of synthetic single (polymeric) bodies	0.39
Metal furniture manufacturing	0.38
Bottle (can) drinking water manufacturing	0.38
MSG manufacturing	0.37
Wood chip processing	0.35
Book, newspaper, publication	0.34
Other special chemical products manufacturing	0.34
Beer manufacturing	0.34
Manufacture of sealing fillers and similar products	0.34
Metal kitchen utensils and tableware manufacturing	0.33
Biochemical pesticides and microbial pesticide manufacturing	0.33
Machine paper and cardboard manufacturing	0.32

[25] The concordance table could be found from Brandt et al. (2017).

Feed processing	0.32
Sugar production	0.32
Nylon fiber manufacturing	0.31
Oral cleaning products manufacturing	0.31
Non-edible vegetable oil processing	0.31
Ferroalloy smelting	0.30
Ironmaking	0.29
Inorganic alkali manufacturing	0.28
Other non-metal processing equipment manufacturing	0.27
Metal shipbuilding	0.26
Plastic artificial leather, synthetic leather manufacturing	0.26
Vegetable, fruit and nut processing	0.25
Manufacture of other non-metallic mineral products	0.23
Electric light source manufacturing	0.23
Battery manufacturing	0.23
Hydraulic and pneumatic power machinery and component manufacturing	0.22
Mica product manufacturing	0.22
Lifting transport equipment manufacturing	0.22
Other rubber products manufacturing	0.21
Other sporting goods manufacturing	0.21
Insulation products manufacturing	0.21
Nuclear radiation processing	0.21
Gear, transmission and drive component manufacturing	0.20
Machine tool accessories manufacturing	0.20
Manufacturing of special equipment for agricultural and sideline food processing	0.20
Gardening, furnishings and other ceramic products manufacturing	0.20
Liquid milk and dairy products manufacturing	0.20
Construction machinery manufacturing	0.19
Auto parts and accessories manufacturing	0.19
Internal combustion engine and accessories manufacturing	0.19

Micromotors and other motor manufacturing	0.19
Camera and equipment manufacturing	0.19
Industrial and mining rail vehicle manufacturing	0.18
Other power transmission and distribution and control equipment manufacturing	0.18
Agriculture, forestry, animal husbandry and fishing machinery parts manufacturing	0.17
Household refrigeration electric appliance manufacturing	0.17
Precious metal calendering	0.16
Motorcycle manufacturing	0.16
Modified car manufacturing	0.15
Manufacture of automobiles and other counting instruments	0.15
Silk knitwear and woven fabric manufacturing	0.15
Leather processing	0.15
Manufacture of other textile products	0.14
Leather shoes manufacturing	0.14
Aluminum smelting	0.13
Chemical drug manufacturing	0.13
Cap	0.12
Printed circuit board manufacturing	0.12
Cotton, chemical fiber textile processing	0.11
Grain grinding	0.11
Other electronic equipment manufacturing	0.10
Aquatic feed manufacturing	0.10
Silk screen dyeing and finishing	0.09
Livestock and poultry slaughter	0.09
Communication terminal equipment manufacturing	0.09
Home audio equipment manufacturing	0.09
Wool textile	0.08
Application of TV equipment and other radio equipment manufacturing	0.08
Electronic computer manufacturing	0.07
Coking	0.07

Nuclear fuel processing	0.07
Cigarette manufacturing	0.07

D Trade Surplus and Environmental Regulation

In this section, we document that environmental regulation is not particularly stringent in a country that tends to run a trade surplus.

To show this point, we first use the environmental regulation stringency index (ERS) collected by OECD Statistics. The ERS is a country-specific and internationally comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies place an explicit or implicit tax on polluting or environmentally harmful behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). The index covers 28 OECD and 6 BRIICS countries. The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution. OECD Stat also releases in stringency of all 14 of these policy instruments as well.[26] Table 11 lists all countries in the ERS index. The left panel presents indexes of BRIICKS and the right panel presents indexes of other OECD countries. Note that developing countries often run a large trade surplus against developed countries. The ERS is significantly lower in BRIICKS.

In Table 12, we regress different measures of environmental regulation indexes on heavy-goods imports and the trade imbalance, including the ERS index, environmental tax index, and the regulation standard index.[27] We also control for the countries' GDP-per-capita level, corruption level, and government efficiency.[28] In all specifications, we do not find a significant

[26]The BRIICS denote Brazil, Russia, India, Indonesia, and China. The details of the data can be found at https://stats.oecd.org/Index.aspx?DataSetCode=EPS.

[27]We define the heavy goods as the goods whose weight-to-value ratio is above the 90th percentile among all HS6 goods.

[28]The corruption index and regulation quality index are collected from the World Bank Governance Indicator dataset. The data can be found at http://databank.worldbank.org/data/reports.aspx?source=worldwide-governance-indicators.

correlation between heavy-goods imports (or trade imbalance) and environmental regulation.

Table 11: ERS Index

BRIICKS	ERS	OECD	ERS
Brazil	0.42	Turkey	0.88
Indonesia	0.44	USA	1.05
South Africa	0.44	Slovak Republic	1.10
India	0.60	Australia	1.17
Russian Federation	0.65	Poland	1.27
China	0.85	Norway	1.42
		Ireland	1.46
		Italy	1.49
		Canada	1.58
		Czech Republic	1.63
		Switzerland	1.69
		Greece	1.73
		United Kingdom	1.73
		Japan	1.90
		Netherlands	1.90
		Belgium	1.98
		France	2.13
		Portugal	2.13
		Hungary	2.33
		Korea, Rep.	2.33
		Austria	2.40
		Finland	2.48
		Denmark	2.59
		Germany	2.67
		Spain	2.75
		Sweden	2.75

Notes: This table lists the environmental-regulation-stringency index of OECD countries and 6 BRIICKS countries in in 2004. High index denotes high regulation.

Table 12: Estimates for Regulation and Heavy-Goods Import across Countries

	(1) ERS	(2) Environment tax	(3) Regulation Standard
ln(Heavy-goods Import)	0.022	0.163	0.087
	(0.072)	(0.267)	(0.070)
ln(Imbalance)	-0.697	-1.646	-0.926
	(0.654)	(2.417)	(0.669)
ln(GDP)	-0.430	-5.113	5.251***
	(1.224)	(4.526)	(1.211)
Corruption	-0.745**	-1.242	-0.135
	(0.322)	(1.164)	(0.319)
Regulation Quality	0.231	-0.931	0.534**
	(0.265)	(0.977)	(0.261)
Country FE	Y	Y	Y
Year FE	Y	Y	Y
Obs.	89	92	89
R-squared	0.94	0.85	0.96

Notes: This table shows the estimation results for environmental regulation. We use three measures of environmental regulation: (1) the EPS index, (2) environmental tax index, and (3) the pollution regulation standard index. Heavy goods are those whose weight-to-value ratio is above the 90th percentiles among all HS6 goods. Imbalance is a country's export divided by the country's import. GDP refers to a country's GDP per capita. The measure for corruption and regulation quality is from World Bank. *** p<0.01, ** p<0.05, * p<0.1.

E Calibration Details

All the following variables are meant to capture outcomes in the first period. For corresponding data, we use Chinese data in 2012. We normalize the 2012 wage to be 1, which implies that the value of one unit in our model is around 24,000 RMB or 3,500 USD. Table 13 summarizes all the parameters and moments we target.

Table 13: Calibration Result

Parameters	Value	Moments	Model	Data
ρ	0.475	Surplus/GDP	0.05	0.05
ω	0.659	light import/total expenditure	0.092	0.092
σ	0.461	labor share in polluting industry	0.52	0.52
λ	0.019	scrap import/total expenditure	0.005	0.005
β	0.333	heavy import/total expenditure	0.123	0.123
M	0.685	light export/total expenditure	0.13	0.13
H	0.299	heavy export/total expenditure	0.117	0.117
ϕ	0.030	scrap export/total expenditure	0	0
b	29.25	Total pollutants emission (ton)/total expenditure	10.75	10.75
ξ	0.338	SO2 ton trade price	0.46	0.46
v	0.089	Column 2 of table 2	-	-

The model fits the data well. For instance, the model predicts the wage per capita is around 0.98, whereas the corresponding number in the data is 1.06.

In the benchmark calibration, we set $\bar{\tau} = 1.2$. As an alternative specification, we re-calibrate our model with $\bar{\tau} = 1.05$ (so that $\bar{\tau} - 1 = \frac{\text{CIF}}{\text{FOB}}$). The calibration strategy is the same as the benchmark model. With the new calibration values, we replicate Table 7. Table 14 shows the results. Compared to Table 7, the results are quite robust.

Table 14: Welfare Effect of Endogenous Shipping Cost When $\bar{\tau} = 1.05$

	(1) Baseline	(2) Exog. shipping cost
Pollution	100	99.17
Scrap import	100	99.30
Heavy import	100	99.30
Heavy goods+scrap export	100	101.94
Wage	100	99.30
Surplus/GDP (%)	5.03	5.17
Utility change from c (%)	0	0.09
Utility change (%)	0	0.41

Notes: This table presents the welfare effect of the endogenous shipping cost when $\bar{\tau} = 1.05$. In column (1), the baseline results are shown, where pollution, scrap imports, and (non-scrap) heavy material imports are all normalized to be 100. In column (2), we assume the shipping cost does not respond to a trade imbalance ($v = 0$).