Trade Surplus, Heavy Imports, and Pollution

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November 8, 2019

Abstract

Trade imbalance affects the composition of trade by altering unit shipping costs. We show that countries with a larger trade surplus systematically import more heavy goods. We explore two novel implications of this insight. First, because scrap metals and most other solid industrial waste have a high weight-to-value ratio, countries with a larger trade surplus import more scraps and waste. Second, we find that industries using more heavy inputs are more polluting. A greater trade surplus, by reducing input costs of these industries, begets more pollution. Finally, we use a model to evaluate the welfare effect of a trade surplus via this channel and that of a ban on imports of industrial scraps.

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1 Introduction

Unbalanced trade is a common feature of international trade and is understood to reflect a gap between a country's savings and investment. By standard open-economy macroeconomics, a trade imbalance is associated with a welfare loss only if the level of savings or the level of investment is sub-optimal. How trade imbalance affects the composition of a country's imports and its well-being is under-studied. This paper explores this relationship. One novel implication will be that, even when there are no distortions in either savings or investment level, a trade surplus may reduce welfare.

A related question is why certain countries, such as China, import so much more industrial waste and other goods with a high weight-to-value ratio than other countries. While the weight-to-value ratio for import bundles for the world as a whole is 0.22 kg per dollar, the ratio for China is more than twice as high, at 0.46 kg per dollar. A big part of the relatively heavy products are 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), with approximately one out of every five tonnes of its imports consist of HS 6-digit product lines that contain either "scrap" or "waste" in their descriptions. This included 45 million tons of scrap metal, used textile and fibers, waste paper, and used plastics, worth over $18 billion in 2016[1]. We will suggest that it is not coincidental that China simultaneously runs a large trade surplus and imports industrial scrap voraciously. We will study whether such pattern generalizes to other countries as well.

This paper proceeds in three parts. In the first part, we study how a country's trade surplus reduces the unit shipping cost of inbound trade, and how that 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 makes it more likely for ships returning to the

[1]Since early 2018, China has banned the imports of many industrial waste, generating a mini-crisis in many countries that have become accustomed to ship industrial scraps and waste to China.

country to be under their full carrying capacity (De Palma et al. (2011) and De Oliveira (2014)). This imbalance reduces the unit shipping cost for the country's imports, making it relatively cost effective to import relatively heavy goods. Conversely, deficit countries have a comparative advantage in exporting relatively heavy goods. These patterns hold not only across countries, but also across port cities in China. By our estimation, if a good's weight-to-value ratio is higher by 10%, its elasticity of imports to the trade surplus is also higher by 0.15%.

In the second part of the paper, we explore some novel implications of this insight. In the first application, we show that our insight helps us to understand why a trade surplus tends to induce the country to import more of scrap metals and other industrial waste, since industrial waste is a quantitatively important category of heavy goods. In the second application, 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, a greater trade surplus, by making the inputs cheaper for the polluting industries, alters a country's comparative advantage towards a more polluting production structure.

In the third part, we construct a quantitative model to evaluate the welfare effect of a trade surplus. In this model, there is no distortion in the savings decision per se. Given the trade surplus, an endogenous reduction in the unit shipping cost on the importing side raises the level of domestic production and the level of consumption relative to a world in which the shipping cost does not respond to a trade surplus. This gain in utility, however, is more than offset by a reduction in utility due to additional pollution. The net effect of allowing shipping cost to respond to a trade surplus is a welfare loss of 1%.

We also use the quantitative model to perform policy experiments. We find that a ban on the import of foreign scraps - a policy experiment that is motivated by a similar policy that China has implemented since early 2018 - could raise welfare by making the inputs more expensive to the polluting production and hence reducing the level of production. However, a direct increase on the pollution tax is far superior to an import ban of foreign scraps. The reason is intuitive but holds important implications for policy design: if the only market failure is a negative externality in pollution, an optimal tax on pollution can directly close the gap between the social and private costs of pollution. In comparison, the effect of banning imported scraps on the private cost of pollution is indirect and imprecise, partly because both domestic industrial scrap and imported non-scrap heavy inputs are substitutes for imported industrial scrap.

A key contribution of the paper is to point out that a trade surplus can alter a country's comparative advantage, inducing an increase in the relatively heavy products as a fraction of its total imports. This change is like to be associated with more pollution in the trade-surplus country, especially if it has a low environmental standard or weak enforcement. The existing literature on the welfare effect of the trade imbalance focuses almost exclusively on the terms of trade channel (Dekle et al. (2007) and Epifani and Gancia (2017)). The welfare effect of the trade surplus is resulted from frictions on the capital market. In comparison, in this paper, a trade surplus magnifies a negative externality in pollution through an endogenous response of the shipping cost and the import composition to a trade surplus. Distortions in the level of savings or investment are not necessary for a trade surplus to generate a welfare loss.

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

Our paper is related to several other strands of literature. First, Hummels and Skiba (2004) and Lashkaripour (2015) emphasize that unit weight is an important feature in the 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 trade imbalance as a determinant of shipping cost or as a source of comparative advantage. Behrens and Picard (2011), Friedt and Wilson (2015), Jonkeren et al. (2010), and Wong (2017) do relate shipping cost to trade balance, but none of them studies the effects on the composition of imports and consequences for pollution.

Second, while there is a large literature on trade and environment (see surveys by Frankel (2009), Kellenberg (2009), Kellenberg (2012) and Lan et al. (2012)), it does not make a connection among trade imbalance, import composition, and the environment. Our contribution is to propose a possible interaction between trade imbalance and weak pollution control: Those developing countries that simultaneously have a weak pollution control regime and a trade surplus might experience especially adverse pollution effects.

The paper is structured in three parts after this introduction. In the first part, we aim to establish a relationship between a country's trade imbalance against an origin country and the tendency for it to import relatively heavy goods from the country. In the second part, we show that a country with a surplus tends to import more of industrial waste and generate more pollution. In the third part, we develop a model and discuss welfare and policy implications.

2 Trade Imbalance and Import Composition

In this section, we show that if the shipping cost depends on a good's weight-to-value ratio, then a modified gravity equation predicts that the import elasticity with respect to shipping cost systematically differs depending on the weight-per-value of a good.

2.1 The logic

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

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

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

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

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

We assume that

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

where $w_{i,nd}$ is the weight per unit of good i, and λ_{nd} is the shipping cost per unit of weight when delivering good from n to d.[2] Notice that we assume the shipping firm does not distinguish the goods it delivers but only charges shipping fee by the weight of the goods. We then get

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

[2]Hummels (2004) have pointed out that the shipping cost is correlated with the goods weight per unit.

The iceberg portion of the shipping cost is standard in the literature. The second component in the shipping cost says that the per value shipping cost equals to per weight shipping cost times weight to value ratio. While the last component is somewhat non-standard, it has an intuitive explanation: if the cargo is heavier, it would use more fuel in transportation, and a profit-maximizing shipping company would naturally charge a higher shipping fee. (From speaking to 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 1/3 full to satisfy the weight restriction. This is approximately the same as charging a shipping fee in portion to the weight of the cargo.) We assume that the weight to value ratio is an exogenous property of the goods.[3]

From equation (1) and the gravity equation, we can see that if λ_{nd} decreases, the import of heavy goods (those with a high weight-to-value ratio) will increase relatively more than the import of light goods (those with a low weight-to-value ratio) because heavy goods enjoy a disproportionately larger decline in the trade cost. We summarize our finding in the following proposition:

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

We now argue that if country d runs a trade surplus with country n, the shipping cost per weight λ_{nd} from n to d is lower. We assume that the total trade goods' weight must be balanced given a country pair n and d.[4] Consider the total export weight from country d to n is fixed at W^*. Then the shipping cost from country n to d is determined such that the total

[3]We will discuss and justify this assumption when we introduce our empirical measure of the weight to value ratio by product.

[4]As an alternative equilibrium restriction, we can assume the traded goods' volume (or the number of shipping containers) are balanced. We consider this alternative condition in Appendix A. Our results still hold.

import weight of country d is equalized at W^*.

To illustrate our argument more explicitly, we use Figure 1, which plots the total import weight of country d from country n on the x-axis and the the shipping cost from country n to d on the y-axis. The vertical line at W^* shows that the total import weight needs to equal to the total export weight. The downward sloping curve means that when the import shipping cost of country d (to country n) declines, the amount of import (and the import weight as a consequence) will increase. The equilibrium shipping cost λ_{nd} is determined by equalizing the total import weight to be W^*. If the aggregate expenditure of country d (E_d) decreases, and hence, the trade surplus of country d against country n increases, the import demand curve will move down. As a consequence, the shipping cost λ_{nd} will decline. We formally state the above argument in Proposition 2:

Proposition 2. *A larger trade surplus tends to produce a lower import shipping cost per weight.*

Combining with Proposition 1 and 2, we have the following proposition.

Proposition 3. *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 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 impossible to compute weight-to-value ratio. Fortunately, the National Tax Agency of Columbia does report both weight and FOB value of imports at the product level. Using this data, for each HS6 product, we compute the average weight to value ratio.[5] To give some

[5]We thank Ahmad Lashkaripour for sharing this data.

concrete examples, we list the top 5 and bottom 5 products in terms of weight-to-value ratio in Table 1.

Throughout our paper, we assume that the weight to value ratio is an exogenous characteristics of the goods. This assumption may not hold strictly. In the Chinese custom data, the weight-to-value ratio can be computed for 3,349 goods (about 60% of all HS6 goods). For these products, we find that the correlation in the weight-to-value ratios computed from the Columbia and China data is 0.75. Furthermore, we find that the weight to value ratio is very persistent over time in both data. For example, the auto-correlation in the weight-to-value ratio between two adjacent years is 0.98 in the Chinese custom data. Based on these findings, we believe that it is justified to assume that the weight-to-value ratio is an exogenous characteristic of goods. In any case, in all subsequent regression analysis, to further enhance the credibility of the exogeneity assumption, we use the weight-to-value ratio extracted from the Colombian data but exclude from the regression sample all country pairs that involve Colombia as either an exporter or an importer.

Shipping Costs

We obtain port-to-port 20-foot dry container freight rates over 2010-2017 for 128 major routes (64 country pairs in two directions) from Drewry, which is a shipping consulting firm. A 20-foot dry container has a cubic capacity of 33.2 m^3 and a payload (weight) capacity of 25,000kg per container[6]. For almost all countries except three (US, China, Canada), the Drewry covers one major port. For US, China and Canada where two ports are available, we use the information of the largest port.[7] For the shipping rate from Port A to Port B in a give year, we use the container freight rate in July of that year. [8]

[6]Source: DSV Global Transport and Logistics. While 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 (2017).

[7]We use LA, Shanghai and Vancouver for these three countries.

[8]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-

Trade Data

We employ two data sets on trade. First, the bilateral trade 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

West the theoretical prediction in section 2.1 in two steps. First, we check whether a negative relationship between a country's trade surplus and the back-haul shipping cost is supported in the data. Second, we check whether the elasticity of imports with respect to shipping cost is systematically bigger for products with a high ratio of weight to value.

2.3.1 Shipping Cost and Trade Imbalance

Consider the following equation:

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

where n and d are the origin and destination countries respectively. Imbalance_{ndt} is the trade surplus country d runs against country n in year t, measured by $\text{Export}_{ndt}/\text{Import}_{ndt} = \text{Import}_{dnt}/\text{Import}_{ndt}$, where Import_{dnt} is country n's import from country d (or country d's export to country n) and Import_{ndt} is country d's import from country n. $\Omega_{\overleftrightarrow{nd}}$ is an origin-

KOR, AUS-USA, BRA-CAN, BRA-CHN, BRA-GBR, BRA-IND, BRA-JPN, BRA-KOR, BRA-USA, BRA-ZAF, CAN-CHN, CAN-GBR, CAN-IND, CAN-KOR, CAN-ZAF, CHN-CHL, CHL-GBR, CHN-COL, CHN-EGY, CHN-GBR, CHN-IND, CHN-IDN, CHN-JPN, CHN-KOR, CHN-MYS, CHN-NZL, CHN-PHL, CHN-RUS, CHN-SAU, CHN-THA, CHN-TUR, CHN-USA, CHN-VNM, CHN-ZAF, GBR-COL, CBR-IND, GBR-JPN, GBR-KOR, GBR-TUR, GBR-USA, GBR-SZF, JPN-IND, JPN-IDN, IND-KOR, IND-USA, KOR-JPN, JPN-NZL, JPN-THA, JPN-USA, KOR-USA, KOR-ZAF, MEX-USA, MYS-USA, NZL-USA, PHL-USA, RUS-USA, THA-USA, TUR-USA, USA-ZAF. We exclude two European ports (Genoa, Rotterndam) and two east Asian hub ports (Singapore, Hong Kong) for which mapping between nationwide bilateral trade volume and bidirectional shipping cost information is not clear.

destination pair-specific component which affects the shipping cost for both directions, such as distance. This fixed effect does not distinguish between the two directions of the route. η_{nt} and η_{dt} are the origin x year pair and destination x year pair fixed effects, respectively, which are meant to absorb time-varying aggregate supply or demand shocks in the exporting and importing countries. e_{ndt} is an i.i.d random component with a zero mean.

The key coefficient of interest is α_1, which measures the responsiveness of the shipping cost to trade imbalance. If Proposition 2 is correct, then $\alpha_1 < 0$. An important challenge is that bilateral trade imbalance may endogenously respond to the shipping cost. For example, if Country d's trade surplus against Country n initially causes the shipping cost from Country n to Country d becomes lower, Country d will increase its imports from Country n, causing the initial trade surplus to diminish or disappear. In addition, there can be factors that simultaneously affect both the shipping costs and bilateral trade balance. The endogeneity problem will make it harder to observe a negative relationship in an OLS regression. We will need to have an instrumental variable approach.

The basic OLS result is reported in Column 1 of Table 2. While the negative estimate of α_1, at -0.006, is consistent with Proposition 2, the estimate is not statistically significant.

To address the possible endogeneity of bilateral trade balance, we use the two countries' relative fiscal shock as an instrumental variable. The idea is that a change in a country's government expenditure is likely to be a change in its national savings. (The empirical literature on fiscal multiplies suggests that the Ricardian equivalence does not hold in the data, or a change in the public sector savings is unlikely to be offset of a change in the private sector savings in the opposite direction.) An increase in government expenditure (or a decline in the public savings) is not only unlikely to be offset by a decline in the national investment, but is likely to be accompanied by an increase in investment. Since a country's trade balance is its savings minus investment, a shock to the two countries' government expenditure is a shock to the two countries' savings level, and would therefore likely affect the bilateral trade balance. On the other hand, a country's government expenditure is unlikely to be affected by bilateral trade balance.

We construct an instrumental variable for Imbalance_{ndt} by the following:

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

where Import_{nd2000} is country d's import from country n in 2000, Import_{d2000} is country d's aggregate import in 2000, and Gov_{dt} is county d's government expenditure in year t. Import_{dn2000}, Import_{n2000} and Gov_{nt} are similarly defined.

We interact this government expenditure with the import share of the partner country in 2000 to construct the partner specific measure. In the first stage estimation, we regress the log trade imbalance on the log of government expenditure constructed in the (3). The coefficient before the government expenditure is about -0.71 and significant at 1% level, suggesting that when the government d's expenditure increases by 1%, its trade imbalance (export/import) would decrease by 0.71%. The F-statistics is around 41 in the first stage regression. The second stage result with the IV regression is reported in the second column of Table 2. The estimate of α_1 is negative and statistically significant: An increase in country d's trade surplus against country n by 10% would lead to a decline in country d's import shipping cost by 1.1%.

Another complication is that if Country A runs a surplus against Country B, ships from A to B need not go back to B right away. This would weaken the shipping cost response to bilateral surplus. 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 then C to A, while always carrying a full load in all routes.

We address this concern in two ways. First, we note that contracting frictions often make complicated re-routing not easy to arrange. As Brancaccio et al. (2019) document, satellite tracking of ships often find empty ships leaving a port to go to the next port, suggesting the existence of non-trivial contracting frictions.

We then estimate a separate elasticity of shipping cost to trade imbalance between a country that runs a surplus against most trading partners and a country that runs a deficit against trading partners. We label such country pairs as pervasive imbalanced pairs. The idea is that if a country runs a surplus against most of its trading partners, then it would be hard to use multi-port route arrangement to avoid having relatively empty ships to come back to its ports. Similarly, for a country that runs a deficit against most of its trading partners, it would be hard to avoid having relatively empty ships leaving its port to other countries. When such two countries are paired (i.e., the pervasive imbalanced pairs), there is a stronger likelihood that relatively empty ships will travel from the pervasive deficit country to the pervasive surplus country.

We create a dummy (”pervasive route”) for these routes involving shipping from a pervasive deficit country to a pervasive surplus country, and add an interaction term between the dummy and the size of the bilateral imbalance. We use the same instrumental variable approach as before, and report the result in Column 3 of Table 2. The coefficient on the interaction term is negative and statistically significant. For country pairs that do not feature a pervasive imbalance, the elasticity of shipping cost with respect to trade imbalance is -0.083; but for country pairs involving a pervasive imbalance, the elasticity increases dramatically to -0.288 (-0.205-0.083). These results support the interpretation that a trade surplus tends to reduce the unit shipping cost on the import side, and the effect is much stronger for countries with a pervasive trade surplus.

2.3.2 Import Elasticity with respect to Shipping Cost

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

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

where n and d are the origin and destination countries respectively, i refers to a HS 6-digit product, $\frac{w_i}{p_i}$ is the weight-to-value ratio of good i, $\eta_{i,nt}$ ($\eta_{i,dt}$) is the origin-good-year (destination-good-year) fixed effect, and $\varepsilon_{i,ndt}$ is an random component with a zero mean.[9] We allow $\varepsilon_{i,ndt}$ to be correlated among the same good across countries, different goods in the same destination country, and different goods in the same origin country.

The weight-to-value ratio for a particular route could be endogenous as the unobserved component $\varepsilon_{i,ndt}$ may affect the import volume of good i. To address this possibility, we use the weight-to-value ratios computed from the Colombian data during the 2007-2013 period. We exclude any bilateral trade involving Colombia as either the destination or the exporting country.

Column 1 of Table 3 reports the benchmark result for equation (4). β_0 is -1.21 and statistically significant at the 1% level. This means that the import of good i from Country A would be 12.1% larger than from Country B if the shipping cost from Country A is 10% lower than from Country B. More importantly, β_1 is -0.127 and statistically significant at the 1% level. This suggests that shipment of relatively heavy goods is more responsive to a given decline in

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

the unit shipping cost that that of relatively light goods. The import elasticity with respect to the shipping cost is higher for good i by 1.27% than for good j if the weight per value of good i is 10% greater than good j.

In the second column of Table 3, we address possible endogeneity of the shipping cost by using the government expenditure shocks, defined in the equation (3), as an instrumental variable.[10] With the instrumental variable approach, the result becomes more pronounced. In particular, the β_1 estimate has increased in absolute value from -0.127 to -0.169.

Some goods such as oil or ores are shipped in bulk rather than in containers. We remove non-metal ores (2 digit HS code 25), metal ores (2 digit HS code 26) and oil and gas (2 digit HS code 27) and re-estimate the equation. The estimated coefficients, reported in the third column of Table 3, do not change much.

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

We show the result of the ambitious set of control variables, including origin-destination-year fixed effects, in the fourth column of Table 3. Such an extension would not allow us to identify the coefficient before the shipping cost variable as it is absorbed by the newly added fixed effects. Import for us, we find that, with this additional and demanding set of controls,

[10] In doing so, we impose an assumption that a country's government expenditure is independent of the composition of goods that it imports. As it is hard to test it directly, we check an implication of our identifying assumption - whether the average weight per import value is correlated with government expenditure. We find no significant relationship in the data.

the key coefficient for the interaction term between a product's weight to value ratio and the shipping cost remains to be negative and statistically significant. This suggests that the notion that a given decline in the shipping costs favors the shipment of relatively heavy goods is a robust feature of the data.

If importation of a good requires a fixed cost, a more permanent reduction in the shipping cost may elicit a stronger response in the import pattern than a transitory change in the shipping cost. To investigate this possibility, we create a dummy variable, "Persist," for country pairs whose bilateral trade imbalance takes on the same sign (e.g., the importing country always runs a bilateral surplus) at least during the three years from 2015 to 2017. In the fifth 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 suggests that the effect of a change in shipping-cost on the composition of imports is indeed more pronounced for country-pairs that features an importing country running a persistent surplus against the exporting country.

In the sixth column of Table 3, we use log imbalance as a proxy for log shipping cost to test the prediction of Proposition 3. The coefficient estimate for ln(imbalance) $\times \ln\left(\frac{w}{p}\right)$ is 0.0147 and significant at the 1% level. This result is consistent with the prediction of the Proposition 3. A greater trade surplus tends to alter the composition of imports towards to more heavy goods.

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

To summarize, the shipping cost is indeed negatively related to trade imbalance. Moreover,

[11] For instance, take the estimates of the second columns in the Table 2 and Table 3, $\hat{\alpha}_1 \times \hat{\beta}_1 = -0.11 \times -0.169 = 0.018$. It is approximate the same magnitude as the column 6 of the Table 3.

a given reduction in the shipping cost benefits the heavy goods more than the light goods as predicted by Proposition 1. This conclusion holds after controlling for a large number of fixed effects, and using an instrumental variable approach to account for possible endogeneity of the trade imbalance. Finally, trade imbalance affects the composition of imports mostly through its impact on the shipping cost of the importers.

2.3.3 Port-level Evidence

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

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

The gravity equation to be estimated is as follows

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

where m denotes a port in China, $I_{i,mnt}$ 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

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

imports into port m from country n. $\eta_{i,mt}$ and $\eta_{i,nt}$ are port-product-year and origin-product-year fixed effects, respectively. The key parameter of interest is β_1. If a greater port-level trade surplus leads to relatively more port-level imports of heavy products, we expect $\beta_1 > 0$.

Table 4 reports the estimation results. In the first column, where we control for both product-port-year triplet fixed effects and product-exporter-year triplet fixed effects, β_1 is estimated to be 0.0098 and statistically significant at the 1% level. That is, the import elasticity with respect to the trade imbalance is higher for heavier products. In the second column, where we also control for port-exporter-pair fixed effect, β_1 is estimated to be 0.0057 and statistically significant. These estimates provide confirmation of our mechanism at the level of ports within a country even after we control for a large number of relatively demanding fixed effects.

3 Applications

3.1 Imports of Industrial Waste

We explore the novel implications of the insight that a trade imbalance systematically alters the composition of a country's imports. The first application is to understand global trade in industrial waste.[13] In particular, why do some countries import industrial waste much more than others?

Our basic answer is that most industrial waste goods have a relatively high weight-to-value ratio, and that countries with a large trade surplus tends to import a large quantity of industrial waste goods as a result. Figure 2 plots the density of weight (kg)/value (US dollar) ratio for waste goods (the solid line) and for other goods (the dashed line). On average, the weight-to-value ratio of non-waste goods is much lower, about 0.1 kg/USD. In contrast, waste goods are much heavier, with the peak of its density at about 1 kg/USD. Given this difference

[13] The waste good is defined as any HS 6-digit product line that contains either "waste" or "scrap" in its name. We list all the waste goods in Table 11 of Appendix C.

in relative heaviness, our theory predicts that surplus countries would import more of waste goods.

To investigate whether the trade pattern of waste goods is related to the mechanism in Section 2, we define "Waste_i" as a dummy that equals to one for any of the HS 6-digit lines that contain the word "scrap" or "waste" in their descriptions, and estimate the following equation:

$$
\begin{aligned}
\ln(\text{Import}_{i,ndt}) =& \beta_0 \ln(\text{Shipping cost}_{ndt}) + \beta_1 \ln(\text{Shipping cost}_{ndt}) \times \text{Waste}_i \\
&+ \eta_{i,nt} + \eta_{i,dt} + \epsilon_{i,ndt}.
\end{aligned} \tag{6}
$$

Note that equation (6) is identical to equation (4) except that we have replaced the value-to-weight variable with the waste-goods dummy.

The estimation results are presented in Table 5. In the first column, where we present the benchmark estimate, β_1 is estimated to be -0.454 and statistically significant. This suggests that the import elasticity with respect to the shipping cost is higher in absolute value for waste products than for other products on average. In other words, a given reduction in the unit shipping cost gives rise to a greater increase in the shipment of waste goods than of other goods.

In the second column, we include $\ln(\text{Shipping cost})_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$ as an additional regressor in equation (6). Once the weight per value is controlled, the import elasticity with respect to shipping cost for waste goods is reduced substantially (from -0.454 to -0.298). This suggests that the relatively heavy nature of the industrial waste goods is an important reason for why it is featured prominently in the imports of countries with a large trade surplus.

In the third and fourth columns of Table 5, we address possible endogeneity of the bilateral shipping costs using an instrumental approach. In particular, we use the IV defined in the equation (3) to instrument for shipping cost. As argued in the previous section, the government expenditures in the exporting and importing countries are correlated with bilateral trade imbalance and hence the shipping cost. (We assume that the government expenditure is not correlated with the weight of the imported goods.) The result still holds. This suggests that a reduction in the shipping cost causes a change in the composition of imports in favor of more waste imports.

The import of waste goods is also affected by the stringency of environmental regulation. However, we argue that within countries with strict environmental regulation, trade surplus countries still import more waste goods than deficit countries.[14] In the last two columns, we test this argument formally. Since the environmental regulation stringency is highly correlated with the development stage of the country, we use 2010 GDP per capita to measure the development of the country, and interact it with the shipping cost and a dummy for waste goods. We see that the coefficient of this interaction term is positive and statistically significant: comparing countries with similar trade imbalance, developed countries import less waste goods. (E.g., Japan imports a smaller quantity of waste goods than China even when they have the same level of trade surplus.) However, the magnitude of this coefficient (0.09) is much smaller than the coefficient before $\ln \lambda \times$ Waste (0.45). So even for developed countries, a rise in trade surplus still generates an increase in waste goods import.

Taken together, these findings suggest that one reason why countries with a trade surplus tend to import more waste goods is due to the endogenous shipping-cost channel. This is especially true for developing countries.

[14]As an example, in Germany, a trade surplus country, the imported waste value is about 0.88% in its total import. While in UK and US, two deficit countries, the waste import values are about 0.49% and 0.44% relative to their total imports.

3.2 Trade Surplus and Pollution

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

Heavy Inputs and Polluting Output

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

We measure each Chinese industry's output pollution intensity based on the data from the World Bank's Industrial Pollution Projection System (IPPS), which covers emissions of three main pollutants, namely, SO2, NO2, and total suspended particles (TSP). In particular, for each sector, we compute ratios of SO2, NO2, and total suspended particles (TSP) emission per dollar value of output, respectively.[15]

Table 6 reports the correlation between sector-level output pollution intensity measures and the sector-level weight-to-value ratio of the intermediate input bundle. The correlation is positive and statistically significantly different from zero for each of the three pollutants. This

[15] This data was assembled by the World Bank using the 1987 data from the US EPA emissions database and manufacturing census. See Bombardini and Li (2016) for more details of this data set.

suggests that industries using heavier inputs tend to be more polluting in their output.

Trade Surplus and Expansion of Polluting Industries

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

$$\ln(\text{Output}_{i,t}) = \beta_1 \ln(\text{Imbalance}_t) \times \text{Polluting-sector}_i + \eta_i + \eta_t + \epsilon_{i,t}. \tag{7}$$

$\text{Output}_{i,t}$ is industry i's total sales in year t. Imbalance_t is China's trade imbalance in year t measured by the ratio of China's exports over imports. $\text{Polluting-sector}_i$ is an indicator variable which equals to 1 if the industry's pollution intensity in terms of SO2 emission is above the median level and 0 otherwise. (We have conducted similar exercises with NO2 and TSP pollution measures, and find similar results. We omit these results to save space.)

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

In the first column of in Table 7, the coefficient on the interaction term is 0.905 and statistically significant. This means that an increase in trade imbalance tends to be associated with an expansion of the more polluting industries relative to other industries. In the second column, we add $\ln(\text{Imbalance}_t) \times \text{Heavy-sector}_i$ as an additional regressor, where Heavy-sector_i is an indicator variable for industries whose input bundles are heavier than the median value across industries. In this case, the coefficient for the new regressor is 0.921 and statistically significant, whereas the point estimate for $\ln(\text{Imbalance}_t) \times \text{Polluting-sector}_i$ becomes smaller and loses statistical significance. In other words, the effect of a larger trade surplus on the sector composition of the aggregate output comes primarily through favoring those industries with heavy inputs.

One may be concerned with possible endogeneity of the trade imbalance. For example, there may be common missing factors that simultaneously affect the size of the trade balance and the relative size of the pollution-intensive sectors. To address this concern, we use the government expenditure as a share of GDP for the United States, Japan, and South Korea (three major trading partners of China) as the instrumental variables for China's trade imbalance$_t$. The idea is that changes in the government expenditure of these three major trading partners of China represent a demand shock for Chinese exports, and hence can generate an exogenous movement in the trade surplus of China. The F statistic of the first-stage regression is 16.10. The second stage IV regressions are shown in the third and fourth columns of Table 7. As we can see, the main findings are robust. That is, the relative size of the polluting industries tends to be larger in times of a greater trade surplus, and the effect comes predominately from industries that use heavy inputs.

3.3 Welfare Loss from Trade Surplus

The two applications discussed above are related. The scrap re-cycling industry is an example of industry that uses heavy inputs (industrial waste and scraps). Recycling of waste and scrap products often involves more pollution and more unhealthy consequences than other imports. For example, imported waste products are often dirty, poorly sorted, or contaminated with hazardous substances. The problem is worse if the importer is a developing country. A film, "Plastic China," shows the environmental damage caused by the country's plastic-recycling industry, which is dominated by many small-scale outfits that often lack proper pollution controls.

Why does the heavy-goods (or scrap-goods) import, induced by trade surplus, matter in terms of aggregate welfare? In sections 3.1 and 3.2, we show that an increase in the trade surplus leads to an increase in the imports of heavy goods including more industrial scraps and waste (to be recycled into industrial inputs) and a relative output expansion of pollution-intensive sectors. Strong environmental regulation can potentially mitigate the pollution consequence of a larger trade surplus. However, in Appendix E, we find that the extra pollution induced by heavy-goods (or waste-goods) processing does not seem to be met by a tougher environmental regulation in those countries. In general, the strength of environmental regulation is not correlated with the share of heavy goods imports or the level of trade imbalance across countries. In such a setting, a trade surplus may bring on a welfare loss via additional imports of heavy goods and additional pollution.

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

4 A Quantitative Model and Policy Evaluations

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

Motivated by the earlier empirical section, the model economy will feature three types of intermediate inputs in production: (recycled) scrap goods, heavy material, and light material.

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

4.1 Consumer problem

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

The representative consumer's utility is $\ln c_1 + \rho \ln c_2 - \eta x_1$. c_1 and c_2 are the consumption levels in the two periods and ρ is the discount factor. x_1 is the pollution in the first period and η measures the disutility of the pollution. Since the agent does not supply any labor in the second period, there is no domestic production hence the pollution in the second period is 0. We will be more specific about this point when introducing the production technology later.

In the consumption procedure, some scrapped goods will be generated. The scrapped goods are assumed to be a fixed proportion $\phi > 0$ of the final consumption goods. The scrapped goods can be used as the intermediate inputs to produce other goods domestically or export to the rest of world (ROW). We use k_t to denote the scrap goods used domestically and $E_{k,t}$ be the scrap goods export. We use $P_{k,t}$ to denote the domestic scrap goods price and $P^*_{k,t}$

to denote the international scrap goods price. To export 1 unit of scrap goods, an ice-berg cost $\tau_{k,t} > 1$ should be paid. To simplify our model, we assume that domestic and foreign goods are perfect substitutes for the ROW firms. Then the domestic scrap price should satisfy $\tau_{k,t}P_{k,t} = P^*_{k,t}$ and the resource constraint of the scrap goods implies

$$k_t + \tau_{k,t}E_{k,t} = \phi c_t. \tag{8}$$

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

The consumer is endowed with heavy material H (such as gold) and light material M (such as stone) in each period. Both material goods can be used in the production or can be traded. The domestic and international price of the light material are denoted as $P_{m,t}$ and $P^*_{m,t}$, respectively. Similarly, the domestic and international price of the heavy material are denoted as $P_{h,t}$ and $P^*_{h,t}$. As before, we have $\bar{\tau}_{m,t}P_{m,t} = P^*_{m,t}$ and $\tau_{h,t}P_{h,t} = P^*_{h,t}$, where $\bar{\tau}_{m,t}$ ($\tau_{h,t}$) is the export trade cost for the light (heavy) material. Note that the export cost for light material is exogenous, whereas the export cost for scrap goods and heavy goods are endogenous, which we will explain below. The total revenue from selling the light and heavy goods is $P_{m,t}M + P_{h,t}H$.

The consumer's problem is as follows:

$$\max_{\{c_t, S_t\}} \ln c_1 + \rho \ln c_2 - \eta x_1 \tag{9}$$

$$\text{subject to} \quad P_{c,1}c_1 + S_1 = w_1 L + P_{k,1}\phi c_1 \tag{10}$$

$$+P_{m,1}M + P_{h,1}H + \Pi_1$$

$$P_{c,2}c_2 = (1+R)\,S_1 + P_{k,2}\phi c_2 + P_{m,2}M + P_{h,2}H + \Pi_2 \tag{11}$$

The two restrictions denote the budgets in the two periods respectively. $P_{c,t}$ is the price of the final consumption goods. w_t is the wage per unit of labor in the home country. S_t is the saving of the country or the current account surplus. Π_t is the lump-sum transfer from the government which will be explained later. The right hand side of the first period budget is the income of the household, including labor income, and income from selling the scrap goods, light and heavy materials, while the left hand side denotes the first period expenditure including the consumption and the saving. In the second period budget, the income only comes from the first period saving and the revenue from selling the scrap goods and materials.

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

$$C_t = \Omega_c y_t^{\alpha} q_t^{1-\alpha}, \tag{12}$$

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

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

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

$$\tau_{h,t} = \bar{\tau}_{h,t} \left(\frac{Export}{Import} \right)^{v}, \tag{13}$$

$$\tau_{k,t} = \bar{\tau}_{k,t} \left(\frac{Export}{Import} \right)^{\upsilon}, \tag{14}$$

where $\upsilon > 0$ and $\bar{\tau}_{h,t}$ and $\bar{\tau}_{k,t}$ are the exogenous trade costs if total export = total import ($S_t = 0$). υ measures the elasticity of export trade costs with respect to the trade imbalance. The above two equations suggests that for a deficit country, the heavy and scrap goods' export cost becomes cheaper when deficit increases. For the import costs of the heavy and scrap goods, two similar equations will be specified later.

4.2 Polluting and Green Sectors' Production

There is a representative firm in both the polluting and green sectors. The output of these two sectors cannot be traded. However, the materials they use are tradeable. Both sectors combine materials and labor to produce. However, notice that there is no labor supply in the second period. So both sectors' output will be 0 and the domestic final goods sector output will be 0 as well.

4.3 Green Sector

We start from the problem of the green sector. The firm uses light material and labor to produce. The light material either comes from the domestic supply or the comes from the import. We use m_t and m_t^* to denote the domestic and foreign imported light material goods.[16] The production function of the green sector is

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

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

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

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

$$P_{y,t} = w_t^{1-\theta} P_{m,t}^{\omega\theta} \left(\bar{\tau}^*_{m,t} P^*_{m,t}\right)^{(1-\omega)\theta} \tag{15}$$

and the demand of each production input is derived as follows

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

4.4 Polluting Sector

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

$$q_t = \Omega_q \left(h_t^{\beta} h_t^{*(1-\beta)}\right)^{\sigma} \left(\gamma k_t^{\frac{\omega_k - 1}{\omega_k}} + (1-\gamma)\, k_t^{*\frac{\omega_k - 1}{\omega_k}}\right)^{\frac{\omega_k}{\omega_k - 1}} L_{q,t}^{1-\sigma-\lambda},, \tag{16}$$

where $\Omega_q = (\beta\sigma)^{-\beta\sigma}((1-\beta)\sigma)^{-(1-\beta)\sigma}(1-\sigma-\lambda)^{\sigma+\lambda-1}$. h_t and h^*_t are the domestic and imported heavy materials. k_t and k^*_t are the domestic and foreign scrap goods. $L_{q,t}$ are the labor hired in this sector. β and γ measure the share of domestic heavy and scrap materials relative to the imported materials. σ and λ measure the share of heavy materials and scrap goods in the total production. ω_k is the elasticity of substitution between the domestic and foreign scraps. We distinguish ω_k away from 1 because that the substitution beween domestic and foreign scraps may be higher than that of other materials.

We use $\tau^*_{h,t}$ and $\tau^*_{k,t}$ to denote the import cost of the heavy material and scrap. More expecifically,

$$\tau^*_{h,t} = \bar{\tau}^*_{h,t} \left(\frac{Export}{Import} \right)^{-v}, \tag{17}$$

$$\tau^*_{k,t} = \bar{\tau}^*_{k,t} \left(\frac{Export}{Import} \right)^{-v}, \tag{18}$$

where $\bar{\tau}^*_{h,t}$ and $\bar{\tau}^*_{k,t}$ are some constants. These two equations say that when the surplus increases, the import costs will decrease.

In the production procedure, the firm will generate pollution bq_t, where b is the pollution intensity, measured by pollutant per unit of production. The firm can reduce the pollution intensity. To reduce the pollution intensity by δ_t, the abatement cost is $w_t \psi (\delta_t) q_t$, where ψ is an increasing and convex function with $\psi(0) = 0$. Then the pollutant emission is $x_t = (b - \delta_t) q_t$. We assume that the government collects T_t for each unit of emission and the tax is transfer back to the consumer as Π_t. The firm's problem is

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

$$\text{subject to} \quad \delta_t \leq b, \quad \text{and equations (16), (17), (18).}$$

The firm's problem implies

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

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

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

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

Finally, the demand of each input is derived as

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

4.5 Equilibrium

The Lump sum transfer Π_t in the budget constraint (10) comes from firm government tax, which is defined as $T_t\,(b-\delta_t)\,q_t$. Notice that in the second period, the lump-sum transfer will be 0 since there is no domestic production.

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

4.6 Calibration

The pollution abatement technology is assumed to be $\psi(\delta) = \frac{\xi}{2}\delta^2$. We assume all parameters, such as international material prices, remain the same for the two periods. For convenience, we ignore the time subscripts of the parameters. We calibrate our economy to match the model moments of period 1 with the Chinese 2012 economy. We normalize the labor supply L to be 1 and the price of the final goods P_c^* to be 1.[17]

[17] One unit value in our model is around 24,000RMB or 3500USD.

First, we calibrate the parameters in the production function. We set $\alpha = 0.6$ to match the expenditure share of polluting sector (60%).[18] We set $\theta = 0.45$ to match the labor share in the green sector (55%). We set ω to match the import of light materials in the total expenditure (9.2%). We assume $\beta = \gamma$ and calibrate σ, λ, β and γ to match the labor share in the polluting sector (52%), the import of heavy goods (12.3%) and import of scrap goods in the total expenditure (0.5%). In the baseline calibration, we set $\omega_k = 5$ following Broda and Weinstein (2006).

Second, we calibrate the international prices P_m^*, P_h^* and P_k^*. From the China's custom data, we classify goods into four categories: final goods, light materials, heavy materials and scraps.[19] We then compute the average price of each goods. By normalizing $P_c^* = 1$, we get $P_h^* = 1.3, P_m^* = 0.98$ and $P_k^* = 0.1$.

Third, regarding the parameters in the endogenous trade cost function, we set all exogenous trade costs $\bar{\tau} = 1.2$, implying that the total transportation cost is around 20% of the trade prices when running a trade balance, according to the Anderson and Van Wincoop (2004).[20] Since China is a persistent trade surplus country, we set the elasticity of scrapped goods trade costs with respect to the trade surplus υ to 0.27, according to our previous analysis (Column 3 of Table 2).

Parameters related to the pollution and regulation are calibrated in the following way. We set the pollution per production, b, to match the tons pollutant emission per value.[21] To

[18] The polluting(green) sector is defined as those industries whose SO2 pollution intensity is above(below) the median.

[19] We first classify each HS6 goods to final consumption goods and materials based on https://unstats.un.org/unsd/tradekb/Knowledgebase/50090/Intermediate-Goods-in-Trade-Statistics. Then for the materials, we first take out the scraps if its name include the keywords "scrap" or "waste". And we define the rest materials as heavy(light) materials if its weight-to-value ratio is above(below) the median.

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

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

calibrate the pollution abatement cost ξ, we use the information on the price of SO2 emission tradeable permits in the United States. (The price per ton of the SO2 emission should equal to the marginal cost of the abatement $w\xi q$.) Assuming the abatement technology is the same in both countries, we set ξ to match it.[22] We assume the environmental tax $T = 0$ in China in our benchmark economy.

In terms of parameters of material endowments and scrap prodution, we calibrate ϕ so that the export of scrap is zero. The endowments M and H are calibrated to match the share of export of light and heavy goods in total expenditure (13.0% and 11.7% respectively).

Finally, for other parameters in the consumer problem, we calibrate ρ to match the trade surplus/GDP ratio (5%). We set the foreign real return $R = 10\%$ (if the annual real interest rate is 2%, this number suggests that a model period is about 5 years). Following Israel (2007), we set $\eta = 0.03$, suggesting that a ton increase of the pollutant equals to 3% consumption drop.[23] We provide the details of the calibration in Appendix F.

4.7 Welfare and Policy Analysis

Welfare Cost of Trade Surplus

The baseline results are recorded in the first column of Table 8 where we normalize the pollutant emission (first row), imports of scrap and heavy material in the first period (second and third rows, respectively), the total export value of heavy goods and scrap (4th row) and the wage per capita (5th row) to be 100. The trade surplus in this case is about 5% of GDP (6th row). For subsequent calculations of the welfare effect of a given policy experiment, we report the percentage change in the part of the utility $\ln(c_1) + \rho \ln(c_2)$ from a change

[22] The SO2 emission trade price in US is 1,600 usd per ton (Burtraw and Szambelan (2009)), which is about 0.46 in terms of model unit value.

[23] Israel (2007) (Table 4) estimates that the marginal benefit of a ton of total SO2 reduction is \$350 in US. Since China's population is about 4 times of US (x in our model means emission per capita), we assume this marginal benefit is \$87 (\$350/4) in China, which is about 3% of Chinese average annual consumption.

in consumption relative to the benchmark case due to the policy experiment while ignoring disutility of pollution (second to the last row), and the percentage change in total utility due to the policy experiment that also takes into account any change in disutility from a change in the pollution level (the last row). By construction, the last two numbers are zero.

We next quantify the welfare cost of trade surplus through our endogenous shipping cost channel when the environmental regulation is weak (i.e., $T = 0$). To accomplish this we set $v = 0$, thereby making the shipping cost independent of the trade surplus. The results are presented in the second column of the table.

With exogenous shipping costs, the welfare is affected in four ways: two working through consumption and two through pollution. First, a higher unit shipping cost raises the input costs of the polluting industry which reduces pollution. Second, a lower unit shipping cost on the export side leads to more exports of scraps and heavy material. This further raises the input costs to the polluting industry and augments the reduction in pollution. The combined consequence of the first two effects is a total reduction of pollution by 2.7% and an increase in utility by about 1%. Third, the higher input costs to the polluting industry lowers the sector's production and lowers the wage rate by 2.7%. This lowers the life-time income by 0.7%. Fourth, the additional exports of domestic scraps and heavy material increases the total revenue, and by itself boosts export revenue by 1.7%, resulting in an increase in the life-time income by around 1%. Because the 4th effect dominates the 3rd effect, the combined consequence of the 3rd and 4th effects is an additional increase of consumption, producing an increase in utility by 0.3%. Overall, the total consequence of all four effects is a welfare increase by 1.36%.

We can also summarize the results in the reverse direction - by going from Column 2 (with no response of the shipping cost to a trade surplus) to Column 1 (with an endogenous reduction in the shipping cost to a trade surplus). There are four channels. First, because a trade surplus can endogenously reduce the unit shipping cost, the country imports more scraps and more heavy material than it otherwise would in the absence of a trade surplus. Second, the endogenous change in the shipping cost on the export side implies a reduction in the exports of the scrap goods and heavy material. Both channels lead to a reduction in the input costs of the polluting industry, leading to more pollution and a lower utility. Third, with a lower price of the polluting industry's output, the consumption goes up. Fourth, the higher shipping cost on the export side implies a reduction in the total export revenue and a lower wage rate. This by itself would depress consumption. The net effect of all four channels is a reduction in welfare by 1.36%.

People may wonder that under different trade surplus (deficit) values, what would be the welfare cost (or gain)? To analyze this, we impose a credit market constraint in the household problem $S \leq \bar{S}$. We vary the parameter $\bar{S}$ to get different trade surplus value. We then compare the utility change when imposing $v = 0$. (In the Table 8, that is the value in the last row of Column 2.) We also compare the utility change excluding the pollution effect. (In the Table 8, that is the value in the second to the last row of Column 2.) The result is shown in Figure 3. The x-axis is the saving/GDP, ranging from a deficit -5% to a surplus 5%. The blue solid line shows the net utility change and the dotted red line shows the utility change only from consumption. As we can see, when the trade surplus shrinks from 5% to 0, the net welfare cost monotonically decreases from 1.3% to 0. When the country runs a trade deficit, the country can enjoy a welfare gain from the trade deficit. The utility change excluding pollution is much smaller, suggesting that the pollution channel stressed in our paper is quantitatively large.

Notice that our calculation is done for the representative household. We might comment on a possible spacial heterogeneity in the welfare effect of additional pollution via this channel. The recycling of imported scraps and the use of heavy material in production tend to be concentrated in port cities in practice. (While a trade surplus reduces the shipping cost of importing scraps and heavy material, their shipping cost on land is still expensive.) Therefore, the welfare loss for people in port cities and adjacent areas could be much higher than the national average. This may be especially relevant for a spatially large country such as China. We do not formally feature this spacial heterogeneity in our calibrations but it could be an interesting direction for future research.

Banning Scrap Import

In the Table 9, we consider several policy experiments. As a comparison, in the first column of Table 9, we copy the baseline model result of Table 8. First, we consider a ban of imports of all scraps (in all periods), which is motivated by a policy that China has implemented since early 2018. The result is shown in the second column of Table 9.

Banning scrap imports raises the input cost of the polluting sector higher. This generates a few effects. First, the output in the polluting sector decreases, and the pollution in turn goes down by 1.4%. The import of heavy goods goes down by 0.8%. Second, the decline of the polluting sector output would result in the decline of the final goods domestic production and decrease the export value of the final goods. In the current setup, this effect dominates the decrease of the import. So the trade surplus decreases to 4.83%. The heavy goods and scrap import cost would increase and the their export cost would decrease. In response to the increase of the export shipping cost, the scrap and heavy goods export increases by 0.61%. Third, the reduced output in the polluting sector pushes down the labor demand (wage decreases by 0.8%). Hence the life-time income decreases and the utility from consumption declines by 0.27%. Finally, the utility loss from lower consumption is more than offset by a utility gain from lower pollution. The net change in welfare is a gain of 0.28% relative to the benchmark case.

In the production function assumption, the baseline assumption for the elasticity of substitution between foreign and domestic scraps is 5. In reality, the elasticity could be higher. To explore this effect, we choose a large $\omega_k = 200$, suggesting that the two scraps are close to perfect substitutes. The results are shown in Column 3. Compared to the second column, both the reduction in consumption and the reduction in pollution become much smaller. The reason is intuitive: as the firm can more easily substitute the imported scrap with domestic scrap, a given rise in the cost of the imported scraps would not alter the production by as much. As a result, the cost of consumption and the level of consumption also change less in Column 3. The net change in welfare is an increase by 0.12%, about half of the welfare gain in Column 2.

Optimal Regulation

Finally, we consider the optimal tax on pollution. That is, we do a grid search over the value of T that maximizes the consumer's welfare. We find that the optimal tax is $T = 0.074$, which is about 1,776 RMB (254 USD) per ton emission. In response to a higher cost of pollution, the representative firm in the polluting sector chooses to cut the emission. This means a smaller production in the polluting sector, a reduced demand for scraps and heavy material, and a higher cost of the output from the polluting sector. As a result, the pollution declines by 78.1%. The consumption declines since the high tax burden. However, the effect of a lower level of consumption (a utility loss of 9.76% as reported in the second to the last row) is more than offset by the consequence of a lower level of pollution. On net, the welfare gain is 21.27% relative to the benchmark case.

A higher pollution cost would reduce demand for both scraps and heavy material, whether they are imported or domestically sourced. From the second and third row, the scrap and heavy goods imports decline by 86.1%. Meanwhile, since the demand of domestic scrap and heavy material decline, the household mainly sell them abroad. As a result, the export of scrap and heavy goods increase by 65.7%.

Because the only market failure in the model is a negative externality associated with pollution, it is not surprising that the optimal pollution tax in the last column produces the highest level of welfare among all columns. In other words, while banning imports of scrap can raise welfare given the structural of the model and the parameter values, one can do far better by switching to an optimal tax on pollution (without banning imports). Banning scrap imports (as China has done) is a poor substitute for an optimal tax on pollution. The effect of raising the cost of importing scraps on closing the gap between the private and social costs of pollution is indirect and imprecise. This is in part because foreign scraps can be substituted by both imported heavy material and domestic scraps.

5 Conclusion

This paper provides the first exploration in the literature of how a trade imbalance can affect composition the imports and the welfare of the importing country. Consistent with our theory, we find that trade surplus countries import more heavy goods, including scrap metals and other industrial waste. With nearly two million observations, we show strong and robust evidence that the composition of trade is affected by shipping costs, and shipping costs are affected by trade balance.

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

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

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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 Ratios	Lowest Weight to Value Ratios
Bitumen and asphalt	Diamond
Limestone flux	Precious metal
Wasted Granulated slag from iron	Gold
Ceramic building bricks	Halogenated derivatives
Scrap glass	Watch

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

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

	(1)	(2)	(3)
	$\ln \lambda_{ndt}$	$\ln \lambda_{ndt}$	$\ln \lambda_{ndt}$
$\ln(\text{Imbalance}_{ndt})$	-0.006	-0.110***	-0.083**
	(0.019)	(0.0354)	(0.038)
$\ln(\text{Imbalance}_{ndt}) \times$ Pervasive-route			-0.205**
			(0.101)
Country-pair FE	Y	Y	Y
Destination-year FE	Y	Y	Y
Origin-year FE	Y	Y	Y
IV		Y	Y
Obs.	434	434	434
R-squared	0.77	0.90	0.90

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

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

	(1) $\ln(\text{Imp}_{i,ndt})$	(2) $\ln(\text{Imp}_{i,ndt})$	(3) $\ln(\text{Imp}_{i,ndt})$	(4) $\ln(\text{Imp}_{i,ndt})$	(5) $\ln(\text{Imp}_{i,ndt})$	(6) $\ln(\text{Imp}_{i,ndt})$
$\ln \lambda_{ndt}$	-1.210***	-1.493***	-1.189***		-1.213***	
	(0.029)	(0.034)	(0.029)		(0.029)	
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$	-0.127***	-0.169***	-0.120***	-0.117***	-0.135***	
	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)	
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right) \times$ Persist					-0.020***	
					(0.001)	
$\ln(\text{Imbalance}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right)$						0.0147***
						(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
IV		Y				
Excluding Oil/Ore			Y			
Obs.	873,074	873,074	861,216	873,074	873,074	873,074
R-squared	0.82	0.82	0.82	0.84	0.83	0.85

Notes: This table shows the estimation results of equation (4). $\text{Imp}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} means 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. We use the log value of equation (3) for an instrumental variable for $\ln \lambda_{ndt}$. Standard errors are clustered at goods, destination, origin level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Trade Imbalance and Import Composition across Chinese Ports

	(1) $\ln(\text{Import}_{i,nmt})$	(2) $\ln(\text{Import}_{i,nmt})$
$\ln(\text{Imbalance}_{nmt})$	0.051***	0.002
	(0.002)	(0.002)
$\ln(\text{Imbalance}_{nmt}) \times \ln\left(\frac{w_i}{p_i}\right)$	0.0098***	0.0057***
	(0.001)	(0.001)
Port-good-year FE	Y	Y
Origin-good-year FE	Y	Y
Port-origin FE		Y
Obs.	4,970,457	4,970,457
R-squared	0.79	0.81

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

Table 5: Shipping Cost and Imports of Industrial Waste and Scrap

	(1) $\ln(\text{Import}_{i,ndt})$	(2) $\ln(\text{Import}_{i,ndt})$	(3) $\ln(\text{Import}_{i,ndt})$	(4) $\ln(\text{Import}_{i,ndt})$	(5) $\ln(\text{Import}_{i,ndt})$	(6) $\ln(\text{Import}_{i,ndt})$
$\ln \lambda_{ndt}$	-0.943***	-1.206***	-1.136***	-1.484***	-1.814***	-2.846***
	(0.015)	(0.017)	(0.018)	(0.029)	(0.097)	(0.135)
$\ln \lambda_{ndt} \times$ Waste	-0.454***	-0.298*	-0.718***	-0.511**	-0.452**	-0.720***
	(0.179)	(0.179)	(0.203)	(0.204)	(0.179)	(0.205)
$\ln \lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$		-0.125***		-0.166***		
		(0.011)		(0.0133)		
$\ln \lambda_{ndt} \times$ Waste$\times$ $\ln(\text{GDP}_d)$					0.090***	0.174***
					(0.010)	(0.014)
Origin-good-year FE	Y	Y	Y	Y	Y	Y
Destination-good-year FE	Y	Y	Y	Y	Y	Y
IV			Y	Y		Y
Obs.	870,119	870,044	870,119	870,044	870,119	870,119
R-squared	0.82	0.82	0.82	0.82	0.82	0.82

Notes: This table shows the estimation results of equation (6). $\text{Import}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from n to d in year t. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. "Waste" is the dummy variable for waste goods. GDP_d is the GDP per capita of destination country d. We use the log value of equation (3) for an instrumental variable for $\ln \lambda_{ndt}$. Standard errors are clustered at goods, destination, origin level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Correlations Between Output Pollution Intensities and Input Weight/Value Ratio across Chinese Industries

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

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

Table 7: Trade Imbalance and the Relative Expansion of the Polluting Industries

	(1)	(2)	(3)	(4)
	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$
$\ln(\text{Imbalance}_t)\times$		0.921**		1.082**
Heavy-sector$_i$		(0.374)		(0.456)
$\ln(\text{Imbalance}_t)\times$	0.905***	0.666	0.983**	0.693
Polluting-sector$_i$	(0.421)	(0.410)	(0.500)	(0.489)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
IV			Y	Y
Obs.	6,630	6,630	6,630	6,630
R-square	0.98	0.98	0.98	0.98

Notes: This table examines the association between trade imbalance and the relative expansion of the polluting industries (equation (7)) in China. The dependent variable, Output$_{it}$ is output of industry i in year t. Imbalance$_t$ = log(Chinese exports)/log(Chinese imports) in year t. Heavy-sector$_i$ and Polluting-sector$_i$ are dummy variables defined in section 3.2. In Columns 3 and 4, the government expenditure as a share of GDP for U.S, Japan, and South Korea (three major trading partners of China) are used as instrumental variables for log of China's trade imbalance$_t$. Indsutry export values to U.S, Japan, and South Korea are excluded from the industry output calculations in the IV regressions. Standard errors are clustered at industry levels. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Welfare Effect of Endogenous Shipping Cost

	(1) Baseline	(2) Exog. shippin cost
Pollution	100	97.33
Scrap import	100	97.73
Heavy goods import	100	97.73
Heavy goods+scrap export	100	106.34
Wage	100	97.73
Surplus/GDP (%)	5.04	5.42
Utility change from c (%)	0	0.30
Utility change (%)	0	1.36

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

Table 9: Welfare Comparisons of Counterfactual Policy Experiments

	(1) Baseline	(2) Ban scrap imports	(3) High elasticity	(4) Optimal tax
Pollution	100	98.63	99.35	21.83
Scrap import	100	0	0	13.88
Heavy goods import	100	99.24	99.65	13.88
Heavy goods+scrap export	100	100.61	100.31	165.71
Wage	100	99.24	99.65	35.90
Surplus/GDP (%)	5.04	4.83	4.93	-0.09
Utility change from c (%)	0	-0.27	-0.14	-9.76
Utility change (%)	0	0.28	0.12	21.27

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

Figure 1: Trade Imbalance and Shipping Cost

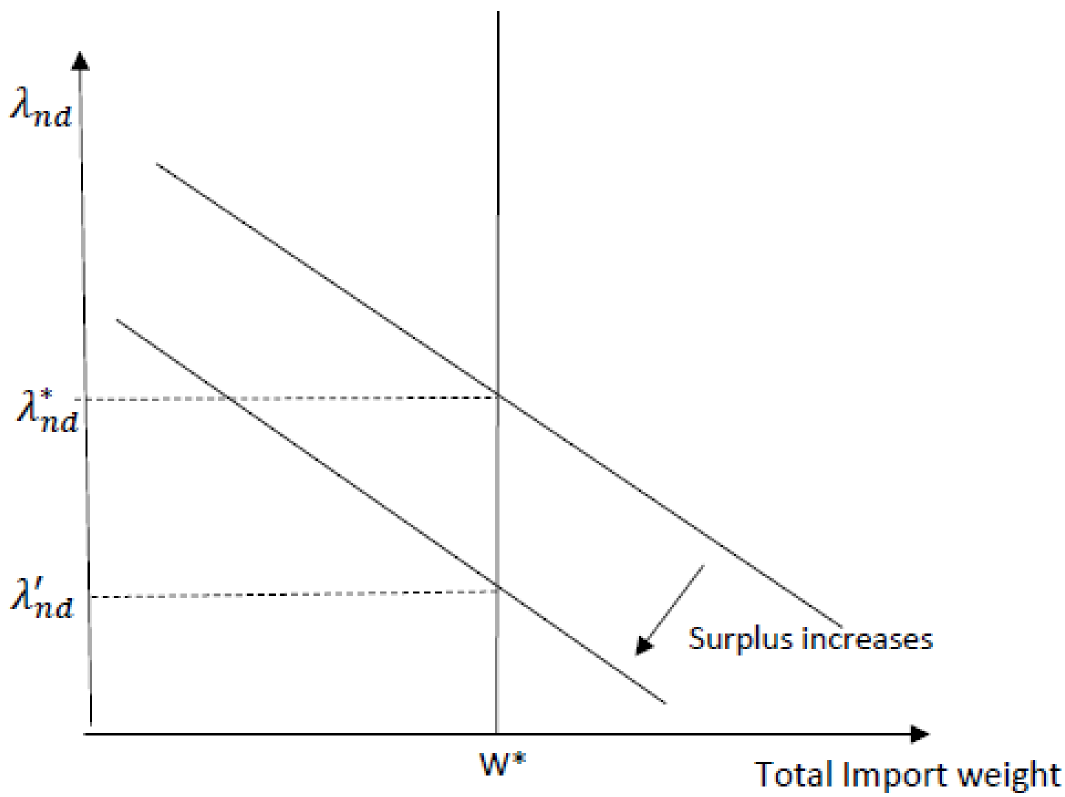
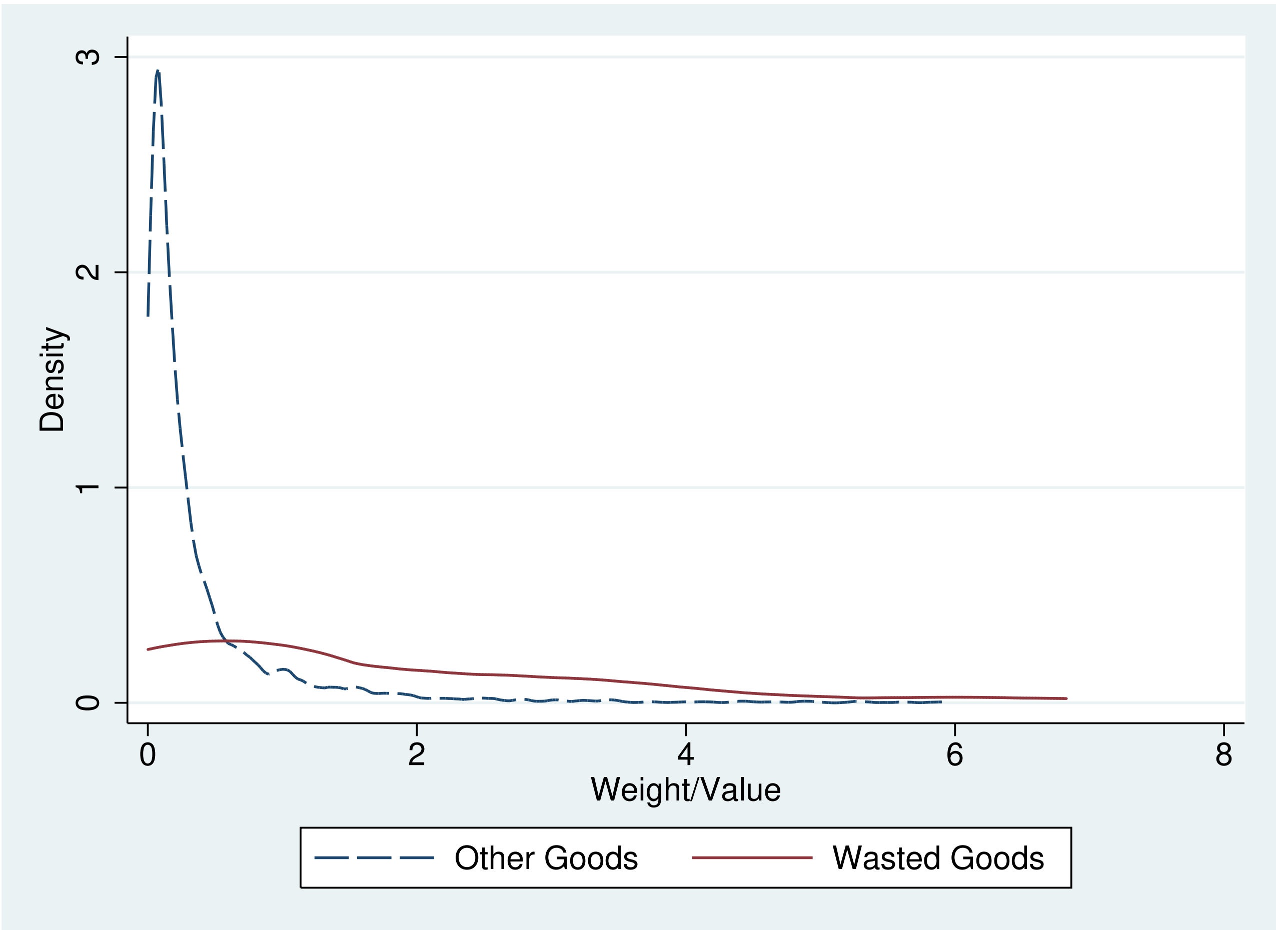
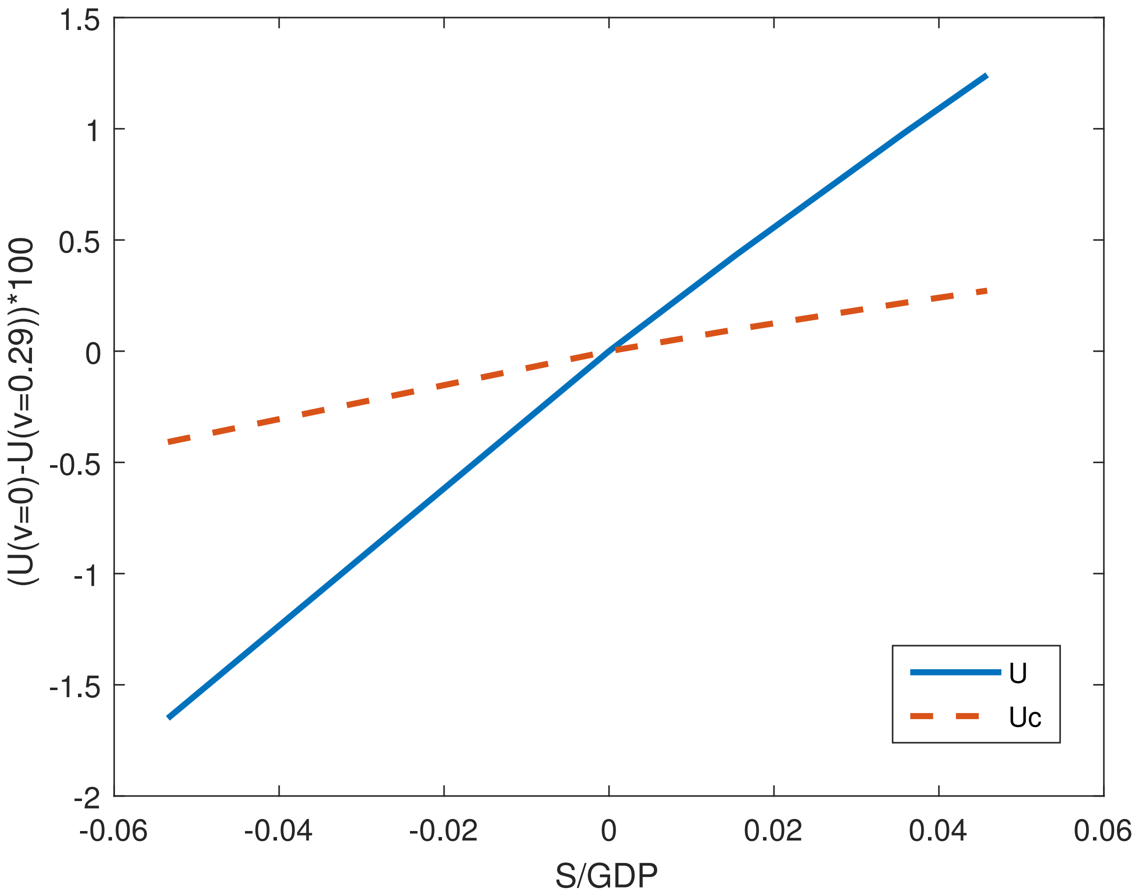


Figure 2: The Weight to Value Ratio (kg/US$) for Industrial Waste Goods versus Other Goods



NOTE: This figure shows the density of the weight to value ratio.

Figure 3: The Welfare Cost of Trade Surplus



NOTE: This figure shows the utility difference when $v = 0.27$ and $v = 0$ under different trade surplus values.

Appendix

A Alternative Equilibrium Restriction

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

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

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

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

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

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

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

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

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

Under the assumption that the container per weight ratio is the same within a 2 digit HS code, we re-test whether the trade-surplus country imports more heavy goods. The results are reported in Table 10. In all regressions, we control the destination-origin-year-2 digit HS code dummies.

Table 10: Estimates for the Log Import Value Regressions

	(1) $\ln(\text{Imp}_{i,ndt})$	(2) $\ln(\text{Imp}_{i,ndt})$
$\ln\lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$	-0.039***	-0.056***
	(0.015)	(0.017)
Origin-good-year FE	Y	Y
Destination-good-year FE	Y	Y
Destination-Origin-Year-HS2 FE	Y	Y
IV		Y
Obs.	868,822	868,822
R-squared	0.86	0.86

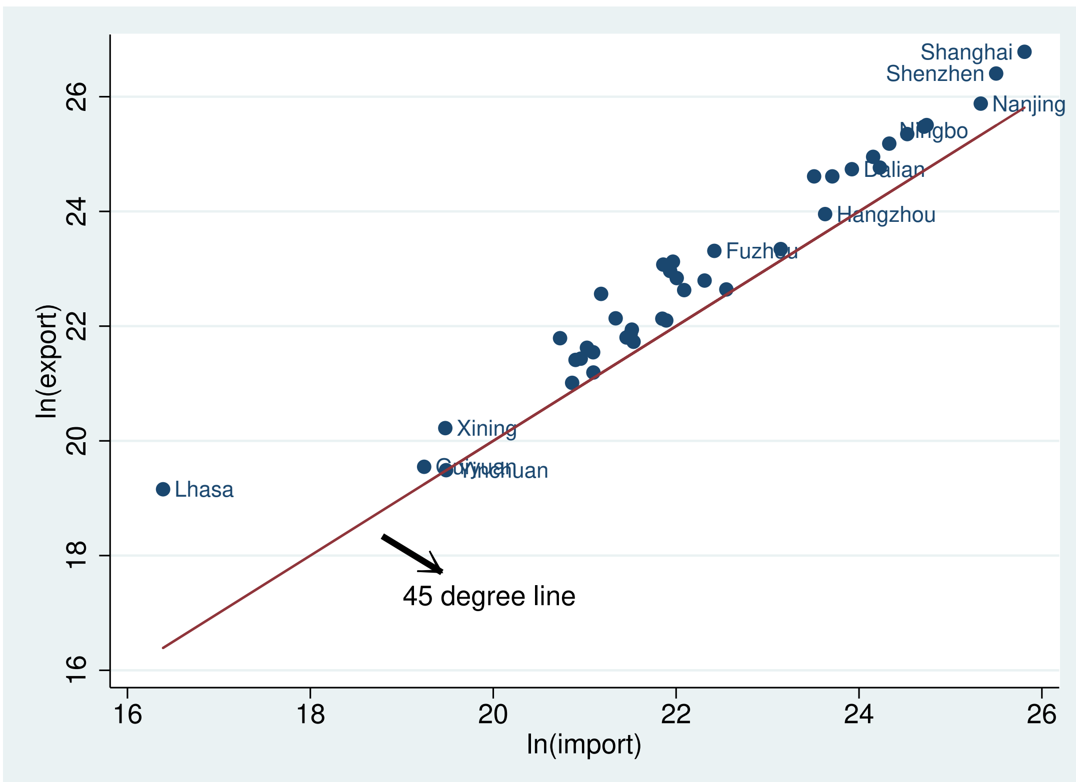
Notes: This table shows the estimation results of equation (4) with additionally controlling for Destination-Origin-Year-HS2 fixed effect. $\text{Imp}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} means 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. We use the log value of equation (3) for an instrumental variable for $\ln\lambda_{ndt}$. Standard errors are clustered at goods, destination, origin level. *** p<0.01, ** p<0.05, * p<0.1.

The first column reports the OLS result. Even under a different equilibrium restriction, we have the same result: The elasticity of import value with respect to the shipping cost is higher for goods with higher weight per value. In the second regression, we use the same instrumental variable for λ_{ndt} as in Table 3, and find our conclusion is robust.

B The Chinese Port Level Data

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

Figure 4: The Export and Import of Chinese Ports



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

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

C The List of All Waste Goods

We identify the waste goods from the keywords "scrap" and "waste." All the goods are listed in Table 11.

Table 11: Waste Goods List

HS6 Code	Name
50100	Unprocessed hair, whether or not washed;
50210	Bristles or pig wool waste
50290	Badger and other brush with animal hair waste
50300	Other horse hair and waste horse hair
50590	Feathers or incomplete feathers of the powder and waste
50690	Bone meal, bone waste
50710	Animal teeth; animal teeth powder and waste
50790	Antelope horn and its powder and waste
50800	Software, crustaceans or echinoderms shells and cuttlefish bone powder and waste
51199	Horse hair and waste horse hair, hair pieces
180200	Cocoa pods, shells, skins and waste
230800	Animal feed with unnamed plant raw materials, waste, residue and so on
230810	Acorns, Aesculus and its waste and solid residues
230890	Raw materials, wastes, residues and by-products of feed plants
240130	Tobacco waste
252530	Mica waste
261900	Smelting steel produced by the slag, scum, oxide and other waste
271091	Wastewater containing polychlorinated biphenyls
271099	Other waste oil
300680	Waste drugs
300692	Waste drugs
382530	Medical waste
382541	Halide waste organic solvent
382549	Other waste organic solvents

382550	Waste metal acid lotion, hydraulic oil, brake oil and antifreeze
382561	Mainly containing organic chemical components and related industries waste
382569	Other waste from chemical industry and related industries
391510	Waste and scrap of ethylene polymer
391520	Styrene scrap and scrap
391530	Waste and scrap of vinyl chloride polymer
391590	Other plastic waste scrap and scrap
400400	Rubber waste scrap, scrap and its powder, grain
401700	Various shapes of hard rubber, including waste and scrap
411000	Leather or recycled leather corner scrap, not suitable for leather products; leather powder
411520	Leather or recycled leather corner scrap; leather powder
440130	Sawdust, wood waste and debris
450190	Deciduous, granular or powdered cork
470620	A fiber pulp extracted from recycled (scraped) paper or paperboard
470710	Recycled (scraped) unbleached kraft paper or corrugated paper and cardboard
470720	Recycling (waste) Bleached chemical wood pulp is made without bulk dyeing paper
470730	A paper or paperboard made mainly of mechanical pulp
470790	Recycling (scraping) of other paper and paperboard, including unselected
500300	Not comb waste silk
500310	Not comb waste silk
500390	Other waste silk
520210	Waste cotton yarn (including waste cotton)
520299	Other waste cotton
530130	Flax staple fiber and waste linen
530290	Other processed but unspecified marijuana; cannabis staple fiber and scrap
530390	Other processed but not spun and other bark fibers and staple fiber and waste Ma
530490	Other processed but unwoven agave fibers and their staple fibers and waste linen
530500	Ramie staple fiber and waste
530519	Other coconut fiber, coconut fiber staple fiber, linen and scrap
530529	Other abaca, abaca fiber staple fiber, linen and waste

530590	Ramie staple fiber and scrap
530599	Ramie staple fiber and scrap
550510	Synthetic fiber waste
550520	Man - made fiber waste
631010	Has been sorted textile fabric broken fabric and waste rope rope cable and its products
631090	Uncategorized Textile Materials Shredding Fabrics and Waste Wire Rope Cables and Articles
700100	Broken glass and waste glass; glass block material
711210	Gold and gold scrap
711220	Platinum and platinum scrap waste
711290	Waste and scrap containing silver and silver compounds
711291	Gold and gold scrap
711292	Platinum and platinum scrap waste
711299	Contains silver and silver compounds of waste and scrap, mainly for the recovery of silver
720410	Cast iron scrap
720421	Stainless steel scrap
720429	Other alloy steel scrap
720430	Tinned steel scrap
720441	Metal scrap produced during metal cutting
720449	Iron and steel scrap
740400	Copper scrap
750300	Nickel scrap
760200	Aluminum scrap
780200	Lead scrap
790200	Zinc scrap
800200	Tin scrap
810191	Unwrought tungsten, including simple sintered strips, rods; scraps
810197	Tungsten waste scrap
810291	Unwrought molybdenum, including simple sintered bars, rods; scraps
810297	Molybdenum waste scrap
810310	Unwrought tantalum and simple sintered into bars, rods; waste scrap; powder

810330	Tantalum waste scrap
810420	Magnesium scrap
810510	Cobalt and other smelting cobalt intermediate products; not forged cobalt and waste; cobalt powder
810530	Cobalt scrap
810600	Unwrought bismuth; waste scrap; powder
810710	Unwrought cadmium; waste scrap; powder
810730	Cadmium waste scrap
810810	Titanium scrap
810830	Titanium scrap
810910	Not forging zirconium; waste scrap; powder
810930	Zirconium waste scrap
811000	Waste scrap;
811020	Antimony scrap
811100	Not forging manganese; waste scrap; powder
811211	Not forging beryllium; waste scrap; powder
811213	Beryllium waste scrap
811222	Chrome scrap
811252	Thallium waste scrap
811291	Not forging gallium, hafnium, indium, rhenium, niobium, thallium; waste scrap;
811292	Unwrought gallium, hafnium, indium, rhenium, niobium; waste scrap; powder
811300	Cermets and their products, including waste and scrap
841780	Radioactive waste
847989	Other Radioactive waste
854810	Original batteries and batteries of waste and scrap; waste batteries or batteries

D The Weight-per-Input-Value Across Industries

To construct the weight to value ratio of intermediate inputs for an industry, we first map each HS6 product to an Chinese 4-digit industry (CSIC).[24] We then map each CSIC code to an input-output table industry. By combining the usage table of the 2012 Chinese input-output table and the weight-to-value ratio from the Colombian data, we compute the average weight-to-value ratio of each industry's input. We list all the ratio in Table 12.

Table 12: The Weight-to-Value Ratio of Intermediate Inputs of Each Industry

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

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

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

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

Nuclear fuel processing	0.07
Cigarette manufacturing	0.07

E Trade Surplus and Environmental Regulation

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

To show this point, we first use the environmental regulation stringency index (ERS) collected by OECD Statistics. The ERS is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies place an explicit or implicit tax on polluting or environmentally harmful behaviour. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). The index covers 28 OECD and 6 BRIICS countries. The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution. OECD Stat also releases in stringency of all these 14 policy instruments as well.[25] Table 13 lists all countries ERS index. The left panel are indexes of BRIICKS and the right panel are indexes of other OECD countries. Note that developing countries often run a large trade surplus against developed countries. The ERS is significantly lower in BRIICKS.

In Table 14, we regress different measures of environmental regulation indexes on heavy goods import and trade imbalance, including the ERS index, environment tax index and the regulation standard index.[26] We also control for the countries' GDP per capita level, corruption level as well as government efficiency.[27] In all specifications, we do not find a

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

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

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

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

Table 13: ERS Index

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

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

Table 14: Estimates for Regulation and Heavy-goods Import across Countries

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

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

F Calibration Details

All the following variables are meant to capture outcomes in the first period. For corresponding data, we use Chinese data in 2012. We normalize the model 1 unit value as 24,000RMB. Table 15 summarizes all the parameters and moments we target.

Table 15: Calibration Result

Parameters	Value	Moments	Model	Data
ρ	0.485	Surplus/GDP	0.05	0.05
ω	0.659	light import/total expenditure	0.092	0.092
σ	0.461	labor share in polluting industry	0.52	0.52
λ	0.019	scrap import/total expenditure	0.005	0.005
β	0.333	heavy import/total expenditure	0.123	0.123
M	0.710	light export/total expenditure	0.13	0.13
H	0.310	heavy export/total expenditure	0.117	0.117
ϕ	0.031	scrap export/total expenditure	0	0
b	29.17	Total pollutants emission (ton)/total expenditure	10.75	10.75
ξ	0.338	SO2 ton trade price	0.46	0.46
v	0.29	Column 4 of table 2	-	-

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

In the benchmark calibration, we set $\bar{\tau} = 1.2$. However, if we interpret the transportation cost as the CIF/FOB ratio, we re-calibrate our model to match $\bar{\tau} = 1.05$. The calibration strategy is the same as the benchmark model. Table 16 show the result. In the first column, we report the model with asymmetric trade cost ($v > 0$) with normalization. In the second column, we impose $v = 0$ and report the change of each endogenous variable relative to the first column. Comparing to the table 8, we can see that the result is quite robust.

Table 16: Welfare Change of Additional Pollution when $\bar{\tau} = 1.05$

	(1) Baseline	(2) Exog. ship cost
Pollution	100	97.32
Scrap import	100	97.72
Heavy import	100	97.72
Heavy goods+scrap export	100	106.37
Wage	100	97.72
Surplus/GDP (%)	5.04	5.45
Utility change from c (%)	0	0.29
Utility change (%)	0	1.36

Notes: This table presents the welfare change of the additional pollution generated by the trade surplus. In Column (1), the baseline results are shown where pollution, scrap impors, and (non-scrap) heavy material imports are all normalized to be 100. In Column (2), we assume that the shipping cost does not respond to trade imbalance ($v = 0$).