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Connecting the (dirty) dots: Current account surplus and polluting production

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Abstract

According to the existing open-economy macroeconomics literature, a current account surplus is associated with a welfare loss only when distortions exist in either savings or investment. We propose a new welfare effect even in the absence of such distortions. In our theory, a trade imbalance − the largest component of a current account imbalance − interacts with a country's pollution control ("cleanness") regime to generate welfare effects outside the standard channels. In particular, a trade surplus alters the shipping costs and composition of a country's imports, producing a welfare loss associated with greater pollution.

1 Introduction

A current account imbalance is both common in the data and often a source of international friction. Because it reflects a gap between a country's savings and investments, a welfare loss occurs in the standard open-economy macroeconomics only if distortions exist in either savings or investments. In this paper, we suggest that by drawing insight from the economics of both endogenous shipping costs and pollution, we may derive a new welfare channel of a current account imbalance.

The basic mechanism can be summarized in two steps. First, we note that for a majority of countries, the merchandise-trade imbalance is a quantitatively important component of the current account imbalance. More precisely, across countries, the trade imbalance co-moves strongly with the current account imbalance. In fact, using data from 2015, a regression of trade imbalance (as a share of GDP) on current account imbalance (as a share of GDP) produces a slope coefficient that is essentially one.[1] For this reason, the welfare effect of a country's trade imbalance is a major element of the welfare effect of its current account imbalance. Second, a trade surplus affects the unit shipping cost in international trade 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.

In other words, this interaction among a trade surplus, endogenous shipping costs, and the pollution control regime, with the last two objects normally being of interest to two separate microeconomic fields, has an important macro consequence. The welfare loss from a large current account surplus implied by this paper is novel.

As a byproduct of our mechanism, we also 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) or so much industrial waste. Whereas the average weight-to-value ratio for world trade is 0.22 kg per dollar, the ratio for Chinese imports is more than four times as high, at 0.96 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).[2] In 2016, waste-products imports included 45 million tons of scrap metals, used textiles and fibers, waste paper, and used plastics worth over 18 billion USD.[3] Our mechanism suggests that it is not a coincidence that China simultaneously runs the largest

[1]In Figure 1, we plot the trade imbalance-GDP ratio against the current account imbalance-GDP ratio across countries in 2015. The correlation is 0.6. When we regress the trade surplus-GDP ratio on the current account-GDP ratio, the slope coefficient is 0.941, but not statistically different from 1, with an R-square of 0.63.

[2]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.

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

trade surplus in the world and is the most voracious importer of industrial scrap.

This paper is divided into two 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 that ships returning to the country will be under their full carrying capacity (De Palma et al. (2011); De Oliveira (2014)). This imbalance reduces the unit shipping cost for the country's imports, making it cost-effective to increase the imports of relatively heavy goods. Conversely, deficit countries have a comparative advantage in exporting relatively heavy goods. 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%.[4]

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. Therefore, the overall "cleanness" of the economy is affected by the size of the trade imbalance.[5]

This paper makes three contributions to the literature. First, we provide the first empirical test of a novel channel for a current account 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 production costs in

[4]In addition to the cross-country evidence, Appendix C finds the same pattern within a country. In particular, across port cities in China, those with a greater trade surplus also import more heavy goods as a share of their total imports. This within-country evidence strengthens our confidence that the key data patterns from the international data are not affected by unmeasured time-varying country-pair features that may be correlated with the unit shipping cost.

[5]In the appendix, we construct a quantitative model to evaluate the welfare effect of a trade surplus as well as to perform policy experiments. We find that the net effect of allowing the shipping cost to respond to a trade surplus can amplify the welfare loss by 33%. A ban on the imports of foreign scraps − a policy experiment that is similar to an actual Chinese policy in place since 2018 − could increase welfare by raising the cost of the inputs for the polluting sectors, hence reducing the level of production in that sector.

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); Epifani and Gancia (2017)). The welfare effect of the trade surplus comes from frictions either in the capital market or in the savings decision. In this paper, however, 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.

Second, while there is literature on trade and environment,[6] the only paper that makes a connection between trade imbalance, shipping cost, and waste trade is Kellenberg (2010). Our paper differs from his in a number of ways. While he offers a theoretical argument without empirical evidence, our key contribution is to provide a sequence of empirical evidence linking shipping costs to trade balance, import composition to shipping cost, and sector-level pollution to the relative heaviness of the inputs by sector. While his theoretical model focuses just on consumption waste, we show that the consequence of endogenous shipping costs is to tilt the imports of a surplus country towards heavy goods, including heavy industrial inputs, not just consumption waste.

Finally, our paper enriches the 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 as 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

[6]See surveys by Frankel (2009), Kellenberg (2009), Kellenberg (2012), and Lan et al. (2012), respectively.

shipping cost disproportionately favors heavy products.

The paper is hereafter structured into four sections. In section 2, we aim to establish empirically a relationship between a country's trade imbalance and import composition. In section 3, we show that a country with a trade surplus tends to generate more pollution. Section 4 concludes.

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. This prediction is borne out strongly in the data.

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 with the following gravity equation at the sector (or product) level:

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

$X_{i,nd}$ 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, $(1 + \tau_{i,nd})p_{i,n}$ 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.

Following Hummels and Skiba (2004), the trade cost per unit of goods ($\tau_{i,nd}p_{i,n}$) depends on the shipping weight:

$$\tau_{i,nd}p_{i,n} = \lambda_{nd} w_{i,n} \times \left(\frac{p_{i,n}}{w_{i,n}}\right)^{\beta},$$

where $w_{i,n}$ is the weight per unit of good i produced by country n, $\frac{w_{i,n}}{p_{i,n}}$ is the weight per value of good i, and λ_{nd} is the trade cost per weight. $(\frac{p_{i,n}}{w_{i,n}})^\beta$ measures the cost of handling goods with different value-to-weight ratios. Thus the price in country d is

$$(1+\tau_{i,nd})p_{i,n} = \left\{1 + \lambda_{nd}\left(\frac{w_{i,n}}{p_{i,n}}\right)^{1-\beta}\right\}p_{i,n}. \tag{2}$$

Based on the estimates of Lashkaripour (2015), we assume $\beta < 1$. It has an intuitive explanation: If the cargo is heavier, it will use more fuel in transportation, and a profit-maximizing shipping company would naturally charge a higher shipping fee.[7] 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 (2), 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 disproportionately larger decline in the trade cost. We summarize our findings 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 to the trade surplus, we make the following assumption.

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

Assumption 1 is motivated by the "backhaul problem," well known in the transportation economics literature. For example, Behrens and Picard (2011) endogenize transportation costs through a market mechanism in a model of trade and

[7]From speaking to some firms that engage in trading in heavy goods, we learn that 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 of satisfying the weight restriction. This weight restriction is approximately the same as charging a shipping fee in proportion to the weight of the cargo. In Appendix A, we show that our results are robust to an alternative assumption that the shipping fee is charged in proportion to the volume of the cargo.

geography. Their model predicts that the growing trade surplus of China against the US will lead to a reduction in the shipping cost from the US to China.[8] 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).

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.*

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 it hard to consistently compute the weight-to-value ratios for all products. Fortunately, the National Tax Agency of Colombia reports 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.[9] As 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 do cross-validation with the Chinese customs data. The weight-to-value ratio can be computed for 3,349 goods (about 60% of all HS6 goods) in the Chinese customs data. 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 Chinese

[8] Ishikawa and Tarui (2018) investigate the implication of the asymmetric shipping costs induced by the backhaul problem on industrial policies such as tariffs.

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

customs data shows that the auto-correlation in the weight-to-value ratio between two adjacent years is 0.98. 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 analyses, 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.

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, 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.[10] When the restriction on weight per container becomes binding, each container can only be partially occupied. For example, each container is typically about 1/3 full of scrap copper. While we do not have information on the volume-to-weight ratios for all goods and do not know how many goods face a binding weight restriction per container, our conversations with an expert from a shipping company and an executive from a trading firm suggest that typically over half of the containers are left partially empty when leaving the New York port.

For all countries except three, the Drewry covers one major port. For the United States, China, and Canada, where two ports are available, we use Los Angeles, Shanghai, and Vancouver, respectively.[11] For consistency, we use the shipping rates in July for all port pairs.[12]

[10] 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).

[11] Our results are robust to using the alternative ports as shown in Table 2.

[12] 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,

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 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:

$$\ln(\text{Shipping cost}_{ndt}) = \alpha_0 + \alpha_1 \ln(\text{Imbalance}_{ndt}) + \Omega_{\overleftrightarrow{nd}} + e_{ndt}, \tag{3}$$

where n and d are the origin and destination countries, respectively. Shipping cost_{ndt} is the shipping cost from country n to country d. Imbalance_{ndt} is 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. 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.

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.

Although container trade accounts for a majority of international trade, some goods such as oil or ores are shipped in bulk rather than in containers. We, therefore, exclude non-metal ores (2 digit HS code 25), metal ores (2 digit HS code 26), and oil and gas (2 digit HS code 27) in calculating the trade imbalance.

The result is reported in the first column of Table 2. α_1 is estimated at -0.129. Focusing on a pair of origin-destination (e.g., China and the U.S), it is a clear data pattern that the country with a higher trade surplus (China) faces a lower back-haul shipping cost than the other country (U.S), consistent with Assumption 1.

In regressing unit shipping costs on bilateral trade imbalance, one may be concerned by the possible endogeneity of the trade imbalance. Indeed, the very logic of our story indicates that an OLS regression is problematic. If a country's initial trade surplus does cause the unit shipping cost on the import side to decline, it will trigger an increase in imports and a decline in exports. The endogenous responses of the import and export volumes would lead to a smaller trade imbalance. They would make it harder to identify a negative relationship between the trade imbalance and the unit shipping cost. In addition, there may also be factors that simultaneously affect both the shipping costs and the bilateral trade balance.

To address the endogeneity challenge, we construct an instrumental variable based on the following idea:

1. Country A is likely to run a greater trade surplus against country B if country A has overall excess savings over its investment, and country B has an overall savings shortage relative to investment.

2. A country's saving-investment difference mirrors the weighted average of its trading partners' saving-investment differences.

3. A component of a trading partner's national savings is affected by government spending, which is likely to be exogenous to countries A and B.[13]

[13]The empirical literature on fiscal multipliers suggests that the Ricardian equivalence does not hold. A reduction in public-sector savings is unlikely to be offset by an increase in private-sector savings. The literature suggests several determinants of government spending (see Facchini (2018) for a survey), but none is related to shipping costs.

Following this logic, we use the ratio of the weighted averages of the government spending of the two countries' respective trading partners as the instrumental variable for Imbalance_{ndt}:

$$\Big\{\Big(\frac{\text{Import}_{nd2000}}{\text{Import}_{d2000}}\Big)\times \text{X}_{dt}\Big\}\Big/\Big\{\Big(\frac{\text{Import}_{dn2000}}{\text{Import}_{n2000}}\Big)\times \text{X}_{nt}\Big\}, \tag{4}$$

where Import_{nd2000} is country d's import from country n in 2000, Import_{d2000} is country d's aggregate import in 2000, and X_{dt} is the trade-weighted average of the government expenditures by the top 5 trading partners of county d in year t (excluding country n if n is one of the top five trading partners of country d).[14] Import_{dn2000}, Import_{n2000}, and X_{nt} are similarly defined. Note that we adjust the X_{dt} and X_{nt} by the share of bilateral trade in the country d and country n's import bundles in 2000, a decade before our sample.

In the second column of Table 2, we report the IV regression result. To absorb all time-varying aggregate supply or demand shocks in the exporting and importing countries, we include the origin-year pair and destination-year pair fixed effects. In the first stage, we regress the log of bilateral trade imbalance on the log of the term in (4). The coefficient before the IV is approximately 0.45 and significant at the 1% level, suggesting that a 1% increase in the IV leads to a 0.45% increase in country d's bilateral trade imbalance (export/import) with country n. With the F-statistic around 69, we can easily reject the null of a weak instrument. 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 reduce country d's import shipping cost from country n by 1.77%.[15]

To allow for the possibility that more traffic on a given shipping route may lower the unit freight rate on that route, we control in Column 3 the total shipping weight $W_{ndt} + W_{dnt}$, where W_{ndt} denotes the total weight from country n to d. We find evidence consistent with the economies of scale: the shipping cost declines

[14]The top five trading partners typically contribute over 80% of a country's trade in our dataset.

[15]To examine a possible non-linear effect, we have also added log(imbalance) squared as an additional regressor. We do not find evidence of a non-linear effect.

when the total weight increases. More importantly, the negative relation between imbalance and the shipping cost still holds.

We use Los Angeles, Shanghai, and Vancouver port information to construct the shipping cost associated with the US, China, and Canada. To check whether our results are robust to using data from alternative ports within each country, we replace the shipping cost associated with the US, China, and Canada using New York, Yantian, and Montreal ports information, respectively. As shown in Column 4, even with the alternative ports information, the relationship between the imbalance and the shipping cost remains the same.

Discussion of multi-country routes

A possible complication is multi-country shipping routes: if country A runs a surplus against country B, shipments 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 on each route. This multi-route arrangement would weaken the shipping-cost response to bilateral surplus. We address this issue in two ways.

First, we note that contracting frictions often make arranging complicated re-routing difficult. As Brancaccio et al. (2019) document, satellite tracking of ships often finds empty ships on the go, suggesting the existence of non-trivial contracting frictions.[16] Indeed, if multi-country re-routing could always be arranged to avoid below-capacity shipping completely, we would not have observed a negative relationship between the shipping cost and bilateral trade imbalance as reported in Table 2.

[16] Brancaccio et al. (2019) examine dry bulk ships. For container ships, we have examined all the cross-Pacific routes by Cosco, a major shipping company, and found that about 70% of the routes are between two countries or only three countries (https://elines.coscoshipping.com/ebusiness/sailingSchedule/searchByService). As long as a country runs a surplus against this bundle of partner countries, the backhaul shipping cost would become lower. In other words, one might interpret the word "bilateral" not always between two countries, but sometimes between a given importing country and a small collection of countries (say, Italy plus Greece, or Argentina plus Uruguay).

Second, we zoom in on those country pairs with a pervasive imbalanced relationship - involving one running a surplus against 2/3 of its trading partners and another running a deficit against 2/3 of its trading partners. For the importing country in such a pair, it would be hard to use a multi-port route arrangement to avoid having relatively empty ships come back to its ports. Similarly, for the exporting country in such a pair, it will be hard to avoid relatively empty ships leaving ports for other countries. When such 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. As reported in the fifth column 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 -0.028, but for pervasively unbalanced country pairs, the elasticity increases dramatically to -0.176 (= -0.028-0.148).

In the sixth column of Table 2, we use an instrumental variable approach similar to column 2. The estimated elasticities are -0.191 and -0.501 (= -0.191-0.310) for non-pervasive and pervasive routes, respectively. These results suggest that a trade surplus reduces the unit shipping cost on the import side, especially for countries with a pervasive surplus.

2.3.2 Import Elasticity with Respect to Shipping Cost

To test Proposition 1 that the share of heavy-goods imports in total imports rises when the shipping cost decreases, we consider the following specification:

$$\begin{aligned}\ln(\text{Import}_{i,ndt}) =& \beta_0 \ln(\text{Shipping cost}_{ndt}) + \beta_1 \ln(\text{Shipping cost}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right) \\ &+ \eta_{i,nt} + \eta_{i,dt} + \epsilon_{i,ndt}, \end{aligned} \tag{5}$$

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, $\eta_{i,nt}$ (or $\eta_{i,dt}$) is the origin-good-year (or destination-good-year) fixed effect, and $\varepsilon_{i,ndt}$ is an random component with a zero mean. 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. Equation (5) is essentially a gravity equation with a long list of fixed effects to absorb many variations in the data.

The first column of Table 3 reports the benchmark result for equation (5). β_0 is -0.711 and statistically significant at the 1% level, suggesting 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 that the 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 importing 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 imbalance takes on the same sign (e.g., the importer always runs a surplus) during 2010-2017. In the second column of Table 3, we add a triple-interaction term among the "persist" dummy (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 confirms that the effect is indeed more pronounced for country pairs with a more persistent imbalance.

The regressions so far already control for both origin-good-year and destination-good-year fixed effects. Still, some trade costs, such as tariff rates, can vary by origin-destination pair or 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. We assume that the weight-to-value ratio has two components: the first is a physical feature that depends on the product but not on country identity, and the second depends on the importing country's income (and other features). Then, we also need to control for origin-destination-year variations.

We present the result with this 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 on the shipping-cost variable because the newly added fixed effects absorb it. Importantly, we find that even with this 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 strongly confirms that a given decline in shipping costs disproportionately favors relatively heavy goods.

In the fourth column of Table 3, we use log imbalance to replace log shipping cost. The coefficient estimate for ln(imbalance) $\times \ln\left(\frac{w}{p}\right)$ is 0.012 and significant at the 1% level. Instrumenting trade imbalance as before (by using equation (4)), we find that the point estimate of the coefficient on the interaction terms becomes bigger (0.032 versus 0.012).[17]

Finally, we check if high-income importing countries differ from developing countries. In the final column of Table 3, we restrict our sample to the high-income countries as importers, defined as those countries whose GDP per capita exceeds USD 16,000, about the median value in the sample of countries with shipping cost data. The estimated slope coefficient is 0.003 but is not statistically significant. In other words, the relationship between trade imbalance and the weight composition of imports is much weaker for high-income countries. As we will show later, many heavy goods are used as inputs in polluting industries. More

[17]The government expenditures of a country's major trade partners are assumed to be independent of the country's composition of imports (in terms of weight/value ratio), which seems reasonable. As it is hard to test this assumption directly, we check an implication of our identifying assumption – whether the average weight-per-import value is correlated with the government expenditure of the trading partners. We find no significant relationship in the data.

stringent environmental regulations in rich countries may dampen their desire to import heavy goods.

To summarize, across different shipping routes, a greater trade surplus clearly reduces the unit shipping cost. Moreover, across shipping routes, goods, and time periods, a given reduction in the shipping cost benefits heavy goods shipment more than light goods as predicted by Proposition 1. These patterns hold after controlling for a large number of fixed effects and accounting for possible endogeneity of the trade imbalance. Overall, trade imbalance is a robust predictor of the composition of trade in terms of weight-to-value ratios. This pattern is most prominent for developing-country importers.

In the evidence reported above, unmeasured time-varying country-pair features can, in principle, be correlated with unit shipping costs. In Appendix C, we also explore variations across different ports within a large country (China). The country-level comparative advantage can be regarded as the same across all ports. Nonetheless, we find that a surplus port tends to import heavier goods than other ports. This result further confirms that trade imbalance is a robust predictor of the heaviness of imports.

3 Trade Imbalance and Pollution

We now explore the implications of our previous findings for pollution. In section 3.1, we show a connection between the pollution intensity of the industries and their relative dependence on heavy goods as inputs. In particular, we show that industries using heavier inputs tend to be more polluting in their output. Because the heavy inputs are cheaper in times of a larger trade surplus, polluting industries tend to expand in times of a larger trade surplus, especially if environmental regulation is weak. In section 3.2, we test the prediction of our theory by using the recent policy change in China that forbids imports of certain industrial scraps.

3.1 Heavy Inputs and Polluting Output

In this subsection, we first show that a sector relying on heavy input generates more pollution using China's input-output table.[18] Then using the cross-country data, we show that trade surplus can induce an expansion of the pollution sector due to a low heavy inputs shipping cost.

We measure the heaviness of each sector's inputs via a two-step procedure. First, every 6-digit HS commodity is assigned as an input into one or more industrial sectors using China's 2012 input-output table. Second, for each industrial sector, the weight-to-value ratio of its input bundle is calculated as the weighted average of the weight-to-value ratios of all inputs, with each input's weight inferred from the input-output table. The details are reported in Appendix B.

The air pollution intensity of each sector's output is measured from the US Environmental Protection Agency's data on SO2, NO2, and total suspended particles (TSP) emission per dollar value of output by sector in 2000. The maintained assumption here is that the relative pollution intensity across sectors is a technical feature of the production processes and is highly correlated across countries.[19]

Table 4 reports the correlation between the output-level pollution intensity and the input-bundle weight-to-value ratio across sectors. The correlation is positive and statistically significant for each of the three pollutants. The pairwise correlations among the pollutants are also high. In other words, different types of air pollution often go together. More importantly, more polluting industries tend to use heavier inputs.

If a greater trade surplus leads to lower prices of the inputs used more intensively in the polluting industries, it should lead to a relatively greater expansion of these industries. We investigate this prediction using cross-country data.[20] In

[18] The world input-output table only covers 18 manufacturing sectors, which is too wide to be matched with the 6-digit HS code. Thus we use the Chinese data at the 4-digit industry level.

[19] We do not have comparable data on other types of pollution. See Bombardini and Li (2016) for more details.

[20] The UNIDO data is used for this analysis.

particular, we run the following panel regression over 2010-2017:

$$\ln(\text{Output}_{ni,t}) = \beta_1 \ln(\text{Shipping cost}_{nt}) \times \text{Pollution}_i + \eta_{ni} + \eta_{nt} + \epsilon_{ni,t}. \quad (6)$$

$\text{Output}_{ni,t}$ is country n and industry i's total domestic output in year t (total industry output minus export). $\text{Shipping cost}_{nt}$ is country n's average import shipping cost in year t. Industry i is a 4-digit ISIC industry. $Pollution_i$ is industry i's air pollution intensity measured by log SO2 emission per dollar value of output in the US EPA data in 2000. It is assumed to be a fixed industry characteristic.[21] We control for both the country-industry and country-year fixed effects to tease out the unobserved country comparative advantage as well as the time-varying country component.

We have also conducted similar panel regressions with NO2 and TSP emissions from the US EPA data as a measure of industry-level pollution intensity, respectively. Because the different air pollutants have similar industry rankings as indicated in the last two columns of Table 4, it is perhaps not surprising that we find similar regression results. We omit these results to save space. Due to a lack of comparable industry-level data on solid or liquid pollutants, we are not able to perform a similar analysis with other pollutants.

In the first column of Table 5, the coefficient on the interaction term is -0.009 and is statistically significant. This finding suggests that a decrease in the import shipping cost is associated with an expansion of the more polluting industries relative to other industries.

In column 2, we add a new triple interaction term: $\ln(\text{Shipping cost}_t) \times \text{Pollution}_i \times \text{Heavy-Input}_i$. Heavy-Input_i, which is defined previously, is industry i's input weight-to-value ratio from Chinese data. We assume this measure captures an industry characteristic. The coefficient for the new triple interaction term is negative and statistically significant, suggesting that the expansion of the

[21]The ranking of air pollution intensity across sectors is highly stable over time. In particular, the correlations for the industry rankings between 1990 and 2000 for SO2, NO2, and TSP, respectively, are 0.98, 0.94, and 0.90. In other words, the industry ranking of the pollution intensity barely changes over the 10-year interval for any of the major air pollutants.

polluting sector is more pronounced for sectors using heavier inputs.

In column 3, we replace Shipping cost_{nt} to the trade imbalance measured with the export-to-import ratio of country n. The coefficient before the interaction term is 0.045, suggesting that a 1% increase in the trade surplus is associated with a 0.045% expansion of the more polluting industries relative to other industries.

One may be concerned with a possible endogeneity of the trade imbalance. We next implement an instrumental variable approach. In particular, for any country n, we use the three biggest trading partners' government expenditures as a share of GDP as the instrumental variables for its trade imbalance. The idea is that a change in major trading partners' government expenditures is likely to be exogenous to country n, but it represents a shock for country n's international trade. The IV estimate is presented in column 4 of Table 5, and is even more pronounced than the OLS result; the polluting industries tend to expand more in times of a greater trade surplus.

Overall, we confirm that pollution-intensive sectors expand relatively more than the rest of the economy in times of a greater trade surplus. This tendency is especially true for those polluting sectors that use heavier inputs.

3.2 The Trade of Industrial Scraps and Wastes

Industrial scraps and wastes are an important class of heavy inputs. Figure 2 plots the densities of the weight (kg)/value (US dollar) ratio for waste goods (the solid line) versus other goods (the dashed line), respectively. While the non-waste goods are lighter, about 0.1 kg/USD on average, industrial scraps and waste goods are much heavier, with the most mass at about 1 kg/USD. Our theory helps to explain why China was the largest importer of industrial scraps and waste until its government imposed an import ban in 2018: With a large trade surplus, its inbound shipping cost is cheap, making it attractive to import scraps and waste (and other heavy goods).

Imported waste products are often dirty, poorly sorted, or contaminated with hazardous substances. The recycling process often produces pollution and other unhealthy consequences. The adverse health effect of waste management has been pointed out in medical research such as Rushton (2003). The film *Plastic China* shows the environmental damage caused by China's plastic-recycling industry, which is dominated by many small-scale outfits that often lack proper pollution controls. This suggests a large trade surplus can generate a welfare loss by indirectly contributing to a higher level of pollution.

Perhaps seeing a connection between imported industrial waste and pollution, the Chinese government began in 2018 to forbid imports of certain industrial scraps with a plan to expand the ban to more scrap types. In Figure 3, we separate the waste goods into four broad categories: chemical product scraps (short dashed line), wood and paper scraps (long dashed line), scrap metals (dash-dot line) and other wastes (solid line), and plot China's import (in the log) from 2014 to 2019 for each category. We see a decline in three of the four types of waste imports since 2018, with scrapped chemical products exhibiting the sharpest drop. As the import ban does not apply to all waste products, some waste products such as cotton scraps have increased slightly.

Since China was the largest waste goods importer in the world, its ban on waste imports imposes a negative shock on other countries' waste exports as they need to find other ways to absorb the waste goods including exporting more of them to other countries. Our theory predicts that, following the Chinese ban, a waste-producing country with a greater trade surplus against other countries decreases its waste exports relatively more than another waste-producing country with a smaller trade surplus. To see whether this prediction is supported in the data, we use i to denote a waste good at the HS6 level and n to denote an origin country, and estimate the following regression:

$$\ln(\text{Export}_{i,nt}) = \beta_0 \ln(\text{Shock}_{i,nt}) + \beta_1 \ln(\text{Imbalance}_{n,2014-16}) \times \ln(\text{Shock}_{i,nt}) + \mu_{in} + \mu_{nt} + e_{i,nt} \tag{7}$$

where $\text{Export}_{i,nt}$ is country n's total export of waste product i to the rest of the world (ROW) except China. Imbalance_n is country n's trade balance with ROW except for China during 2014-2016. $\text{Shock}_{i,nt}$ is a measure of the impact of China's waste import ban on country n with regard to product i, and is defined as

$$\text{Shock}_{i,nt} = \frac{\text{Country n's exports to CHN}_{i,2014-2016}}{\text{CHN Total Waste Import}_{i,2014-2016}} \times \text{CHN Total Waste Import}_{i,t}$$

where the first term is the average share of country n in China's total imports of waste goods i in the three years before the waste import ban was announced, and the second term is China's total waste import of product i in year t.[22] The shock differs by both the exporting country and the product.

Note $\beta_0 + \beta_1 \ln(Imbalance_{nt})$ is the elasticity of country n's exports of product i with respect to the change in China's waste import. If a country can easily divert its waste goods to other countries after a decline in China's imports, the elasticity would be positive. Otherwise, it would be around zero. We expect to see that if country n runs a surplus against non-China ROW, it is more difficult for it to divert its waste goods. Thus $\beta_1 < 0$. That is, the elasticity should be smaller for countries that run a surplus.

In equation (7), the country-product pair fixed effect, μ_{ni}, captures the time-invariant heterogeneity of comparative advantage of each country in goods i, while the country-year fixed effect, μ_{nt}, controls for the aggregate origin country-year specific shocks, such as its aggregate productivity. $e_{i,nt}$ is the error term. While this specification does not identify the overall impact of China's import ban, we can check the relationship between a country's waste export to the rest of the world following the China shock and its trade balance.

From Column 1 of Table 6, we can see that $\beta_1 = -0.151$ and significant at the 5% level. This confirms that a country that runs a trade surplus with ROW has more difficulty exporting its waste goods after China's import ban.

The effect of the China shock may differ in developing and developed countries since they have different environmental regulations.[23] For instance, consider

[22]As the 2018 import ban was announced in 2017, we use information during 2014-2016 to construct all pre-ban variables.

[23]The OECD's Environmental Regulation Stringency (ERS) index captures the environmental regulations across countries. The ERS is an internationally-comparable measure based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution. Stringency is defined as the degree to which environmental policies place an explicit

two developed countries. One runs a trade surplus, and the other has a deficit. Since both have strong pollution regulations, firms in both countries that previously exported waste goods to China would have stronger incentives to export the waste to other countries (as opposed to absorbing the waste at home). Thus although the surplus developed country would still increase its export to ROW less than the deficit country, the difference would be less pronounced. However, for developing countries with weak environmental regulations, their waste exports are more likely to respond to shipping costs. Hence when facing the China shock, a deficit developing country is less likely to divert its waste export from China to ROW than a surplus developing country. Therefore, we expect the effect of the China shock to be more sensitive to a trade surplus among developing countries than developed countries. In the second and third columns of Table 6, we split the sample into high- and low-income groups the same as column 6 of Table 3: high (low) income countries are those with 2011 GDP per capita above (below) 16,000 USD. Consistent with our conjecture, the results suggest that the difference in the response to the China shock between a surplus and a deficit high-income exporter is smaller than that within low-income countries.

3.3 A Possible Externality

A stronger pollution regulation can, in principle, mitigate the pollution consequence of a larger trade surplus. For example, developed countries may adopt production techniques that result in less pollution. Because compliance with pollution control is costly, firms in developed countries may have a reduced incentive to import pollution-prone products. It is, therefore, not surprising that the import composition of a developed country is less sensitive to its trade surplus (as shown in column 6 of Table 3). However, the trade surplus in developing countries, which usually lack strict environmental regulations, can lead to a welfare cost due to the extra pollution.

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or implicit tax on polluting or environmentally harmful behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). Table 7 lists the ERS index of each country. The ERS index is significantly lower in developing countries than in developed countries.

Is the welfare loss from our channel quantitatively important? We investigate these questions through the lens of a quantitative model in Appendix D. 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 decreases the overall utility by increasing the pollution externality. The net effect of allowing the shipping cost to respond to a trade surplus can amplify the welfare loss by 33%. We also use the quantitative model to perform policy experiments. We find that a ban on the imports of foreign scraps − a policy experiment that is similar to an actual Chinese policy in place since 2018 − could increase welfare by raising the cost of the inputs for the polluting sectors, hence reducing the level of production in that sector. Hence the policy can increase welfare because the scraps are pollution intensive.

4 Conclusion

This paper provides a new channel for a trade imbalance to have welfare consequences. In particular, with endogenous responses of the unit shipping cost to the size of the trade imbalance, and the weak pollution control, a greater trade surplus leads to a greater welfare loss.

The first ingredient of our theory is that shipping costs and the composition of a country's imports respond to the size of the trade imbalance. We find strong empirical evidence that trade-surplus countries import more heavy goods, including scrap metals and other industrial waste. With nearly two million observations, we show robust evidence that the composition of trade is affected by shipping costs, and shipping costs in turn are affected by a trade imbalance.

This theory helps explain why China imports so many scraps and industrial waste: With a large trade surplus, China's inbound shipping cost is low which makes it attractive to import industrial scraps and waste (and other heavy goods). 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.

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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 five 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 Shipping Routes

	(1)	(2)	(3)	(4)	(5)	(6)
				Alternative ports		
ln(Imbalance$_{ndt}$)	-0.129***	-0.177***	-0.216***	-0.143**	-0.028	-0.191***
	(0.021)	(0.062)	(0.075)	(0.06)	(0.022)	(0.063)
$ln(Q_{ndt} + Q_{dnt})$			-0.054**			
			(0.024)			
ln(Imbalance$_{ndt}$) × Pervasive-route					-0.148**	-0.310***
					(0.073)	(0.102)
Country-pair FE	Y	Y	Y	Y	Y	Y
Destination-year FE		Y	Y	Y	Y	Y
Origin-year FE		Y	Y	Y	Y	Y
IV		Y	Y	Y		Y
Obs.	785	728	728	728	728	728
R-squared	0.77	0.93	0.93	0.93	0.93	0.93

Notes: This table shows the estimation results of equation (3). The dependent variable is the log value of 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. Q_{ndt} (Q_{dnt}) is the total weight of goods imported by country d from n (n from d). Pervasive route=1 if the destination country runs a trade surplus against 2/3 of its trade partners and the origin country runs a trade deficit against 2/3 of its trade partners. We use the log value of equation (4) for an instrumental variable for log Imbalance$_{ndt}$. In column 4, we replace the shipping cost associated with US/Canada/China using New York/Montreal/Yantian ports information. The first-stage F-statistics are 69, 54, 69, and 34 in columns 2, 3, 4, and 6, respectively. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Shipping Costs and Heavy Goods Imports

	(1)	(2)	(3)	(4)	(5)	(6) Developed importers
$\ln \lambda_{ndt}$	-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)			
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right) \times$ Persist		-0.017***				
		(0.001)				
$\ln(\text{Imbalance}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right)$				0.012***	0.032*	0.003
				(0.004)	(0.017)	(0.005)
Origin-good-year FE	Y	Y	Y	Y	Y	Y
Destination-good-year FE	Y	Y	Y	Y	Y	Y
Destination-origin-year FE			Y	Y	Y	Y
IV					Y	
Obs.	1,836,440	1,836,440	1,836,440	1,976,537	1,976,537	1,037,736
R-squared	0.80	0.80	0.83	0.83	0.83	0.86

Notes: This table shows the estimation results of equation (5). The dependent variable is the log value of good i's import value 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. In column 5, we use the log value of equation (4) for an instrumental variable for log Imbalance$_{ndt}$. The first-stage F-statistics are around 38 in column 5. In column 6, the sample is restricted to countries with an above-median GDP per capita (measured in 2011). Standard errors are clustered at the goods, destination, and origin levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Correlations between Pollution Intensities and Input's Weight-to-Value Ratios across Chinese Industries

	Kg-per-input val.	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 5: Trade Imbalance and the Relative Expansion of the Polluting Industries

	(1)	(2)	(3)	(4)
ln(Shipping cost$_{nt}$)×Pollution$_i$	-0.009**	-0.007**		
	(0.004)	(0.004)		
ln(Shipping cost$_{nt}$)×Pollution$_i$		-0.008**		
×Heavy-sector$_i$		(0.004)		
ln(Imbalance$_{nt}$)×Pollution$_i$			0.045*	0.112*
			(0.028)	(0.059)
Country-year FE	Y	Y	Y	Y
Country-industry FE	Y	Y	Y	Y
IV				Y
Obs.	85,789	85,789	85,789	85,789
R-squared	0.11	0.11	0.11	0.11

Notes: This table shows the estimation results of equation (6). The dependent variable is the log value of the domestic output of country n and industry i in year t. The Shipping cost$_{nt}$ is the average import shipping cost of country n in year t. Imbalance$_{nt}$ refers to exports/imports of country n in year t. Heavy-sector$_i$ is the weight-per-input-value for industry i. In column 4, the government expenditure as a share of GDP for three major trading partners of country n is used as instrumental variables for the log of trade imbalance. The first-stage F-statistics is around 15. Standard errors are clustered at country-industry-year levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Waste Export and China Shock

	(1) All countries	(2) High-income	(3) Low-income
$\ln(\text{Imbalance}_n)\times\ln(\text{Shock}_{i,nt})$	-0.151**	-0.0582	-0.158*
	(0.0768)	(0.0941)	(0.0949)
$\ln(\text{Shock}_{i,nt})$	0.00924	0.0478**	0.0206
	(0.0190)	(0.0219)	(0.0293)
Origin-goods FE	Y	Y	Y
Origin-year FE	Y	Y	Y
Obs.	27,855	9,262	18,593
R-squared	0.887	0.890	0.820

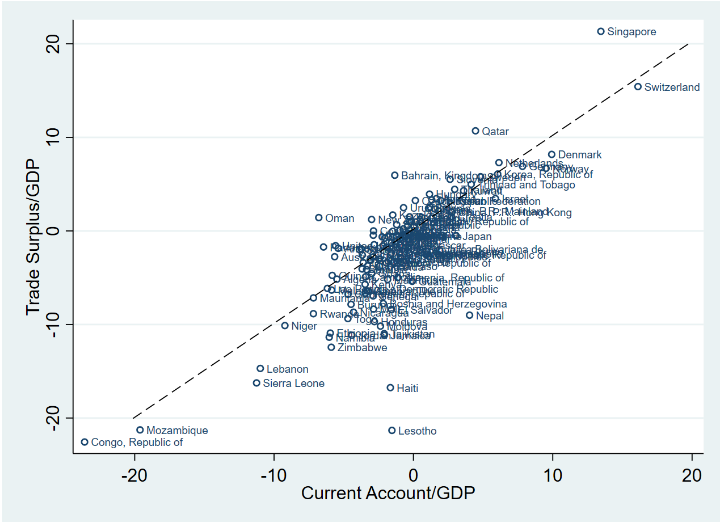
Notes: This table shows the estimation results of equation (7). The dependent variable is the log value of the export of waste goods i from country n in year t. The Imbalance_n refers to exports/imports of country n to the rest of the world other than China between 2014 and 2016. $\text{Shock}_{i,nt}$ measures the shock from the decline of waste import i of China from country n. In the second (third) column, the sample is restricted to countries with GDP per capita in 2011 above (below) 16,000 USD. Standard errors are clustered at country-year levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: ERS Index

BRICS	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

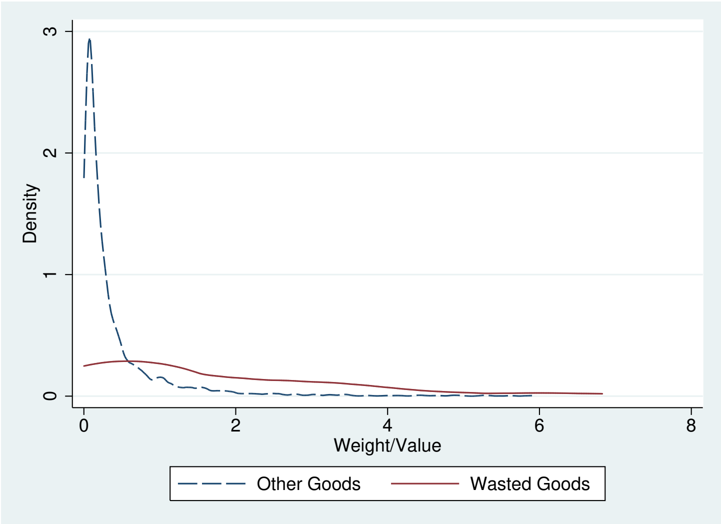
Notes: This table shows the environment regulation stringency index of OECD countries and 6 BRICS countries in 2004. A high index denotes high regulation.

Figure 1: The Current Account Imbalance and the Trade Imbalance



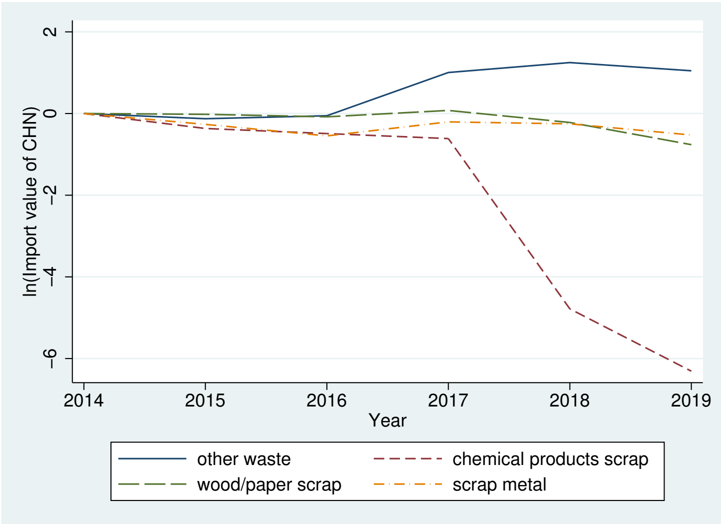
NOTE: This figure shows the correlation between the current account-GDP ratio and the trade surplus-GDP ratio across countries in 2015. The trade surplus is defined as export−import. The dashed line is the linear fit: Trade surplus/GDP $= -0.884(0.628) + 0.941^{***}(0.098) \times$ Current Account/GDP. The standard errors are reported in the parenthesis.

Figure 2: The Weight-to-Value Ratios for Industrial Waste Goods and Other Goods



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

Figure 3: The Waste Import of China of Broad Categories



NOTE: This figure shows the import of China (in log) of four broad waste categories: chemical product scraps, wood and paper scraps, scrap metals, and other wastes. The value in 2014 of each category is normalized to 0.

Online Appendix (not for publication in print)

A Alternative Specification

In Section 2, we assume that the shipping company charges a shipping fee by weight. In this appendix, we instead assume that the shipping fee is charged by the volume of the goods and show that our results stay the same.

We redefine the trade cost per unit of goods ($\tau_{i,nd}p_{i,n}$) to depend on the shipping volume:

$$(1+\tau_{i,nd})p_{i,n} = \Big\{1+\lambda_{nd}\Big(\frac{v_{i,n}}{p_{i,n}}\Big)^{1-\beta}\Big\}p_{i,n}$$

where $v_{i,n}$ is the number of containers per unit of good i produced by country n, $\frac{v_{i,n}}{p_{i,n}}$ is the number of containers per value of good i produced by country n, and λ_{nd} is the shipping cost per container from country n to country d. $(\frac{p_{i,n}}{v_{i,n}})^{\beta}$ measures the cost of handling goods with different value-to-volume ratios. We can rewrite the above equation as

$$(1+\tau_{i,nd})p_{i,n} = \Big\{1+\lambda_{nd}\Big(\frac{w_{i,n}}{p_{i,n}}\frac{v_{i,n}}{w_{i,n}}\Big)^{1-\beta}\Big\}p_{i,n}.$$

Although we do not observe $\frac{v_{i,n}}{p_{i,n}}$, if the container-per-weight ratio is similar across goods, it will still be true that a country with a greater trade surplus imports more heavy goods.

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 by controlling the destination-origin-year-2-digit HS code dummies. The results are reported in Table 8.

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

Table 8: Shipping Costs and Heavy Goods Imports: Alternative Specification

	(1)
$\ln \lambda_{ndt} \times \ln \left(\frac{w_i}{p_i} \right)$	-0.011**
	(0.005)
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 (5) with additionally controlling for destination-origin-year-HS2 fixed effect. The dependent variable is the log value of good i's import value 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. *** p<0.01, ** p<0.05, * p<0.1.

B The Weight-per-Input-Value across Industries

To construct the input-level weight-to-value ratio for an industry, we first map each HS6 product as an intermediate input to one or more Chinese 4-digit industries (CSIC).[24] We then map each CSIC code to an input-output table. Specifically, we use the 2012 Chinese input-output table to calculate the weighted average of the weight-to-value ratio of all inputs for each industry. The input-level weight-to-value ratio for each industry is listed below in Table 9.

Table 9: 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

[24] The concordance table can be found from Brandt et al. (2017).

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
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

C The Chinese Port-level Evidence

In the cross-country evidence reported in the main text, unmeasured time-varying country-pair features can, in principle, be correlated with unit shipping costs. In this appendix, we explore variations across ports within a country and examine the robustness of the relationship between trade imbalance and the heaviness of imports.

We work with Chinese port-level customs data during 2000-2006. For a given port, HS6 good, and a trading partner, we compute bilateral imports and exports, respectively.[25] We then estimate the following gravity equation:

$$\ln(\text{Import}_{i,mnt}) = \beta_0 \ln(\text{Imbalance}_{mnt}) + \beta_1 \ln(\text{Imbalance}_{mnt}) \times \ln\left(\frac{w_i}{p_i}\right) + \eta_{i,mt} + \eta_{i,nt} + \varepsilon_{i,mnt}, \tag{8}$$

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 $\beta_1 > 0$.

In Column 1 of Table 10, 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. This finding suggests that the import elasticity with respect to the trade imbalance is greater for heavier products. In Column 2, where we additionally control for port-exporter-pair fixed effects, β_1 is estimated to be 0.0064 and statistically significant. We conclude that the within-country data pattern is similar to the cross-country pattern, confirming that a trade imbalance affects the composition of imports, even after we control for a large number of relatively demanding fixed effects.

D A Quantitative Model and Policy Evaluations

D.1 Economic Structure

The model is an extension of Dekle et al. (2007). There are N countries that can potentially trade with each other. Each country is endowed with L_n amount of labor and has an exogenous trade surplus of S_n. Each country has a non-tradeble goods sector (NT) and three tradable sectors. The latter consists of a recycling sector (RS), a polluting sector (P), and a green sector (G). The output from each

[25] By port, the customs data refers to the city where the port is located. We exclude non-coastal cities in this exercise.

Table 10: Trade Imbalance and Import Composition across Chinese Ports

	(1)	(2)
$\ln(\text{Imbalance}_{nmt})$	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 (8). The dependent variable is the log value of good i's import value 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.

sector can be used either as intermediate inputs or for final consumption. Scraps (non-treated) are generated in the consumption process and are used as inputs of the recycling sector to produce recycled scraps.

Motivated by the data patterns described earlier, the green sector produces goods that have a low weight-to-value ratio (i.e., light), whereas both the polluting sector and the recycling sector produce heavy goods. The international shipping cost per unit of heavy goods is assumed to depend on the size of the bilateral trade balance, whereas for simplicity, that for light goods does not.

We denote these four sectors as $j \in \{NT, RS, P, G\}$. The distinction between recycled scraps and the polluting good (the other heavy goods) is important in our exercise. First, not all pollution-generating inputs in the data are recycled scraps. Second, because the Chinese import ban applies to industrial scraps but not to other pollution-generating material, we would like to allow for substitution between industrial scraps and other pollution-generating material in the policy simulations.

Denote C_n^j as the quantity of final consumption of sector j. The final goods bundle is defined as

$$C_n = \prod_j \left(C_n^j\right)^{\alpha_n^j} \tag{9}$$

where α_n^j is the preference over sector j, with $j \in \{NT, RS, P, G\}$, and $\sum_j \alpha_n^j = 1$. For each tradable sector $j \in \{RS, P, G\}$, C_n^j is an aggregation of a continuum of varieties i:

$$C_n^j = [\int_0^1 (Q_n^j(i))^{\frac{\sigma-1}{\sigma}} di]^{\frac{\sigma}{\sigma-1}} \tag{10}$$

Here i denotes a variety and $\sigma > 0$ is the elasticity of substitution among the varieties. $Q_n^j(i)$ is the amounts of variety i in sector j consumed by country n. For each tradable good, country n will consume variety i from the cheapest source country given the bilateral trade cost, as explained later.

The representative household's utility is defined as

$$\ln C_n - \eta \ln \Delta_n, \tag{11}$$

where Δ_n is the pollution in country n, and η measures the dis-utility per unit of pollution. The production in the polluting sector generates pollution, but the producers in the sector do not take the household's dis-utility of pollution into account unless a pollution tax is imposed.

Non-treated scrapped goods are generated at a fixed proportion $\phi > 0$ of the final consumption goods. So the total scraps generated is $K_n = \phi C_n$. The recycling sector buys them from the household to produce the recycled scraps.

The aggregate expenditure of the consumer, denoted by X_n, is

$$X_n = w_n L_n + X_n^K - S_n, \tag{12}$$

where S_n is the trade surplus of country n. P_n^K is the price of the scrap goods, and $X_n^K = P_n^K K_n$ is the income from selling the scraps and $w_n L_n$ is the labor income.

D.2 Production

We describe the production in the four sectors one by one. Their input-output relationships are summarized in Table 11.

Non-tradable sector In the non-tradable sector, a representative firm produces a homogeneous non-tradable good only using the labor force with a constant marginal production cost technology:

$$c_n^{NT} = P_n^{NT} = \kappa_n^{NT} w_n,$$

where c_n^{NT} is the marginal cost in country n, P_n^{NT} is the price of the non-tradable good, and κ_n^{NT} measures the labor required per unit of non-tradable goods (i.e. the sector productivity in country n). The non-tradable goods are used as intermediate inputs of the polluting sector and green sector, as well as the final consumption.

Recycling sector In the recycling sector, each country has a continuum of firms and each firm can produce one variety i. The output of each firm is aggregated to the sector bundle using the aggregator the same as equation (10). Recycling sector goods will be used as inputs for the polluting sector and green sector, as well as the final consumption.

To produce, a firm combines untreated scraps and labor to generate recycled scraps. The cost of a unit output for firm i is

$$\frac{1}{z_n^{RS}(i)} \underbrace{\frac{1}{Z_n^{RS}} \left(\beta_n^{RS}\right)^{-\beta_n^{RS}} \left(1-\beta_n^{RS}\right)^{-\left(1-\beta_n^{RS}\right)} \left(w_n\right)^{\beta_n^{RS}} \left(P_n^K\right)^{\left(1-\beta_n^{RS}\right)}}_{c_n^{RS}} \tag{13}$$

Here β_n^{RS} is the labor share in this sector and Z_n^{RS} is the sector's aggregate productivity. $z_n^{RS}(i)$ represents the firm productivity in country n, which follows a Frechet distribution $\Pr\left(z_n^{RS}(i) \leq \bar{z}\right) = \exp\left(-T_n \bar{z}^{-\theta}\right)$, where T_n is country n's aggregate productivity, and θ is the shape parameter. The term after firm productivity in (13), denoted as c_n^{RS}, is the cost to produce a unit sector output in RS in country n.

Following Eaton and Kortum (2002), firms from country n face an iceberg cost $\tau_{dn}^{RS} \geq 1$ to sell their products to another country d. Then the probability that country n exports to country d in sector RS is

$$\pi_{dn}^{RS} = \frac{T_n \left(c_n^{RS} \tau_{dn}^{RS}\right)^{-\theta}}{\sum_{n=1}^{N} T_n \left(c_n^{RS} \tau_{dn}^{RS}\right)^{-\theta}} \tag{14}$$

The price index of the recycling sector in the country n is

$$P_n^{RS} = \Gamma\left(\frac{\theta-\sigma+1}{\theta}\right) \left(\sum_{d=1}^{N} T_d \left(c_d^{RS} \tau_{nd}^{RS}\right)^{-\theta}\right)^{-\frac{1}{\theta}} \tag{15}$$

where Γ is a gamma function.[26]

Note that τ_{dn}^{RS} is a function of the bilateral trade balance as estimated in the previous empirical section, since recycled scraps are heavy goods.

Denote by Y_n^{RS} the gross output value of the recycling sector. Then from the production technology assumption in (13), the expenditure on untreated scraps

[26] It is assumed that $\theta - \sigma + 1 > 0$.

K in the production is

$$X_n^K = \left(1 - \beta_n^{RS}\right) Y_n^{RS} \tag{16}$$

Assuming $K_n = \phi C_n$, the price of the scrap, P_n^K, in country n satisfies

$$\frac{P_n^K}{P_n^C} = \frac{X_n^K / K_n}{X_n / C_n} = \frac{X_n^K}{\phi X_n} \tag{17}$$

Here $P_n^C = \kappa_n^C \prod_j \left(P_n^j\right)^{\alpha_n^j}$ is the price of the final consumption and $\kappa_n^C = \prod_j \left(\alpha_n^j\right)^{-\alpha_n^j}$ is a constant, which are derived from (9).

Polluting sector In the polluting sector, all assumptions are similar to the recycling sector, except that: (1) Firms in this sector combine labor and products from all sectors j (not the non-treated scraps K) to produce; (2) Pollution will be generated, and the pollution intensity increases with units of recycled scraps used in the production; (3) Firms produced in the country n face environmental regulation t_n and can choose pollution abatement. The output from the polluting sector again is used as inputs for other sectors and consumed in the final consumption.

To save space, we directly write down the cost of producing a unit of output in this sector and country n as:

$$c_n^P = t_n \kappa_n^P \left(w_n\right)^{\beta_n^P} \prod_j \left(P_n^j\right)^{\gamma_n^{Pj}\left(1-\beta_n^P\right)} \tag{18}$$

where κ_n^H is a constant.[27] γ_n^{Hj} is the share of sector j in the material bundle of the polluting sector. $\sum_j \gamma_n^{Pj} = 1$. $t_n \geq 1$ measures the strength of environmental regulation (one plus the pollution tax). In other words, $t_n = 1$ represents no environmental regulation. [28]

A higher pollution tax can induce more pollution abatement. The emission

[27]In a Cobb-Douglas function, $\kappa_n^j = \frac{1}{Z_n^j}\left(\beta_n^j\right)^{-\beta_n^j} \Pi_{j'} \left(\gamma_n^{jj'}\left(1-\beta_n^j\right)\right)^{-\gamma_n^{jj'}\left(1-\beta_n^j\right)}$, where Z_n^j is the productivity of sector j in country n .

[28]We do not introduce pollution in the recycling sector because the available country-level pollution data does not allow us to apportion it to different sectors, especially the recycling sector.

per output x_n is given by

$$x_n = t_n^{-\psi_n} \delta \left(q_n^{P,RS} \right) \tag{19}$$

where $\psi_n > 0$ measures the efficiency of the abatement technology in country n. A larger ψ_n means more abatement at a given level of pollution tax. The function $\delta(.)$ represents the pollution per unit of output in the absence of environmental regulation. We allow δ to depend on $q_n^{P,RS}$, the units of recycled scraps used to produce one unit of the polluting sector's out, and assume $\delta' \geq 0$ (recycled scraps may be more polluted).

Green sector For the green sector, all assumptions are similar, but firms do not generate any pollution. The key difference is that the output from this sector is assumed to be light so that the trade cost does not depend on the trade imbalance. Again we directly write down the cost of one unit of output in this sector as

$$c_n^G = \kappa_n^G (w_n)^{\beta_n^G} \prod_j \left(P_n^j \right)^{\gamma_n^{Gj} \left(1 - \beta_n^G\right)} \tag{20}$$

where κ_n^G and γ_n^{Gj} are defined in a similar way.

Given the firm productivity in all three tradable sectors follows the same Frechet distribution, the probability that country n exports tradable good $j \in \{RS, P, G\}$ to the country d shares the same functional forms:

$$\pi_{dn}^j = \frac{T_n \left(c_n^j \tau_{dn}^j \right)^{-\theta}}{\sum_{n=1}^N T_n \left(c_n^j \tau_{dn}^j \right)^{-\theta}} \tag{21}$$

where $\tau_{dn}^j \geq 1$ is the ice-berg trade cost. The key is that the trade cost τ_{dn}^P and τ_{dn}^{RS} are endogenous, which depends on the trade imbalance between d and n, but τ_{dn}^G is assumed to be exogenous.

The aggregate price index P_n^j in these 3 sectors is:

$$P_n^j = \Gamma \left(\frac{\theta - \sigma + 1}{\theta} \right) \left(\sum_{d=1}^N T_d \left(c_d^j \tau_{nd}^j \right)^{-\theta} \right)^{-\frac{1}{\theta}} \tag{22}$$

D.3 Endogenous shipping cost and equilibrium

Denote the aggregate expenditure and the gross output in sector j by Y_n^j and X_n^j, respectively. Country n's trade surplus against country d in percentage term, denoted by B_{dn}, is defined as the ratio of country n's exports to d and country d's exports to n:

$$B_{dn} = \frac{\sum_j \pi_{dn}^j X_d^j}{\sum_j \pi_{nd}^j X_n^j}$$

We assume that the import cost of country d from n is

$$\tau_{dn}^j = B_{dn}^{\nu^j} \bar{\tau}_{dn}^j \tag{23}$$

where $\bar{\tau}_{nm}^I$ is the trade cost if $B_{dn} = 1$. ν^j is the elasticity of the import cost of country d from country n with respect to the bilateral imbalance B_{dn}.

Our earlier empirical results show that an increase in the trade surplus tends to reduce the unit shipping cost on the importing side of the surplus country. Furthermore, both polluting goods and industrial scraps tend to have a higher weight-to-value ratio on average. To capture these features, we assume $v^j > 0$ for both polluting goods and recycled scraps. On the other hand, for green goods (which are light), we assume $v^G = 0$ for simplicity.

The aggregate expenditure of each sector j can be written as

$$X_n^j = \alpha_n^j X_n + \sum_{j' \neq RS} \left(1 - \beta_n^{j'}\right) \gamma_n^{j'j} Y_n^{j'} \ , \tag{24}$$

where $\alpha_n^j X_n$ is the value absorbed by the aggregate demand. The second term is the sum of the values used as intermediate inputs, where $\gamma_n^{j'j}$ denotes sector j's share in sector j''s input bundle, and $\sum_j \gamma_n^{j'j} = 1$. (Recall that the recycling sector uses only scraps and labor as inputs.)

The labor share in each country and sector is

$$w_n L_n^j = \beta_n^j Y_n^j \tag{25}$$

To close the model, the market for each sector j has to clear:

$$Y_n^j = \sum_{d=1}^{N} \pi_{dn}^j X_d^j, \tag{26}$$

Finally, the current account for each country n satisfies

$$\sum_j Y_n^j = \sum_j X_n^j + S_n \tag{27}$$

The total pollution is

$$\Delta_n = x_n Y_n^P \tag{28}$$

An equilibrium given S_n and t_n is a set of wage w_n, the price of the scrap P_n^K, the expenditures X_n^K, X_n^j, X_n, the gross output Y_n^j, trade cost τ_{dn}^j, and labor market allocations L_n^j that solves equations (16), (17), (23), (24), (25), (26), (27), and also clears the labor market $\sum_j L_n^j = L_n$.

D.4 Calibration

In principle, solving for the equilibrium requires the knowledge of the parameter values of $\bar{\tau}_{dn}^j$, κ_n^j, t_n, T_n, ϕ, L_n, β_n^j, $\gamma_n^{j'j}$, α_n^j, v^j, θ, and σ as well as the aggregate imbalance S_n. To solve for pollution and its dis-utility, we further need to know ψ_n, δ_n and η. A challenge is that the existing literature does not give us a precise guide on many of these parameter values.

A technique known as "hat algebra", proposed by (Dekle et al. (2007)), allows one to perform many counter-factual thought experiments - small changes from the current equilibrium - without having to know many parameter values. An important insight from this technique is that $\bar{\tau}_{dn}^j, \kappa_n^j, t_n$ and T_n are contained in the current trade shares, ϕ is contained in the current expenditure on scraps, L_n is within the total labor income, and S_n is observed in the data. Hence parameters left to calibrate are only β_n^j, $\gamma_n^{j'j}$, α_n^j, v^j, θ, and σ, and the parameters directly related with pollution ψ_n, δ_n and η.[29]

[29] The technique is popular in the international trade literature. We are willing to provide the

To calibrate our model, we use the world input-output (WIOD) data in 2014 and consider a three-country world: China, the U.S., and the ROW (an aggregation of all other countries). We aggregate all service sectors into a non-tradable sector.

For the three tradable sectors, we take the recycling and waste collection industry in the input-output table as the recycling sector in the model. The polluting sector in the model is an aggregation of those manufacturing and mining industries in the input-output table whose pollution intensities exceed the median value. The green sector is an aggregation of the remaining industries.

We match our model with the data as follows:

Parameters related with pollution, ψ_n, δ_n and η We first explain how we estimate the pollution intensity equation (29) to get ψ_n and δ_n. We focus on four air pollutants measures: SOX, NOX, and VOC, measured in metric tons, plus PM10 measured in $\mu g/m^3$.[30] Using estimates of willingness to pay (WTP) for each pollutant, we convert these pollutants in a given country into a one-dimensional measure of "pollution", denoted as Δ_n in the model.

We estimate the pollution intensity equation (19) and ψ_n. Assuming

$$\ln \delta_n = \ln b + \rho^{RS} \ln \left(\frac{Q_n^{P,RS}}{Y_n^P} \right) + \varepsilon_n$$

where b is a constant, $Q_n^{P,RS}$ is the total weight of the recycled scraps used in the production of polluting good, with $\frac{Q_n^{P,RS}}{Y_n^P}$ as the weight of the recycled scraps per unit of output, and ε_n is a random noise, then ρ^{RS} captures the elasticity of pollution intensity to recycled scraps. Assuming further that environmental regulation stringency, ERS_n, is proportional to t_n, and the abatement technology ψ_n is the same across countries, our model implies that the pollution intensity $\frac{\Delta_n}{Y_n^P}$ follows

$$\ln \frac{\Delta_n}{Y_n^P} = \ln(b) - \psi \ln(ERS_n) + \rho^{RS} \ln \left(\frac{Q_n^{P,RS}}{Y_n^P} \right) + \varepsilon_n \tag{29}$$

details of this analysis upon request.

[30] Data source: data.oecd.org/air/air-and-ghg-emissions.htm

By our estimation, $\psi = 1.63$ and $\rho^{RS} = 0.12$.

The dis-utility of pollution η is challenging to pin down. Existing estimates of willingness to pay (WTP) for reducing pollution are highly dispersed.[31] One of the most cited estimates is Bajari et al. (2012), which uses a hedonic pricing approach and accounts for time-varying correlated unobservable, The WTPs for PM10 ($1\mu g/m^3$), SOX (1 ppb), and the VOC+NOX (1 ppb) are estimated to be US$103, 178 and 180 (in 2003 dollars), respectively (Table 6 in their paper).

As SOX, VOC, and NOX in China and many other countries are often reported in weight, we need to convert weight of emission to degree of concentration. As the US EPA reports both concentration and tonnage of these pollutants, we estimate a simple linear relationship between the two using US data over 1990-2018. We find that one million tons of SOX, and VOC+NOX emissions increase the concentration by 4.56 ppb, and 0.99 ppb, respectively. The monetary costs of one million tons of emission of SOX, and VOC+NOX are estimated to be 811.68 (178×4.56), and 178.2 (180×0.99), respectively. We then use the WTP estimates to convert all pollutants to a single pollution measure in the model Δ_n in US dollar term. This means that $\eta = 1$, when the US consumption bundle is used as the numeraire. Based on our computation, the per capita monetary loss from pollution in China is about US$2600 per year, while the corresponding per capita loss in the United States is about US$900 per year.

It is hard to say whether our estimate of the dis-utility of pollution is too high or too low. On the one hand, the available data only covers four air pollutants, PM10, SOX, NOX, and VOC, but the list of health-harming pollutants are surely longer than these. By ignoring other pollutants, we may have underestimated η. On the other hand, our estimate is based on US data. Bayer et al. (2016) show that the WTP of pollution is lower for developing countries. Thus, we may have overestimated η in the other economies.

[31] For instance, the WTP for reducing TSP emission reported in Smith and Huang (1995) varies from US$ -239.8 to US$ 1,807. Sieg et al. (2004) Similarly, the WTP estimates for ozone reduction vary from US$ 8 to US$ 181.

Other parameters We calculate β_n^j and $\gamma_n^{j'j}$ from the value-added share and intermediate input shares in each country/sector, and α_n^j from the expenditure share of the country n's GDP. The estimates are reported in Table 12 and Table 13.

We set v^j based on the estimates from our empirical section. In particular, $v^j = 0.501$ for the polluting and recycling sector as in column 4 of Table 2. As explained earlier, for simplicity, $v^j = 0$ for light (green) goods. Finally, we set $\theta = 3.6$ and $\sigma = 3.79$ as Bernard et al. (2003). We then can solve for all variables except for pollution.

D.5 Welfare and Policy Analysis

China is the home country in the model. Using calibrated parameters, we perform counterfactual thought experiments. We first quantify the welfare cost of a trade surplus due to an endogenous response of the shipping cost to a trade surplus. To do so, we study what happens when we set $\nu = 0$, i.e., making the shipping cost independent of the trade surplus. Relative to endogenous shipping costs, the import shipping cost rises and the export shipping cost declines. For any variable x, Table 14 shows the percentage change $(\hat{x} - 1) \times 100$.[32]

With exogenous shipping costs, the imports of scraps and heavy materials (goods from the polluting sector) decline by 0.029% and 0.035%, respectively (in the second and third row). A higher unit shipping cost on the import side increases the input costs of the polluting industry, which reduces pollution by 0.028% (the first row). As this also reduces the labor demand, the wage declines by 0.032%. While the consumption goes down (in the last row), the negative effect on utility is more than offset by a reduction in pollution. The net effect is an increase in the overall utility by 0.027%.

With an endogenous shipping cost, a change in trade imbalance alters import composition. We consider a small perturbation of China's trade surplus from the current level by $\pm 1\%$ (and adjusting the trade deficits of USA and ROW

[32] $\hat{x} = \frac{x'}{x}$, where x is the current equilibrium value, and x' is the counter-factual value.

accordingly),[33] and compare the changes in pollution externality in China under $\nu = 0.501$ (endogenous shipping cost) and $\nu = 0$ (exogenous shipping cost), respectively.

The results are presented Figure 4. On the x-axis, the change in Chinese aggregate trade surplus varies from -1% to 1% relative to the observed Chinese aggregate surplus. We then trace the changes in pollution in the two cases (endogenous versus exogenous shipping cost) on the vertical axis. As we can see, a higher trade surplus is associated with more pollution. Importantly, the increase in pollution is greater when the trade cost is endogenous (the solid line). For instance, with a greater trade surplus by 1%, the pollution would increase by 0.32% when $v = 0.501$, but by 0.21% only when $\nu = 0$ (dashed line). In other words, the endogenous shipping cost channel raises pollution by an extra 1/3 ($\frac{0.32-0.21}{0.32}$), compared to the case of an exogenous shipping cost.

The interaction between a trade surplus and pollution generates a new welfare effect of a change in a trade imbalance that is new to the existing literature on current account imbalances.[34] Our calibration results suggest that the effect is also economically significant. When China's trade surplus increases by 1%, it suffers a welfare loss from the pollution externality by 0.32%; about 1/3 of the welfare loss is due to the endogenous shipping channel.[35]

Banning Scrap Imports vs. Stronger Environmental Regulation

We now examine the effects of public policies that aim to improve upon the outcomes. In particular, we analyze a ban on imports of all scraps, representing an actual Chinese policy put in place in 2018. We compare it with a policy of imposing stronger environmental regulation.[36]

[33] The relative changes in the trade deficits in USA and ROW are proportional to their trades with China.

[34] In the NBER working paper version, we present a dynamic small open economy model that endogenizes the current account imbalance and find that the welfare channel of our endogenous shipping channel is also quantitatively important.

[35] Gourinchas and Jeanne (2006) and Mendoza et al. (2007)) estimate that the welfare loss of a current account imbalance associated with financial frictions is about 1% of the consumption.

[36] In both counter-factual experiments, we hold constant the value of the trade imbalance. As the value of the scrap imports accounts for less than 1% of the total imports in the data, banning

The results of the import ban are reported in the second column of Table 14. The ban raises the input cost of the polluting sector, which in turn generates several effects. First, the output in the polluting sector decreases, and the pollution in turn decreases by 0.42%. The import of polluting goods increases by 0.008% due to a substitution effect between polluting goods and scraps. Second, the scrap import ban reduces the labor demand and causes a decline in wages by 0.25%. Meanwhile, the price of the consumption bundle rises, and the consumption declines. The overall utility rises by about 0.41%, driven by lower pollution.

In the third column, we report a sensitivity analysis by setting $\rho^{RS} = 0$ when banning scrap imports. That is, we consider an alternative assumption that recycling is no more pollution-intensive than other heavy goods production. In this case, pollution only declines by 0.29%. The overall utility increases by 0.28%, which is only about 2/3 of the utility change in the second column.

Finally, in the fourth column, we raise the pollution tax by 1%. Not surprisingly, the pollution declines by 1.22%. The scrap imports also decline since they are mainly used in pollution-intensive production. However, the imports of non-scrap heavy goods increase to substitute for the lower scrap imports. Since the pollution tax increases the production cost of the polluting sector, the wage declines by 1.13% and the consumption declines by 0.83%. Nonetheless, thanks to reduced pollution, the overall utility increases by 0.4%. Comparing to the second column, we see that the scrap import ban is comparable to a 1 percentage point increase in pollution tax in terms of the effect on utility. However, a higher pollution tax can yield even better welfare gains.[37]

the scrap imports is assumed to have no effect on the value of China's overall trade surplus.

[37]With a higher pollution tax, the trade imbalance may change. While we ignore this effect here, the dynamic model in the NBER working paper version takes this into account. Furthermore, while the "hat algebra" technique is not conducive to deriving the optimal pollution tax, the dynamic model in the NBER working paper version suggests that the import ban is much inferior to an optimal pollution tax.

Table 11: Production Structure of the Model

Sector	Inputs	Outputs
Recycle sector	Untreated scraps from consumption K + labor	Recycled scraps Y^{RS} (a heavy material)
Polluting sector	Heavy materials(RS,P)+light material(G) +non-tradable material(NT)+labor	Polluting output Y^P(a heavy material) +pollution
Green sector	Heavy materials(RS,P)+light material(G) +non-tradable material(NT)+labor	Green output Y^G (light material)
Non-tradable sector	Labor	Non-tradable output Y^{NT}
Final consumption	Outputs of all above 4 sectors	Consumption goods+scraps

Table 12: Calibration Result: γ

Source sector	Usage sector	CHN	USA	ROW
NT	NT	0.485	0.786	0.707
G	G	0.198	0.078	0.107
P	P	0.315	0.128	0.174
RS	NT	0.006	0.019	0.022
NT	G	0.180	0.318	0.300
G	P	0.549	0.423	0.461
P	NT	0.269	0.257	0.229
RS	G	0.003	0.005	0.011
NT	P	0.193	0.290	0.317
G	NT	0.171	0.183	0.149
P	G	0.634	0.519	0.521
RS	P	0.008	0.012	0.015

Notes: This table shows the $\gamma_n^{j'j}$ in the calibration.

Table 13: Calibration Result: α and β

	α	β
CHN		
NT	0.307	-
G	0.374	0.261
P	0.310	0.211
RS	0.008	0.360
USA		
NT	0.719	-
G	0.128	0.404
P	0.140	0.337
RS	0.012	0.538
ROW		
NT	0.581	-
G	0.206	0.356
P	0.190	0.300
RS	0.018	0.498

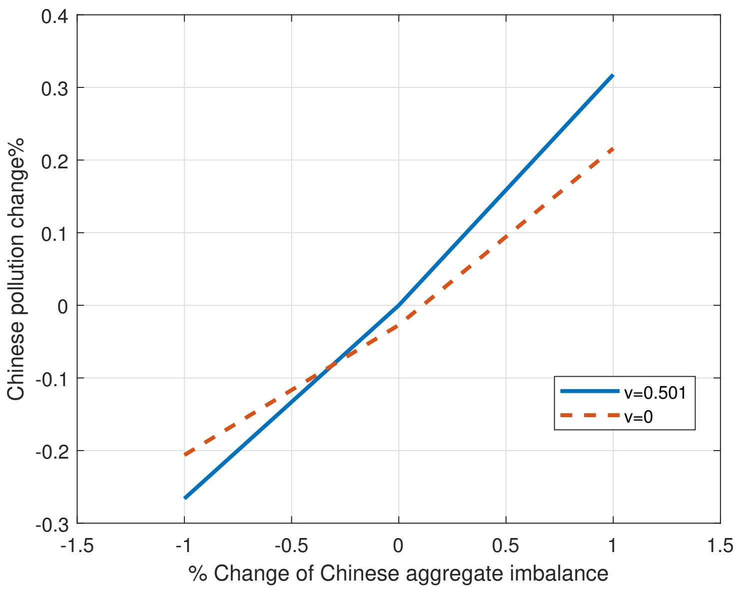
Notes: This table shows the α_n^j and β_n^j in the calibration.

Table 14: Welfare Comparisons of Counterfactual Policy Experiments

China	(1) $\nu = 0$	(2) Ban scrap import	(3) Ban scrap imp $\rho^{RS} = 0$	(4) $\hat{t}_{CHN} = 1\%$
Pollution	-0.028	-0.425	-0.299	-1.225
Scrap import	-0.029	0.000	0.000	-0.106
Heavy goods import	-0.035	0.009	0.011	4.208
Wage	-0.032	-0.257	-0.257	1.133
U	0.027	0.413	0.283	0.402
C	-0.003	-0.018	-0.019	-0.849

Notes: This table presents the model predictions about the Chinese economy for different counterfactual experiments. In column 1, the Chinese shipping cost is exogenous $\nu = 0$. In column 2, a ban on scrap imports is imposed. In column 3, a ban on scrap imports + low pollution intensity of recycling scraps ($\rho^{RS} = 0$) is imposed. In column 4, the Chinese environmental regulation increases by 1%.

Figure 4: The Pollution and Trade Surplus



NOTE: This figure shows the pollution change in China when $v = 0.501$ and $v = 0$ under different trade-surplus values.