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Abstract

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

JEL Classification: F18, F32

Keywords: trade surplus, pollution, and transportation cost

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The Welfare Cost of a Current Account Imbalance: A "Clean" Effect

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Abstract

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

1 Introduction

A current account imbalance is both common in the data and often a source of international frictions. Because it reflects a gap between a country's savings and investment, a welfare loss occurs in the standard open-economy macroeconomics only if distortions exist in either savings or investments. In this paper, we propose a new welfare channel of a current account imbalance by connecting microeconomic

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variables that have not been previously connected. A welfare loss occurs even if there are no distortions associated with savings or investment per se.

The basic mechanism can be summarized in two steps. First, we recognize that for a majority of countries, the merchandise-trade imbalance is a quantitatively important component of the current account imbalance. More precisely, across countries, the trade imbalance co-moves strongly with the current account imbalance. In fact, using data from 2015, a regression of trade imbalance (as a share of GDP) on current account imbalance (as a share of GDP) produces a slope coefficient that is essentially one.[1] For this reason, the welfare effect of a country's trade imbalance is a major element of the welfare effect of its current account imbalance. Second, a trade surplus affects the unit shipping cost and alters the composition of a country's imports in a way that tends to lead to more pollution in the country, especially if its pollution tax is low. This suggests a novel channel for welfare loss from a large current account surplus in countries such as China, Russia, and Malaysia.

Using our calibrated model, we show that as a country's trade surplus becomes greater, the welfare loss also becomes greater when the shipping cost is endogenous than when it is exogenous.[2] In other words, this interaction among a trade surplus, endogenous shipping costs, and the pollution control regime, with the last two objects normally being of interest to two separate microeconomic fields, has a consequence that is important to open-economy macroeconomics.

As a byproduct of our mechanism, we also provide a new explanation for why certain countries with a large trade surplus, such as China, import so many heavy goods (i.e., goods with a high weight-to-value ratio) or so much industrial waste. Whereas the 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 0.96 kg per dollar. Relatively heavy products include industrial scraps and waste,

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

[2] Our calculation controls for the direct effect on the welfare from the shock to the trade balance.

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).[3] In 2016, waste-products imports included 45 million tons of scrap metals, used textile and fibers, waste paper, and used plastics worth over 18 billion USD.[4] Our mechanism suggests that the fact that China simultaneously runs the largest trade surplus in the world and is the most voracious importer of industrial scrap is not a coincidence.[5]

This paper is divided into three parts. In the first part, we study how a country's trade surplus reduces the unit shipping cost of inbound trade, and how that reduction in turn alters the composition of the country's imports. We provide both a simple model and statistical evidence. A key observation is that a country's trade surplus increases the likelihood that ships returning to the country will be under their full carrying capacity (De Palma et al. (2011); De Oliveira (2014)). This imbalance reduces the unit shipping cost for the country's imports, making it cost effective to import more relatively heavy goods. Conversely, deficit countries have a comparative advantage in exporting relatively heavy goods. By our estimation, if a good's weight-to-value ratio is higher by 10%, its elasticity of imports to trade surplus increases by 0.12%. Besides the evidence from cross-country data, we also examine data across port cities within China and find qualitatively the same pattern. That is, those ports with a greater trade surplus also import more heavy goods as a share of their total imports. This within-country evidence strengthens our confidence that the key data patterns from the international data are not affected by unmeasured time-varying country-pair features that may be correlated with the unit shipping cost.

In the second part of the paper, we explore some novel implications of this insight. In particular, we show that polluting industries (e.g., ceramics, cement,

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

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

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

copper wire production) tend to use more heavy inputs (including but not restricted to recycled scrap metals and other industrial waste). As a result, by making the inputs cheaper for the polluting industries, a greater trade surplus alters a country's comparative advantage toward a more polluting production structure. Therefore, the overall "cleanness" of the economy is affected by the size of the trade imbalance.

In the third part, we construct a quantitative model to evaluate the welfare effect of a current account imbalance (which is driven by a trade surplus in our model as in the data). The model features an endogenous response of the unit shipping cost to a trade surplus, which lowers the input costs of the relatively polluting industry and ultimately increases the overall consumption relative to a world in which the shipping cost does not respond to a trade surplus. The gain in utility from more consumption, however, is more than offset by a reduction in utility due to the additional pollution. The net effect of allowing the shipping cost to respond to a trade surplus is a welfare loss of around 2.4%.

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

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

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

Third, while a large literature has studied interactions between trade and environment,[6] it does not make a connection between a trade imbalance, shipping costs, and the environment. We address this gap by proposing a new chain of linkages from a trade imbalance to a worse environmental outcome. In other words, a trade surplus alters the comparative advantage of importing dirty inputs. Those developing countries that simultaneously have a weak pollution-control regime and a trade surplus may experience an especially serious deterioration of the pollution problem.

Finally, our paper enriches the literature on endogenous transportation costs. Hummels and Skiba (2004) and Lashkaripour (2015) emphasize that unit weight is an important feature in international shipping, whereas Djankov et al. (2010)

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

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

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

2 Trade Imbalance and Import Composition

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

2.1 The logic

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

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

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

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

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

We assume

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

where $w_{i,n}$ is the weight per unit of good i produced by country n, and λ_{nd} is the shipping cost per unit of weight when delivering a good from n to d.[7] Notice we assume the shipping firm does not distinguish the goods it delivers but only charges a shipping fee by the weight of the goods. In Appendix A, we also use an alternative assumption that the shipping firm charges a shipping fee by the volume of the goods and show that our results are robust to this alternative specification.

We then get

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

The iceberg portion of the shipping cost is standard in the literature. The second component in the shipping cost says that the per-value shipping cost equals the per-weight shipping cost times the weight-to-value ratio. Although the last component is somewhat non-standard, it has an intuitive explanation: If the cargo is heavier, it would use more fuel in transportation, and a profit-maximizing shipping company would naturally charge a higher shipping fee.[8] We assume the weight-

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

[8] From speaking to some firms that engage in trading in heavy goods, we learn that shipping

to-value ratio is an exogenous property of the goods. We discuss and justify this assumption when we introduce our empirical measure of the weight-to-value ratio by product.

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

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

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

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

Assumption 1 is motivated by the "backhaul problem," well known in the transportation literature. Given that ships must come back after unloading their original cargo at the destination country, an opportunity cost is associated with the backhaul trip with cargo that is under capacity. In response to this problem, the shipping company would adjust the freight rates in both directions. Behrens and Picard (2011) formalize this idea by endogenizing transportation costs through a market mechanism in a model of trade and geography. Their model predicts that the growing trade surplus of China against the US will lead to a reduction in the shipping cost from the US to China.[9] Empirically, a causal effect of trade surplus on the inbound shipping cost is estimated by Jonkeren et al. (2010) (for

companies usually put a weight limit per container. For example, if a company ships scrap copper, which is relatively heavy, each container is only about one third full to satisfy the weight restriction. This weight restriction is approximately the same as charging a shipping fee in proportion to the weight of the cargo.

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

northwestern European inland waterways) and Wong (2019) (for containerized US trade). In section 2.3.1, we 2 additionally document a causal effect of trade surplus on the inbound shipping cost across the world.

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

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

2.2 Data

The Weight-to-Value Ratio

We wish to extract information on the weight-to-value ratio for each HS 6-digit product from customs data. However, most countries do not report product-level weight information, making computation of the weight-to-value ratio impossible. Fortunately, the National Tax Agency of Colombia does report both the weight and FOB value of imports by product. Using these data, for each HS6 product, we compute the average weight-to-value ratio.[10] To give some concrete examples, we list the top five and bottom five products in terms of the weight-to-value ratio in Table 1.

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

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

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.[11] In practice, if the goods are too heavy, a container's space can not be fully occupied, and the weight restriction becomes tight. In this case, the container shipping cost is charged per weight. We do not know exactly how many goods are applied to the weight restriction, but by talking with an expert from a shipping company, over half containers still have empty space when leaving New York port.

For all countries except three (US, China, and Canada), the Drewry covers one major port. For the US, China, and Canada, where two ports are available, we use Los Angeles, Shanghai, and Vancouver, respectively. For the shipping rate from Port A to Port B in a given year, we use the container freight rate in July of that year.[12]

Trade Data

We employ two datasets on trade. First, the bilateral trade data at the HS 6-digit level between 64 country-pairs (in both directions) from 2010-2017 are obtained

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

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

from the UN Comtrade Database. Second, the data on exports and imports at the HS 6-digit product level for individual Chinese ports during 2000-2006 are obtained from the Chinese customs database.

2.3 Empirical Evidence

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

2.3.1 Shipping Cost and Trade Imbalance

Consider the following equation:

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

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

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

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

To address the endogeneity of bilateral trade balance, we adopt an instrumental variable approach. Here is the idea. First, country A is more likely to run a trade surplus against country B if country A has an overall excess savings over its investment, and country B has an overall savings shortage relative to investment. Second, a country's saving-investment difference is the mirror image of the weighted average of its trading partners' saving-investment differences. Third, a component of a trading partner's national savings is affected by its government spending, which is likely to be exogenous to country A or B.[13]

Using this logic, we construct the instrumental variable for the bilateral imbalance by the ratio of the weighted averages of the government spending of the two countries' respective trading partners. Specifically, the instrumental variable

[13]The empirical literature on fiscal multipliers suggests that the Ricardian equivalence does not hold in the data, and a change in the public-sector savings is unlikely to be offset by a change in the private-sector savings in the opposite direction. The literature on government spending provides several determinants (e.g., political ideology), but none is related to shipping costs (see, e.g., Facchini (2018)).

for Imbalance_{ndt} is:

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

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

The OLS result is reported in the first column of Table 2. While the sign of the estimate α_1, at -0.019, is consistent with Assumption 1, the estimate is not statistically significant. In the second column of Table 2, we report the IV regression result. In the first stage, we regress log (bilateral trade imbalance) on log of the term in (3). The coefficient before the IV is approximately 0.45 and significant at the 1% level, suggesting that a 1% increase in the IV leads to a 0.45% increase in country d's bilateral trade imbalance (export/import) with country n. With the F-statistic around 69, we can easily reject the null of a weak instrument. The IV estimate of α_1 is negative and statistically significant: An increase in country d's trade surplus against country n by 10% would lead to a decline in country d's import shipping cost by 1.77%. [15]

Discussion of multi-country routes

A complication is that if country A runs a surplus against country B, ships from A to B do not need to go back to A right away. Consider an extreme example: Suppose A runs a surplus against B, B runs a surplus against C, and C runs a surplus against A, and each country has a balanced overall trade. In this case,

[14]The top five trading partners typically contribute over 80% of the trade.

[15]To examine whether the effect of the trade imbalance is non-linear, we have also added log(imbalance) squared as an additional regressor, but found the coefficient on the new regressor to be statistically insignificant. The result is not reported to save space.

a ship can travel from A to B, B to C, and C to A, while always carrying a full load in each route. This multi-routes arrangement would weaken the shipping-cost response to bilateral surplus.

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

Second, we zoom in on those country pairs involving one running a surplus against 2/3 of its trading partners and another running a deficit against 2/3 of its trading partners. These country pairs are labeled as pervasive imbalanced pairs. For the importing country in such a pair, it would be hard to use a multi-port route arrangement to avoid having relatively empty ships come back to its ports. Similarly, for the exporting country in such a pair, it will be hard to avoid relatively empty ships leaving its ports for other countries. When such two countries are paired, the likelihood that relatively empty ships will travel from the pervasive deficit country to the pervasive surplus country is stronger. If our endogenous shipping-cost story is correct, the elasticity of the shipping cost to the trade imbalance should be greater for these country pairs.

We create a dummy ("pervasive route") for such country pairs, and add an interaction term between the dummy and the size of the bilateral imbalance. We report the result in the third column of Table 2. The coefficient on the interaction term is negative and statistically significant. For country pairs that do not feature a pervasive imbalance, the elasticity of the shipping cost with respect to the trade imbalance is -0.028, but for pervasively unbalanced country pairs, the elasticity increases dramatically to -0.176 (= -0.028-0.148).

In the fourth column of Table 2, we use an instrumental variable approach similar to column 2. The estimated elasticities are -0.191 and -0.501 (= -0.191-0.310) for non-pervasive routes and pervasively unbalanced routes, respectively. 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

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

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

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.[16] 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. This is essentially a gravity equation with a long list of fixed effects to absorb many variations in the data.

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

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

shipping cost is 0.62% higher for good i than for good j if the weight per value of good i is 10% greater than good j.

If importation of a good requires a fixed cost, a more permanent reduction in the shipping cost may elicit a stronger response in the import pattern than a transitory change in the shipping cost. To investigate this possibility, we create a dummy variable, "Persist," for country pairs whose bilateral trade imbalance takes on the same sign (e.g., the importing country always runs a bilateral surplus) during 2010-2017. In the second column of Table 3, we add a triple-interaction term among the "persist" dummy (for the country pair), the shipping cost (for the bilateral route), and the log weight-to-value ratio (for the imported product). The coefficient on the triple interaction is negative and statistically significant. This finding suggests the effect of a change in shipping costs on the composition of imports is indeed more pronounced for country pairs that feature an importing country running a persistent surplus against the exporting country.

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

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

In the fourth column of Table 3, we use log imbalance to replace log shipping cost. The coefficient estimate for ln(imbalance) $\times \ln\left(\frac{w}{p}\right)$ is 0.012 and significant at the 1% level. Instrumenting log trade balance as before (column 5), we find that the point estimate of the coefficient on the interaction terms becomes bigger (0.032 versus 0.012).[17]

Finally, we check whether the relationship between trade imbalance and the weight composition of trade is less pronounced among high income countries. In the final column of Table 3, we restrict our sample to the high income countries, which are defined as countries with an above-median GDP per capita in the sample (the median GDP per capita is about 16,000 USD in 2011 value). The estimated coefficient is 0.003, with the standard error being 0.005. The result indicates that the relationship between trade imbalance and the weight composition of trade is much weaker for high GDP countries.[18] One possible explanation is that heavy materials may generate extra pollution (we will show it in the next section). Developed countries tend to have stringent environmental regulation, which may dampen their incentives to import heavy goods.

To summarize, across different shipping routes, the unit shipping cost is negatively affected by the trade imbalance. Moreover, across shipping routes, goods, and time, a given reduction in the shipping cost benefits heavy goods shipment more than light goods as predicted by Proposition 1. These patterns hold after controlling for a large number of fixed effects, and accounting for possible endogeneity of the trade imbalance. Overall, trade imbalance is a robust predictor for the composition of trade in terms of weight to value ratios.

[17]In doing so, we assume that the government expenditure of the major trade partners is independent of the composition of goods (in terms of weight/value ratio) that a country imports from other origin countries. As it is hard to test this assumption directly, we check an implication of our identifying assumption − whether the average weight-per-import value is correlated with the government expenditure of the trading partners on average. We find no significant relationship in the data.

[18]Readers may be concerned about whether our finding still holds for countries other than 64 country pairs used here. In Appendix B, we show that countries tend to import more heavy goods when they run a trade surplus, and this effect is less pronounced among rich countries.

In the cross-country evidence reported above, unmeasured time-varying country-pair features can, in principle, be correlated with unit shipping costs. In Appendix C, we explore variations across ports within a country (China) as a robust check. We find that a surplus port tends to import heavier goods comparing to other ports within a country. This result further confirms that trade imbalance is a robust predictor of the heaviness of imports.

3 Application: Trade Surplus and Pollution

In this section, we investigate the relationship between the trade imbalance and pollution. We show a connection between pollution intensity of the industries and their relative dependence on heavy goods as inputs. In particular, we show that industries using heavier inputs tend to be more polluting in their output. Because the inputs used more intensively in the polluting industries (i.e., relatively heavy inputs) tend to be cheaper in times of a larger trade surplus, the relative size of polluting industries in an economy tends to expand in times of a larger trade surplus if environmental regulation is not properly imposed.

3.1 Heavy Inputs and Polluting Output

We measure each sector's input heaviness via a two-step procedure. First, we map every 6-digit HS commodity to industrial sector classification in China's 2012 input-output table. Second, we estimate the weight-to-value ratio of the intermediate input bundle for each industry by combining sector-level weights on each input implied by the input-output table and the product-level weight-to-value ratio extracted from the Colombian customs data. The details of the estimate are 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) for 2000, 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.[19]

Table 4 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 finding suggests industries using heavier inputs tend to be more polluting in their output.

An example of a polluting sector is one that uses industrial wastes. Most industrial waste goods have a relatively high weight-to-value ratio. Figure 2 plots the density of the weight (kg)/value (US dollar) ratio for waste goods (the solid line) and for other goods (the dashed line). On average, the weight-to-value ratio of non-waste goods is much lower, about 0.1 kg/USD. By contrast, waste goods are much heavier, with the peak of their density at about 1 kg/USD. Recycling of waste and scrap products often involves more pollution and more unhealthy consequences than other imports. For example, imported waste products are often dirty, poorly sorted, or contaminated with hazardous substances. The problem is worse if the importer is a developing country. The 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.[20]

Developed countries also import some heavy goods. However, since developed countries have stringent environmental regulation, heavy goods imported by them could be quite different from those heavy goods imported by developing countries. In Appendix E, we document that heavy goods that developed countries tend to import are less polluted than other heavy goods.

If a greater trade surplus leads to lower prices of the inputs that are used more intensively in the polluting industries, it should lead to a relatively greater expansion of these industries. In Appendix F, we document findings consistent with this prediction. Using Chinese data, we confirm that in times of a greater

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

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

trade surplus, pollution-intensive sectors expand relatively more than the rest of the economy. This is especially true for those polluting sectors that use heavier inputs.

3.2 A Note on the Trade Pattern and Pollution

If a trade surplus leads to more emission of pollutants, it can cause a loss of utility. In principle, a stronger pollution regulation can mitigate the pollution consequence of a larger trade surplus. For example, although developed countries with a trade surplus tend to import more heavy materials (as shown in column 6 of Table 3), the pollution can be limited due to stringent environmental regulation. However, proper environmental regulation often lacks in developing countries.[21]

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

Although we use China as an example to quantitatively assess the welfare implication of trade imbalance, the results can provide valuable insights to other developing countries facing a similar situation characterized by a large trade surplus and weak environmental regulation.

4 A Quantitative Model and Policy Evaluations

We construct a two-country model to evaluate the welfare effects of various policies including a ban on imports of industrial waste, which is motivated by an actual policy introduced by China in 2018. We use the model to conduct counterfactual thought experiments that take into account endogenous responses by both

[21]The environmental regulation stringency index (ERS) is significantly lower in developing countries than in developed countries. The ERS is a country-specific and internationally comparable measure of the stringency of environmental policy collected by OECD. Stringency is defined as the degree to which environmental policies place an explicit or implicit tax on polluting or environmentally harmful behavior. The index ranges from 0 (not stringent) to 6 (highest degree of stringency).

domestically generated scrap goods and imports of non-scrap heavy goods.

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

4.1 Consumer problem

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

The representative consumer's utility is $\ln c_1 + \rho \ln c_2 - \eta x_1$. c_1 and c_2 are the consumption levels in the two periods, and ρ is the discount factor. x_1 is the pollution in the first period and η measures disutility per unit of the pollution. Because the agent does not supply labor in the second period, no domestic production exists, and the second-period pollution is zero. The assumption that there is no pollution in the second period is meant to capture some key features of developing countries like China - they tend to have a weak pollution control regime when they are in a low-income or middle-income stage, but their pollution control is likely to become stronger when they become richer in the future.[22]

[22]Suppose there exist production and pollution in the second period. Note that, in a two-period model, a trade surplus in the first period is accompanied by a trade deficit in the second

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

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

The revenue from selling the scrap goods at home and abroad is $P_{k,t}k_t + P^*_{k,t}E_{k,t} = P_{k,t}\phi c_t$.

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

period. If the deficit developing countries can export heavy goods to developed countries with a trade surplus (the rest of the world in our model), the overall welfare effect of the pollution will be reduced. However, as shown in Table 3 and Appendix B, developed countries are less likely to import heavy goods even when they run a trade surplus. Thus the additional pollution from an increase in the trade surplus in the first period will not be entirely offset by a reduction in pollution in the second period.

The consumer's problem is as follows:

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

$$\text{subject to} \quad P_{c,1}c_1 + S_1 = w_1 L + P_{k,1}\phi c_1 + P_{m,1}M + P_{h,1}H + \Pi_1 \tag{5}$$

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

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

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

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

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

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

We assume that the unit export costs for heavy materials and scrap goods are affected by the trade imbalance, measured by total exports divided by total imports. Specifically,

$$\tau_{h,t} = \bar{\tau}_{h,t} \left(\frac{Export}{Import} \right)^{\upsilon}, \tag{6}$$

$$\tau_{k,t} = \bar{\tau}_{k,t} \left(\frac{Export}{Import} \right)^{\upsilon}, \tag{7}$$

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

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

4.2 Non-polluting (Green) Sector

The representative firm in the non-polluting sector uses light material and labor to produce. The light material comes from either domestic supply or imports. We use m_t and m_t^* to denote the domestic and foreign imported light material goods.[23] The production function of the non-polluting sector is

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

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

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

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

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

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

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

4.3 Polluting Sector

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

$$q_t = \Omega_q \left(h_t^{\beta} h_t^{*(1-\beta)}\right)^{\sigma} \left(\gamma k_t^{\frac{\omega_k-1}{\omega_k}} + (1-\gamma)\, k_t^{*\frac{\omega_k-1}{\omega_k}}\right)^{\frac{\lambda\omega_k}{\omega_k-1}} L_{q,t}^{1-\sigma-\lambda}, \tag{8}$$

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 shares of domestic heavy and scrap materials, respectively, relative to the imported counterparts. σ and λ measure the shares of heavy materials and scrap goods, respectively, in the total production. ω_k is the elasticity of substitution between domestic and foreign scraps. We allow ω_k to be different from 1 because the substitution between domestic and foreign scraps may be higher than that between other materials. Because we wish to explore later the sensitivity of the policy experiments to different degrees of substitution between domestic and imported scraps, we use a slightly more general functional form to describe this particular substitution than that between domestic and imported heavy material.

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

$$\tau^*_{h,t} = \bar{\tau}^*_{h,t} \left(\frac{Export}{Import} \right)^{-v}, \tag{9}$$

$$\tau^*_{k,t} = \bar{\tau}^*_{k,t} \left(\frac{Export}{Import} \right)^{-v}, \tag{10}$$

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

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

The firm's problem is

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

$$\text{subject to} \quad \delta_t \leq b, \quad \text{and equations (8), (9), and (10).}$$

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

Finally, the demands for each input are derived, respectively, as

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

4.4 Equilibrium

The lump-sum transfer Π_t in the budget constraint (5) comes from the government's pollution tax, which is defined as $T_t\,(b-\delta_t)\,q_t$. Notice that in the second period, the lump-sum transfer is 0 because no domestic production exists.

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

4.5 Calibration

The pollution-abatement technology is assumed to be $\psi\,(\delta) = \frac{\xi}{2}\delta^2$. We assume all parameters, such as international material prices, remain the same for the two periods. We calibrate the model economy so that the model moments in period

1 match with those in the Chinese economy in 2012 (based on an input-output table in that year). We normalize the labor supply L to be 1 and the wage per person to be 1.[24]

To calibrate the parameters in the production function, we set $\alpha = 0.6$ to match the expenditure share of the polluting sector (60%).[25] We set $\theta = 0.45$ to match the labor share in the non-polluting sector (55%), and choose ω to match the import share of the light material in the total expenditure (9.2%). We assume $\beta = \gamma$ and calibrate σ, β, λ, and γ to match the labor share in the polluting sector (52%), the import share of heavy goods (12.3%), and the import share of scraps in the total expenditure (0.5%), respectively. In the baseline calibration, following Broda and Weinstein (2006), we set $\omega_k = 5$.

For international prices P_m^*, P_h^*, and P_k^*, we use the information in China's customs data and the 2012 input-output table. We classify all goods into four categories. First, we assign each HS6 good to either final consumption goods or intermediate inputs.[26] Among the intermediate inputs, a good is defined as a scrap if its name description contains either "scrap" or "waste." The remaining intermediate inputs are placed in the heavy-material basket if their weight-to-value ratios are above the median value across all non-scrap goods, and in the light-material basket otherwise. In terms of the average prices of each type of goods, by normalizing $P_c^* = 1$, we infer that $P_h^* = 1.3, P_m^* = 0.98$, and $P_k^* = 0.1$.

For the unit trading costs, we assume the exogenous component of all trade costs $\bar{\tau}$ is the same, and calibrate it so that the total transportation costs are around 20% of the trade values when the trade is balanced. This assumption is consistent with the estimates in Anderson and Van Wincoop (2004).[27] Because China is a perennially trade-surplus country, we set the elasticity of the unit

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

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

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

[27] Another way to think about the transportation cost is to connect it to the ratio of the cost of insurance and freight (CIF) and the free-on-board cost (FOB). According to Gaulier et al. (2008), the Chinese CIF/FOB ratio is around 3% to 7%. As an alternative specification. we set $\bar{\tau} = 1.05$ and find our model predictions are robust.

trading cost for heavy goods and scraps with respect to a trade surplus, υ, to 0.501, based on the empirical estimates in column 4 of Table 2.

We assume that the pollution tax is zero in the benchmark case.[28] In the model, we choose the unit of x as a ton of emission, and set the pollution generated per unit of output, b, to match the number of tons of pollution emission per value of output.[29] For pollution-abatement cost ξ, we do not have China-specific information and thus use the price of tradeable permits for SO2 emission in the United States, which is about US$ 1,600 per ton (Burtraw and Szambelan (2009)), or 0.46 model unit value. This value should be equal to the marginal cost of the abatement $w\xi q$, and allows us to back out ξ.[30]

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

For the remaining parameters (mostly in the consumer's problem), we calibrate ρ to generate a trade surplus that is about 5% of GDP (which is roughly the level for China in the recent past). We set the foreign real return $R = 10\%$. (If we consider one period in the model is ten years, the annual real interest rate is 1%.)

The parameter for the disutility of pollution, η, is both important for our inferences and challenging to pin down from the data. Existing papers that estimate a willingness to pay (WTP) for reducing pollution almost always focus on changing concentration of a particular pollutant. We need to convert tonnage of emission in our model to the degree of concentration. We estimate a relationship between concentration and tonnage of pollution emission using US EPA data over 1990-2018. We find that one ton of PM10, SO2, and VOC+NOX emissions increase

[28]China's pollution discharge fee was considered too low, and the enforcement was considered weak (Li and Chen (2018)).

[29]From the China city statistical yearbook, we aggregate air, solid, and water pollutants, and divide it by the total GDP.

[30]One caveat to bear in mind is that ξ may differ across pollutants and across countries. So the US information may not be a good guide for China. On the other hand, in the benchmark case when the pollution tax is zero, the exact value of ξ does not matter for the calibrations, because no firm will choose to reduce the emission. ξ will affect the counterfactual simulations, when the optimal pollution tax is imposed.

the concentration of PM10, SO2, and the ozone by $2.46\mu g/m^3$, 4.56 ppb, and 0.99 ppb, respectively. Unfortunately, the empirical literature on the WTP to reduce the pollutant concentration contains a too wide range of the estimates to provide a sharp guide for us.[31]

We decide to base our parameter value on Bajari et al. (2012), which appears to be one of the most cited WTP estimates. It uses a hedonic price-regression approach and handles the time-varying correlated unobservables. Their estimates (Table 6 in their paper) suggest that the WTP of PM10 ($1\mu g/m^3$), SO2 (1 ppb), and the ozone (1 ppb) are US$ 103, 178 and 180 (in 2003 dollars), respectively. Hence, the monetary costs of one ton of emission of PM10, SO2, and the ozone are 253.38 (103×2.46), 811.68 (178×4.56), and 178.2 (180×0.99), respectively. We take the WTP of one ton of emission as the max of these three numbers (811.68), which implies $\eta = 0.03$.[32]

It is hard to say whether our choice is an under- or over-estimate of the true disutility of pollution. On the one hand, we have included three air pollutants, PM10, SO2, and the ozone, but the list of health-reducing pollutants is surely longer than three. By ignoring other pollutants, we may have underestimated η. On the other hand, our estimate is based on the US data. Bayer et al. (2016) show that the WTP of pollution is low for low income-groups. Thus, we may have overestimated η in the Chinese economy. The calibrated parameters chosen to target data moments are summarized in Table 5.

4.6 Welfare and Policy Analysis

Welfare Cost of Trade Surplus

The baseline results are recorded in the first column of Table 6, where we normalize the pollutant emission (in the first row), imports of scrap and heavy material in the first period (in the second and third rows, respectively), the total export value

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

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

of heavy goods and scrap (the fourth row), and the wage per capita (the fifth row) to 100. The trade surplus in this case is about 5% of GDP (the sixth row). For subsequent thought experiments, we report the percentage change in the part of the utility $\ln(c_1)+\rho\ln(c_2)$ from a change in consumption relative to the benchmark case while ignoring any disutility of pollution (second to the last row), and the percentage change in total utility due to the thought experiment that also takes into account any change in disutility from a change in the pollution level (the last row). By construction, the last two numbers are zero in the baseline case.

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

With exogenous shipping costs, the welfare is affected in four ways: two working through consumption and two through pollution. First, a higher unit shipping cost on the import side increases the input costs of the polluting industry, which reduces pollution. Second, a lower unit shipping cost on the export side leads to more exports of scraps and heavy material, which further increases the input costs to the polluting industry and augments the reduction in pollution. The combined consequence of the first two effects is a total reduction of pollution by 4.58% and an increase in utility by about 1.84%. Third, the higher input costs to the polluting industry lowers the sector's production and lowers the wage rate, which in turn lowers the life-time income. Fourth, the additional exports of domestic scraps and heavy material increase total revenue and boost export revenue, resulting in an increase in the lifetime income. We find the fourth effect numerically dominates the third effect, and the combined consequence of the third and fourth effects is an additional increase in consumption, leading to a 0.54% increase in utility. Overall, the total consequence of all four effects is a 2.38% welfare increase.

With an endogenous response of the shipping cost to the trade imbalance, an increase or decrease in the trade imbalance may have systematically different welfare consequences. To illustrate, we impose a credit market constraint on the household problem $S \leq \bar{S}$. Then, variations in $\bar{S}$ generate variations in the level of the trade imbalance. The results from varying $\bar{S}$ are plotted in Figure 3. On the x-axis, the saving/GDP ratio increases from a deficit -5% to a surplus 5%. For a given trade imbalance, we plot the difference with and without endogenous responses of the shipping cost. This difference is the total effect on welfare that incorporates the changes in welfare due to changes in both pollution and consumption (solid line). To isolate the importance of the pollution channel, we also report the partial utility change resulting from a change in consumption without a change in pollution (dashed line). As we can see, when the trade surplus increases from 0% to 5%, the welfare level in a world in which the shipping costs responds to the trade balance relative to one with an exogenous shipping cost declines monotonically from 0% to 2.38%. The utility change excluding pollution is much smaller, suggesting the pollution channel is a quantitatively important part of the story.[33]

Banning Scrap Imports

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

We summarize the results in Table 7. For ease of comparison, we copy the baseline results of Table 6 and paste them into the first column of the current table. The result on banning scrap imports is shown in the second column of Table 7. Banning scrap imports raises the input cost of the polluting sector higher, which in turn generates several effects. First, the output in the polluting sector decreases, and the pollution in turn decreases by 1.40%. The import of heavy goods decreases by 0.78%, because the polluting sector shrinks. Second, the contraction of the

[33] The open-economy macroeconomics literature (for instance, Gourinchas and Jeanne (2006) and Mendoza et al. (2007)) quantifies the welfare loss of current account imbalance by removing the financial friction. Those studies find that the welfare cost is about 1% of the consumption drop. Compared to their estimates, our channel is quantitatively important.

polluting sector results in a decline of the final good production at home and a decline of the export revenue of the final goods. Because this effect dominates the decrease in imports, the trade surplus reduces by 4.83%. While the reduction in the trade surplus pushes up the unit shipping cost of importing heavy goods and scraps, it pushes down the unit shipping costs on the export side. In response to a lower export shipping cost, the exports of heavy material and scraps increase by 0.66%. Third, the reduced output in the polluting sector pushes down the labor demand (so that the wage declines by 0.78%). Hence, the lifetime income decreases and the utility from consumption declines by 0.26%. Finally, the utility loss from a lower consumption is more than offset by a utility gain from lower pollution. The net change in welfare is a gain of 0.30% relative to the benchmark case.

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

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

where b_0 and b_1 are two positive parameters. This equation suggests the pollution intensity is increasing when the firm uses more heavy material relative to the scrap. We choose $b_1 = 0.1$ and calibrate b_0 to match the tons of pollutant emission per value. The results in column 3 are intuitive. First, because no pollution tax exists, the effect of pollution is not internalized, and all variables except for the pollution emission (reported in the first row) and the utility change (the last row) are the same as in column 2. Second, because the heavy material is more polluting, the pollution level is 4% higher than in the baseline case, and the overall utility is 1.87% lower. In other words, banning scrap imports can lower the overall welfare when the heavy material is more polluting than the scrap itself.

The second sensitivity exercise investigates the consequence of a higher degree of elasticity of substitution between foreign and domestic scraps. Whereas the elasticity in the baseline case is set at 5, which follows Broda and Weinstein (2006), we now increase it dramatically to $\omega_k = 200$. In other words, we assume they are close to perfect substitutes. The results are shown in column 4. Compared to the second column, both the reduction in consumption and the reduction in pollution become much smaller. The reason is intuitive: Because the firm can more easily substitute the imported scrap with domestic scrap, a given increase in the cost of the imported scraps would not alter the production by as much. As a result, the impacts on consumption and pollution also become smaller. Relative to the baseline case in column 1, the net welfare effect is a 0.12% increase, which is smaller than the case in column 2 when the elasticity is substantially smaller. Because the elasticity of substitution increases substantially from column 2 to column 4 without dramatically altering the end result, one may also conclude the welfare analysis of banning scrap imports is not sensitive to the assumption on elasticity of substitution between foreign and domestic scraps.[34]

Optimal Regulation

We now consider the optimal tax on pollution. Specifically, we do a grid search over the value of T that maximizes the consumer's welfare. We find the optimal tax is $T = 0.58$, which is about 14,000 RMB (2,000 USD) per ton of pollution emission. We should note at the outset that the welfare is maximized when the

[34]We have also checked the sensitivity of our result to η. we find that as long as $\eta \geq 0.015$ (half of American's WTP), the ban of scrap import can bring a welfare gain.

optimal pollution tax is imposed, because pollution externality is the only source of market failure in our model. This qualitative conclusion can be reached even without looking at the numbers. One purpose of the calibration exercise is to study how close other policies − such as a ban on imports of scraps − can approximate the optimal pollution tax in terms of the welfare changes.

After imposing this pollution tax, the representative firm in the polluting sector responds by cutting emissions, which leads to 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 emission declines by 99.9%. The consumption also declines given the higher cost of production. However, a utility loss from a lower level of consumption (a utility loss of 5.54% as reported in the second to the last row in column 5) is more than offset by a utility gain from a lower level of pollution. On net, the welfare gain is 34.53% (the last row in column 5) higher than in the benchmark case.

The most important reason for the relatively big welfare gain is that a higher pollution cost has reduced the demand for both scrap and heavy material, whether they are imported or domestically sourced. From the second and third rows, the scrap- and heavy-goods imports decline by 99.98%. Meanwhile, because the demand for domestic scrap and heavy material declines, the household would choose to sell them abroad. As a result, the revenue from exporting scrap and heavy goods increases by 183.96%.

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

5 Conclusion

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

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

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

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

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Tables and Figures

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

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

NOTE: This table shows the top and bottom 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 Shipping Routes

	(1) $\ln \lambda_{ndt}$	(2) $\ln \lambda_{ndt}$	(3) $\ln \lambda_{ndt}$	(4) $\ln \lambda_{ndt}$
$\ln(\text{Imbalance}_{ndt})$	-0.019	-0.177***	-0.028	-0.191***
	(0.022)	(0.062)	(0.022)	(0.063)
$\ln(\text{Imbalance}_{ndt}) \times$ Pervasive-route			-0.148**	-0.310***
			(0.073)	(0.102)
Country-pair FE	Y	Y	Y	Y
Destination-year FE	Y	Y	Y	Y
Origin-year FE	Y	Y	Y	Y
IV		Y		Y
Obs.	728	728	728	728
R-squared	0.93	0.93	0.93	0.93

Notes: This table shows the estimation results of equation (2). λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} is the bilateral trade imbalance between a country-pair (n and d) in a year, measured by the total export of d to n divided by the total import of d from n. Pervasive route=1 if the destination country runs trade surplus against 2/3 of its trade partners and the origin country runs a trade deficit against 2/3 of its trade partners. We use the log value of equation (3) for an instrumental variable for log Imbalance_{ndt}. The first-stage F-statistics are around 69 and 34 in columns 2 and 4, respectively. *** p<0.01, ** p<0.05, * p<0.1.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{Imp}_{i,ndt})$	$\ln(\text{Imp}_{i,ndt})$	$\ln(\text{Imp}_{i,ndt})$	$\ln(\text{Imp}_{i,ndt})$	$\ln(\text{Imp}_{i,ndt})$	$\ln(\text{Imp}_{i,ndt})$
$\ln\lambda_{ndt}$	-0.711***	-0.714***				
	(0.017)	(0.017)				
$\ln\lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right)$	-0.062***	-0.051***	-0.06***			
	(0.007)	(0.007)	(0.007)			
$\ln\lambda_{ndt} \times \ln\left(\frac{w_i}{p_i}\right) \times$ Persist		-0.017***				
		(0.001)				
$\ln(\text{Imbalance}_{ndt}) \times \ln\left(\frac{w_i}{p_i}\right)$				0.012***	0.032*	0.003
				(0.004)	(0.017)	(0.005)
Origin-good-year FE	Y	Y	Y	Y	Y	Y
Destination-good-year FE	Y	Y	Y	Y	Y	Y
Destination-origin-year FE			Y	Y	Y	Y
IV					Y	
High income country						Y
Obs.	1,836,440	1,836,440	1,836,440	1,976,537	1,976,537	1,037,736
R-squared	0.80	0.80	0.83	0.83	0.83	0.86

Notes: This table shows the estimation results of equation (4). $\text{Imp}_{i,ndt}$ is the import of good i from an origin country (n) to a destination country (d) in year t. λ_{ndt} is the shipping cost from an origin country (n) to a destination country (d) in year t. Imbalance_{ndt} is the bilateral trade imbalance between a country pair (n and d) in year t, measured by the total export of d to n divided by the total import of d from n. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. "Persist" is the dummy variable indicating one partner within a pair (n and d) runs a persistent trade surplus to the other partner. "High income country" indicates countries with an above-median GDP per capita (measured in 2011) in the sample. In column 5, we use the log value of equation (3) for an instrumental variable for log Imbalance_{ndt}. The first-stage F-statistics are around 38 in column 5. Standard errors are clustered at the goods, destination, and origin level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Correlations between Pollution Intensities and Input Weight/Value Ratios across Chinese Industries

	Kg-per-input val.	ln(SO2)	ln(NO2)
ln(SO2)	0.219***		
	(0.061)		
ln(NO2)	0.189*	0.980***	
	(0.106)	(0.000)	
ln(TSP)	0.194*	0.929***	0.944***
	(0.098)	(0.000)	(0.000)

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

Table 5: Calibration Result

Parameters	Value	Target Moments	Model	Data
θ	0.45	labor share in the non-polluting sector	0.55	0.55
ω	0.659	light import/total expenditure	0.092	0.092
σ	0.461	labor share in polluting industry	0.52	0.52
$\beta = \gamma$	0.333	heavy import/total expenditure	0.123	0.123
λ	0.019	scrap import/total expenditure	0.005	0.005
b	29.08	total pollutants emission (ton)/total expenditure	10.75	10.75
ξ	0.340	SO2 ton trade price	0.46	0.46
ϕ	0.032	scrap export/total expenditure	0	0
M	0.743	light export/total expenditure	0.13	0.13
H	0.325	heavy export/total expenditure	0.117	0.117
ρ	0.497	surplus/GDP	0.05	0.05

Notes: The variables capture outcomes in the first period. For corresponding data, we use Chinese data in 2012. We normalize the 2012 wage to be 1, which implies that the value of one unit in our model is around 24,000 RMB or 3,500 USD. The polluting sector in the model corresponds to an aggregation of the Chinese industries whose SO2 pollution intensities are above the median across all industries.

Table 6: Welfare Effect of Endogenous Shipping Cost

	(1) Baseline	(2) Exog. shipping cost
Pollution	100	95.42
Scrap import	100	96.10
Heavy goods import	100	96.10
Heavy goods+scrap export	100	111.08
Wage	100	96.10
Surplus/GDP (%)	5.04	5.75
Utility change from c (%)	0	0.54
Utility change (%)	0	2.38

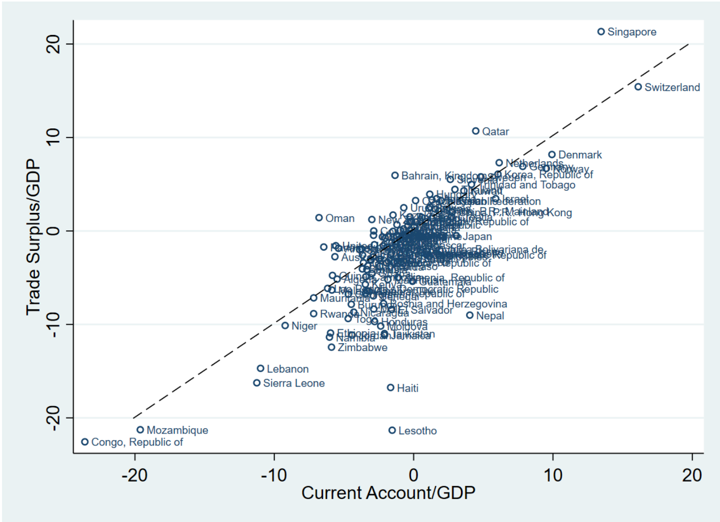
Notes: This table presents the welfare effect of the endogenous shipping cost. In column 1, the baseline results are shown where pollution, scrap imports/exports, (non-scrap) heavy material imports/export, and wage are all normalized to be 100. In column 2, we assume the shipping cost does not respond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

Table 7: Welfare Comparisons of Counterfactual Policy Experiments

	(1) Baseline	(2) Ban scrap imports	(3) Dif pollution Intensity	(4) High elasticity	(5) Optimal tax
Pollution	100	98.60	104.01	99.37	0.01
Scrap import	100	0	0	0	0.02
Heavy goods import	100	99.22	99.25	99.66	0.02
Heavy goods+scrap export	100	100.66	100.57	100.27	283.96
Wage	100	99.22	99.25	99.66	5.76
Surplus/GDP (%)	5.04	4.83	4.83	4.93	-0.94
Utility change from c (%)	0	-0.26	-0.27	-0.14	-5.54
Utility change (%)	0	0.30	-1.87	0.12	34.53

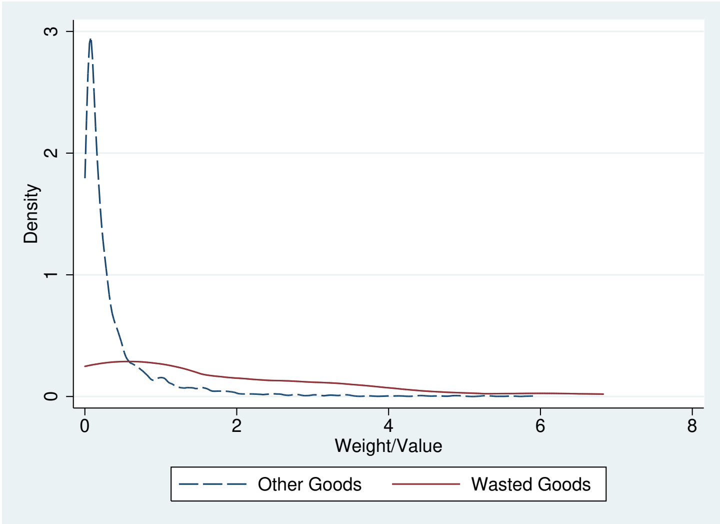
Notes: This table presents the model predictions for different counterfactual experiments. In column 1, the baseline results are shown where pollution, scrap imports/exports, (non-scrap) heavy material imports/export, and wage are all normalized to be 100. In column 2, a ban on scrap imports is imposed.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

Figure 1: The Current Account Imbalance and the Trade Imbalance



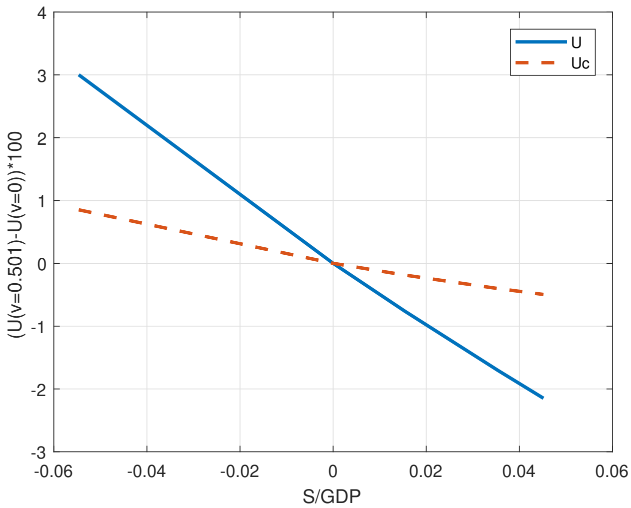
NOTE: This figure shows the correlation between the current account-GDP ratio and the trade surplus-GDP ratio across countries in 2015. The trade surplus is defined as export−import. The dashed line is the linear fit: Trade surplus/GDP $= -0.884(0.628) + 0.941^{***}(0.098) \times$ Current Account/GDP.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

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



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

Figure 3: The Welfare Cost of Trade Surplus



NOTE: This figure shows the utility difference when $v = 0.501$ and $v = 0$ under different trade-surplus values. U refers to the net utility change. U_c refers to the partial change in welfare ignoring pollution.

Online Appendix (not for publication in print)

A Alternative Specification

In our theory (section 2), we assume that the shipping firm charges a shipping fee by the weight of the goods. In this section, we instead assume that the shipping firm charges a shipping fee by the volume of the goods and show that our results are robust to this alternative specification.

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

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

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

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

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

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

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

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

Under the assumption that the container-per-weight ratio is the same within a 2-digit HS code, we re-test whether the trade-surplus country imports more heavy goods. Note we control the destination-origin-year-2-digit HS code dummies. The results are reported in Table 8.

Table 8: Estimates for the Log Import Value Regressions

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

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

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

B The Import Weight and Trade Imbalance

In this section, we show the correlation between weight per import dollar and the trade imbalance. We use the weight per value ratio of each HS6 goods to compute the average weight per import dollar for each country-year level. We define the trade imbalance as export value divided by import value. The sample covers those countries without any missing values from 2000-2014.

The results are shown in Table 9. In both regressions, we control the GDP per capita and the population. We also control the country and year fixed effects. The first regression indicates that when a country's trade surplus increases by 1%, the average weight of the importing bundle will increase by 0.054kg. High GDP per capita or small population country tends to have a lighter import bundle, but the effect is not significant. In the second column, we restricts our sample to developed countries, which are defined as countries with GDP per capita higher than 12,000 USD (in 2011 value). The imbalance elasticity of the import weight declines to 0.023, and insignificant. Hence it suggests that the correlation between trade surplus and heavy goods import is less pronounced within rich countries.

Table 9: Average Weight-per-Import Dollar and Trade Imbalance

	(1) Weight_{dt}	(2) Weight_{dt}
Imbalance_{dt}	0.054**	0.023
	(0.025)	(0.024)
$\ln(\text{GDP per capita})_{dt}$	-0.088	-0.168**
	(0.127)	(0.076)
$\ln(\text{Population})_{dt}$	0.177	0.384***
	(0.167)	(0.082)
Country FE	Y	Y
Year FE	Y	Y
Developed Country Sample		Y
Obs.	975	678
R-squared	0.85	0.91

Notes: This table shows the estimation results of regressing weight per import dollar on the trade imbalance. Weight_{dt} is the average weight per import dollar of a destination country (d) in year t. Imbalance_{dt} is the aggregate trade imbalance of a country d in year t, measured by the total export divided by the total import of d. Column 2 restricts sample to developed countries which are defined as countries with GDP per capita higher than 12,000 USD (in 2011 value). Standard errors are clustered at the country and year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C The Chinese Port-level Evidence

In the cross-country evidence reported above, unmeasured time-varying country-pair features can, in principle, be correlated with unit shipping costs. In this section, we explore variations across ports within a country as a robust check. Specifically, we use port-level trade data of the Chinese customs from 2000-2006.

This is intended to provide further confirmation that trade imbalance is a robust predictor of the heaviness of imports.

In the Chinese customs data, for a given pair of port and HS6 good and a given trading partner, we sum up all bilateral imports and bilateral exports in a year, respectively. For example, we know Shanghai port's total exports to the US by product, and the same port's total imports from the US by product.[35]

The gravity equation to be estimated is as follows:

$$\begin{aligned}\ln(\text{Import}_{i,mnt}) =& \beta_0 \ln(\text{Imbalance}_{mnt}) + \beta_1 \ln(\text{Imbalance}_{mnt}) \times \ln\left(\frac{w_i}{p_i}\right) \\ &+ \eta_{i,mt} + \eta_{i,nt} + \varepsilon_{i,mnt}, \end{aligned} \tag{11}$$

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

Table 10 reports the estimation results. In the first column, where we control for both product-port-year triplet fixed effects and product-exporter-year triplet fixed effects, β_1 is estimated to be 0.0095 and statistically significant at the 1% level. That is, the import elasticity with respect to the trade imbalance is higher for heavier products. In the second column, where we also control for port-exporter-pair fixed effects, β_1 is estimated to be 0.0064 and statistically significant. These estimates provide confirmation of our mechanism at the level of ports within a country even after we control for a large number of relatively demanding fixed effects.

[35] Although we use the word port, we actually mean a city in customs data. For instance, even though Xining is not a coastal city, customs data are recorded for Xining. Because our story does not only hold for maritime trade, we include those inland cities in the analysis.

Table 10: Trade Imbalance and Import Composition across Chinese Ports

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

Notes: This table shows the estimation results of equation (11). $\text{Import}_{i,nmt}$ is the import of good i from an origin country (n) to a Chinese port (m) in year t. Imbalance_{nmt} is the bilateral trade imbalance between an origin (n)-port (m) pair in year t, measured by the total export of m to n divided by the total import of m from n. "w_i/p_i" is the weigh-to-value ratio of good i from the Colombian data. Standard errors are clustered at goods, origin level. *** p<0.01, ** p<0.05, * p<0.1.

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).[36] We then map each CSIC code to an input-output table industry. By combining the usage table of the 2012 Chinese input-output table and the weight-to-value ratio from the Colombian data, we compute the average weight-to-value ratio of each industry's input. We list all the ratios in Table 11.

Table 11: 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
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

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

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 Heavy Imports: Developed vs. Developing Countries

We investigate whether developed and developing countries with a trade surplus import different types of heavy goods (due to differences in environmental standards or preferences). We find that the answer is yes. We then show that those heavy inputs favored by developed surplus countries tend to contribute less to pollution on the output side.

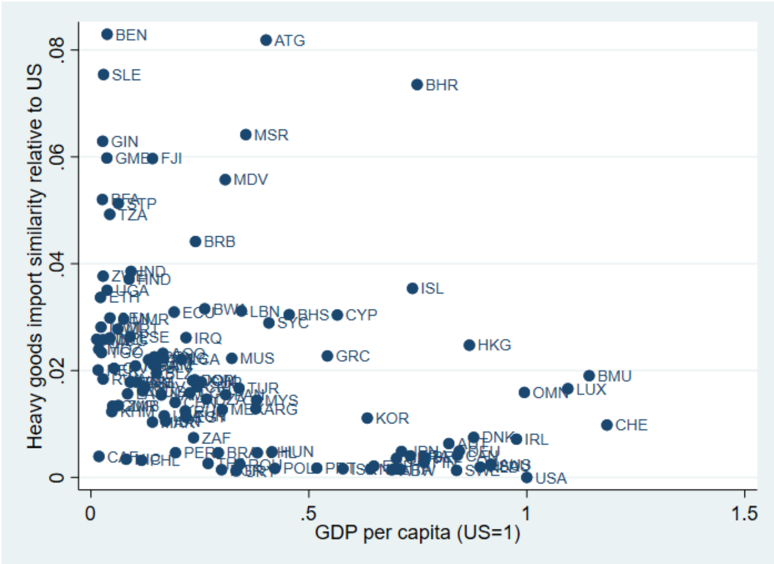
For the first point, we compare the composition of heavy goods imports across countries. Using the United States import composition as a reference, we compute the degree of dissimilarity of import composition between a given country n and the United States by the following index:

$$\text{Dissimilarity}_n = \sum_i (\text{Import share}_{i,n} - \text{Import share}_{i,US})^2,$$

where i is an heavy HS6 product (whose weight-to-value ratio is above the median value across all products). The Dissimilarity$_n$ is the Euclidean distance between the import share vector of country n's heavy goods imports and that of the US. If the two countries have identical import shares for all products, the index is equal to zero. Otherwise, the greater the value, the more different the two are. Figure 4 plots the value of the index against GDP per capita of the country n (relative to US). For developed countries, the pattern of heavy goods import is similar to the US. However, the pattern of heavy goods import is different from the US for developing countries.

The systematical difference documented above suggest that there is a set of heavy goods favored relatively more by developed importing countries. We now show that industries using heavy goods that are favored by developed countries

Figure 4: The Dissimilarity of Heavy Goods Import



Note: This figure shows the dissimilarity index of heavy goods import against GDP per capita (relative to US) across countries.

tend to contribute less to pollution on the output side. Define an HS6 product as favored by developed countries if the average of its import share by developed countries is greater than the average import share by developing countries. Developed countries are countries with GDP per capita above 12,000 USD in 2011 values. A heavy good favored by developed country (developed-country-heavy input) is an HS6 digit product favored by developed countries and with a weight-to-value ratio above the median value.

We construct the share of the developed-country-heavy input for an industry. We map each HS6 product to a Chinese input-output table industry, similar to Appendix D. By combining the usage table of the 2012 Chinese input-output table and the information of the developed-country-heavy input, we compute the average share of the developed-country-heavy input of each industry.[37] If an industry has a greater share of this measure, the industry uses more heavy intermediary inputs that developed countries tend to use.

In Table 12, we show the correlation between various pollution intensity mea-

[37]To save the space, we omit listing this ratio here.

sures (ln(SO2), ln(NO2) and ln(TSP)) and the share of the developed-country-heavy input across industries. As we can see, the pollution intensity is significantly lower for industries that use more developed-country-heavy inputs. This finding suggests that heavy goods imported by developed countries tend to generate less pollution.

Table 12: Correlations between Output-Pollution Intensities and Share of the Developed-Country-Heavy Input across Chinese Industries

	Share of the developed-country-heavy input
ln(SO2)	-0.511***
	(0.000)
ln(NO2)	-0.533***
	(0.001)
ln(TSP)	-0.427***
	(0.001)

Notes: This table shows the correlations between output pollution intensities and the share of the developed-country-heavy input across Chinese industries. *** p<0.01, ** p<0.05, * p<0.1.

F Trade Surplus and Expansion of Polluting Industries

If a greater trade surplus leads to lower prices of the inputs that are used more intensively in the polluting industries, it should lead to a relatively greater expansion of these industries. We investigate this prediction using Chinese data. In particular, we run the following panel regression over 1999-2017:

$$\ln(\text{Output}_{i,t}) = \beta_1 \ln(\text{Imbalance}_t) \times \text{Pollution}_i + \eta_i + \eta_t + \epsilon_{i,t}. \tag{12}$$

$\text{Output}_{i,t}$ is industry i's total domestic sales in year t (total industry output minus export). Imbalance_t is China's trade imbalance in year t measured by the ratio of China's exports to imports. Industry i is a 4-digit CSIC industry. $Pollution_i$ is industry i's air pollution intensity measured by log SO2 emission per dollar value of output in the US EPA data in 2000. It is assumed to be a fixed industry characteristic.[38] We control for both the industry fixed effects and year fixed effects.

We have also conducted similar panel regressions with NO2 and TSP emissions from the US EPA data as a measure of industry-level pollution intensity. Because the different air pollutants have similar industry rankings as indicated in the last two columns of Table 5, it is perhaps not surprising that we find similar regression results. We omit these results to save space. Due to a lack of comparable industry level data on solid or liquid pollutants, we are not able to perform a similar analysis with other pollutants.

In the first column of Table 13, the coefficient on the interaction term is 0.306 and is statistically significant. This suggests that an increase in the trade surplus is associated with an expansion of the more polluting industries relative to other industries.

One may be concerned with possible endogeneity of the trade imbalance. We next implement an instrumental variable approach. In particular, we use the government expenditures as a share of GDP by the United States, Japan, and South Korea, three major trading partners of China, as the instrumental variables for China's trade imbalance. The idea is that changes in major trading partners' government expenditures are likely to be exogenous to China, but to represent a shock for Chinese international trade. We check and confirm that there is no significant correlation over 1999-2017 between the pollution intensity of the Chinese import bundles and the government expenditure as a share of GDP of any of these trading partners. The IV estimate is presented in column 2 of Table 13, and is similar to the OLS result: The polluting industries tend to expand more in times of a greater trade surplus.

In column 3, we add a new triple interaction term: $\ln(\text{Imbalance}_t) \times \text{Pollution}_i \times \text{Heavy-Input}_i$. The heavy-inputs sectors are defined as those industries whose input-bundles' weight to value ratios are in the top 25th percentile of the distri-

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

bution. The coefficient for the new triple interaction term is positive and statistically significant. This suggests that the expansion of polluting sector is more pronounced for sectors using heavier inputs. In column 4, we implement an instrumental variable regression in which log imbalance is instrumented in a similar way as in column 2. The IV results are similar to the OLS, with somewhat larger point estimates. Overall, we confirm that in times of a greater trade surplus, pollution-intensive sectors expand relatively more than the rest of the economy. This is especially true for those polluting sectors that use heavier inputs.

Table 13: Trade Imbalance and the Relative Expansion of the Polluting Industries

	(1)	(2)	(3)	(4)
	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$	$\ln(\text{Output}_{i,t})$
$\ln(\text{Imbalance}_t)\times\ln(\text{SO2})_i$	0.306***	0.411***	0.177**	0.261***
	(0.051)	(0.073)	(0.063)	(0.073)
$\ln(\text{Imbalance}_t)\times\ln(\text{SO2})_i$ $\times\text{Heavy-sector}_i$			0.348**	0.403**
			(0.159)	(0.182)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
IV		Y		Y
Obs.	5,917	5,917	5,917	5,917
R-square	0.98	0.98	0.98	0.98

Notes: This table shows the estimation results of equation (12). The dependent variable, Output_{it} is domestic output of industry i in year t. Imbalance_t = Chinese exports/Chinese imports in year t. Heavy-sector_i is the dummy variable defined in section F. In columns 2 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. The first-stage F-statistics are around 17 and 15 in columns 2 and 4, respectively. Standard errors are clustered at year levels. *** p<0.01, ** p<0.05, * p<0.1.