# Welfare Effects of International Trade in Waste*

Prakrati Thakur†
*University of Illinois*

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**Abstract**

I quantify the welfare effects of international trade in waste. I build a structural gravity model in which the generation of waste, including recyclables, is expressed as a byproduct of manufacturing. My estimates reveal that low-value waste is more sensitive to trade barriers than high-value waste, while richer countries import a greater share of high-value waste than low-value waste. I find that existing patterns of waste trade make countries of all income levels better off. Trade in low-value waste, which creates large negative externalities relative to its private value, makes low-income countries better off, while middle-income countries are worse off. I estimate that China's 2018 ban on low-value waste imports made China and several lower-income countries better off. Depending on the type of waste trade banned, manufacturing production in countries is also differentially affected. While a high-value waste trade ban reduces manufacturing output for rich countries, a low-value waste trade ban reduces the output for lower-income countries.

Keywords: Trade, Environment, Waste, Environmental Regulations
JEL Classification: F18, F64, H23, Q56

*I am grateful to the World Bank for providing me with price data from the International Comparison Program's 2017 cycle. This paper would not have been possible without continued guidance and support from my advisor, George Deltas. I also owe my gratitude to Dan Bernhardt, Tatyana Deryugina, Ana Cecilia Fieler, Greg Howard, and Stefan Krasa, whose insightful comments have led to significant improvements in this work. I also thank the seminar participants at the University of Illinois Urbana-Champaign, Heartland 2019, the Western Economic Association International 2021, and the Midwest Economics Association 2021.

†Department of Economics, University of Illinois Urbana-Champaign, 214 David Kinley Hall, 1407 W. Gregory Dr, Urbana, IL 61801. Email: pthakur2@illinois.edu. Website: economics.illinois.edu/profile/pthakur2.

International trade in waste, including recyclables, has experienced considerable growth over the past three decades, with a five-fold increase in its trading volume from 33.9 million tons in 1988 to 156.7 million tons in 2015. However, international trade in waste is contentious among countries because its economic and environmental ramifications on all trading partners are unclear. Although trade in waste has benefits similar to trade in other commodities such as lower prices of recycled materials, increased employment opportunities, and additional income, it also creates local negative externalities in importing countries via the health and environmental hazards posed by waste (Kirby, 1994). Over the years, health and environmental considerations have led countries to put a range of controls on waste trade, from multilateral agreements, such as the Basel Convention implemented in 1992, to the unilateral ban on imports of select waste types by China in 2018. However, little evidence quantifies the effects of such waste trade controls on welfare, waste generation, and the primary source of waste generation, manufacturing production.

I quantify the welfare effects of international trade in waste. Specifically, I estimate the *gross* gains—benefits due to changes in real income—and compare them with the environmental costs of waste trade across countries. To this end, I extend the Ricardian model of trade in manufactured goods by Eaton and Kortum (2002) by adding the generation of waste as a byproduct of manufacturing. To my knowledge, this is the first paper to formulate a structural gravity model that provides theoretical microfoundations for waste generation and waste flows. To assess heterogeneity in welfare by type of waste, I decompose the waste flows into high- and low-value waste. Empirically, richer countries import a higher fraction of high-value waste than low-value waste. I interpret this finding as *non-homothetic* production in a country's recycling sector that uses the two types of waste to produce a recycled good. Apart from the nature of their trade flows, the two types of waste also differ in ease of recycling. High-value waste, which mainly comprises precious metals and yarn, is easier to recycle than low-value waste, which comprises mixed waste, including plastics. Thus, decomposing waste flows aids in quantifying the heterogeneity by waste type not only in the gains but also in the externality costs due to disposal from waste trade.

The size of gains to trade crucially hinges on the elasticity of the trade value of manufactured goods, high-value waste, and low-value waste with respect to trade barriers. To my knowledge, this is also the first paper to estimate the trade elasticities for international waste flows. I estimate these trade elasticities using geographic barrier, distance, as an instrument for a measure of trade barriers constructed using price data. My estimates reveal that low-value waste is more sensitive to trade barriers than high-value waste and manufactured goods. Specifically, I find that a 1% decrease in trade costs causes a 7.3% increase in manufactured goods, a 7.3% increase in high-value waste, and a 9.8% increase in low-value waste flows. To quantify the externality of waste in monetary terms, I rely on existing estimates of the social marginal cost of waste disposal (Bond et al., 2020; McKinsey, 2016) and extrapolate them to the countries in my sample. To estimate the other key parameters of the model, I simulate the world economy using cross-sectional trade data for 91 countries, representing over 90% of world trade in the three sectors in 2015.

A third contribution of my paper is to study a variety of counterfactual simulations to quantify the welfare consequences of waste trade. My results show that the existing patterns of waste trade make countries of all income levels better off even after accounting for negative externalities of waste disposal. The global gains to waste trade comprise 0.43% of gains to all trade even though waste trade accounts for only 0.07% of overall trade by value. Thus, per unit of trade value, waste trade generates more than five times the welfare gains of regular trade. Differentiating the gains to waste trade by income level, I find that poor countries have the largest gains, at 0.021% of GDP. Further, allowing waste trade decreases the environmental costs for all income levels, but for the poor, it does so by the largest amount of 0.024% of GDP. The decline in environmental costs reflects the scale and compositional changes in the generation of the two types of waste. As countries gain access to import opportunities from opening up to trade in waste, their recycling sector shifts its expenditure toward high-value waste and away from low-value waste. Thus, the scale of generating low-value waste, which has higher disposal intensity and creates high externality costs, counterintuitively decreases even as more options for dealing with waste become available through the waste trade.

I also study heterogeneity in welfare by type of waste. I find that the high-value waste trade creates gains and environmental costs qualitatively similar to the overall waste trade. Thus, countries of all income levels are better off due to trade in high-value waste. However, rich countries, which both specialize in and disproportionately import high-value waste, realize the largest *net* benefits of 0.049% of GDP. In contrast, low-value waste trade harms the primary importers of this type, i.e., middle-income countries. Even though poor countries are also primary importers of low-value waste, middle-income countries place a higher social marginal cost on waste disposal than low-income countries.

Finally, a fourth contribution is to examine the welfare implications of recent policies regulating waste trade, beginning with China's 2018 ban on select waste imports. China's ban on low-value waste imports has qualitatively similar welfare effects to a ban on all low-value waste trade, albeit with smaller magnitudes. This policy helps China on both fronts—by increasing gross benefits and decreasing environmental costs—while also benefiting other lower-income countries such as India and the Philippines. Similar to an overall low-value waste trade ban, the scale of low-value waste generation declines, making lower-income countries better off. Regulations on waste trade differentially affect manufacturing production in countries depending the type of waste trade that is banned. I find that banning trade in all or only high-value waste reduces manufacturing output by high-income countries, while increasing output by middle-income and poor countries. In contrast, only banning trade in low-value waste decreases the manufacturing output of both poor and rich countries. Although the effects of waste trade bans on manufacturing production across income levels are small, they indicate that trade bans on the type of waste a country specializes in have the potential to adversely affect its manufacturing sector.

This paper contributes to studies on factors determining international trade in waste by providing theoretical microfoundations for the generation of waste and international waste flows. Papers in this line of research either use a reduced-form approach to test for the *waste haven* effects, where waste is relocated to lower environmental regulation countries (Baggs, 2009; Kellenberg, 2012), or employ a Heckscher-Ohlin framework to conclude that countries sufficiently abundant in land import more waste assuming that landfill disposal is its final destination (Copeland, 1991). However, the economic incentives to import waste are, most likely, created through demand for recycled waste in local manufacturing production. Hence, in my framework, I abstract away from land-filling to create demand for waste by a country in its recycling sector for "productive" reasons rather than for final disposal. To my knowledge, the only paper studying the effects of waste trade policies on waste trade is Kellenberg and Levinson (2014), who estimate the effects of the Basel Convention using a difference-in-differences approach. My use of a structural framework allows me to incorporate general equilibrium forces, to consider a richer set of counterfactuals and to explicitly draw welfare conclusions that would not be possible with a reduced-form framework.

My paper also contributes to the literature studying the welfare effects of trade in goods using a structural gravity framework by building in environmental damages of an oft-overlooked component of international trade: trade in "bads" and, in particular, trade in waste.[2] Shapiro (2016) also builds a structural gravity model estimated to quantify the effects of international trade on $CO_2$ emissions, which depend directly on equilibrium production and consumption decisions. By contrast, I extend the Ricardian formulation by Eaton and Kortum (2002) by allowing the generation of waste to be endogenous to manufacturing. My formulation allows for a rich interaction between trade in manufactured goods, trade in waste, and the overall scales of production that plays out in the counterfactual simulations used to capture welfare effects. Using the structural gravity framework also allows comparison of gains to trade with those obtained from several richer Ricardian models. Methodologically, I contribute to this literature by proposing a new formulation to quantify environmental costs from waste—a nested CES formulation across goods and externality terms—and an analytically straightfor-

[2]Papers in this line of research have derived gravity equations under a variety of theoretical microfoundations, including perfect competition (Eaton and Kortum, 2002), Bertrand competition (Bernard et al., 2003), monopolistic competition with homogeneous firms (Krugman, 1980), and monopolistic competition with firm-level heterogeneity (Chaney, 2008; Arkolakis, 2010; Arkolakis et al., 2008; Eaton et al., 2011).

ward approach to estimating trade costs—calculating "wedges" that match simulated flows with actual flows.

The paper is organized as follows: Section 1 presents the data and the patterns in waste trade. Section 2 presents stylized facts related to aggregate waste flows and different types of waste. Section 3 presents the theoretical framework and the strategy for counterfactual calculations. Section 4 presents the estimation strategy for model parameters and their estimates. Section 5 presents the results from the counterfactuals and Section 6 concludes.

# 1 Data

With the goal of studying the effects of waste trade on welfare and manufacturing production in a static framework, I use cross-sectional bilateral trade data for waste and manufactured goods. I use the data first to describe empirical facts and then to estimate the structural model. Section 1.1 describes the trade data, while Section 1.2 describes the other variables used to gather the stylized facts. Section 1.3 presents the patterns of waste trade in the raw data.

## 1.1 Trade Data

Since the focus of this paper is on waste trade, I augment the data used in prior structural trade work with data on bilateral waste trade from the UN Comtrade database for 2015. To identify the categories of waste, I use the six-digit Harmonized System (HS) categories for which the commodity description primarily uses the keywords *waste*, *scrap*, or *residual*, following Kellenberg (2012). Table A.1 lists the 62 six-digit HS categories of waste in detail. For each waste category, the database provides the value in U.S. dollars and weight in kilograms (kg) of bilateral flows among 220 countries and territories.

Since industrial waste represents 94-97% of global waste (Liboiron, 2016; Kaza et al., 2018) and the categories of traded waste in my sample are primarily industrial in nature, I also obtain data on bilateral trade in manufactured goods. I use data on bilateral trade for codes 1-8, most closely related to manufactured goods, under SITC.Rev4 for 233 countries and territories in U.S. dollar terms.[3]

[3] The 8 SITC.Rev4 codes broadly represent the following commodities: beverages and tobacco, crude materials, mineral fuels, lubricants and related materials, animal and vegetable oils, fats and waxes, chemicals and related products, manufactured goods, machinery and transport equipment, and miscellaneous manufactured articles.

## 1.2 Environmental Regulation, Income, and Geographic Barriers

I use several variables to gather stylized facts from the data. To capture the level of environmental regulation in a country, I use data on the Environmental Performance Index (EPI) for 2016 (Hsu et al., 2016). The EPI quantifies the environmental performance of a country's policies by combining different indicators on the protection of human health and ecosystem vitality. Although the EPI is an imperfect measure of the stringency of environmental policies of a country, it provides data on a comprehensive list of countries. Starting in 2006, the EPI Report is published every other year, so the EPIs for 2015 were unavailable. Thus, I use 2016 EPIs as a proxy for the stringency of environmental regulation in each country. Other variables of interest include income levels, wage rate, and output per unit of land. Thus, I obtain data on gross domestic product (GDP), GDP per capita, used as a proxy for wage rate, and land area from the World Development Indicators (WDI) database. The GDP and GDP per capita are measured in U. S. dollar terms, while land area is measured in square kilometers (sq. km).

I also use data on geographic barriers, trade agreements, and treaties to serve as a proxy for barriers to trade. The measure of distance, in kilometers, is constructed using the geographic coordinates of most important cities in a country by Mayer and Zignago (2011). Their data set also provides dummies for contiguity and common official language between pairs of countries that I use. I also construct dummies for pairs of countries that are part of a free trade agreement (FTA) using data from the World Trade Organization (WTO).[4]

## 1.3 Patterns in Waste Trade

To begin, I examine patterns in total waste exports and imports across the world. Figure A.1 displays the value of total waste exports as a share of GDP, while Figure A.2 displays the value of total waste imports as a share of GDP across countries. As a share of GDP, high-income countries, mainly in the European and North American regions, are the largest exporters of waste. In contrast, as a share of GDP, the largest importers of waste comprise not only low-income countries such as Pakistan, Turkey, and Vietnam but also high-income countries such as Belgium, Finland, and South Korea. Thus, the pattern of aggregate waste flows reveals that waste exports primarily come from rich countries, while countries of all income levels—rich to poor—are among the major importers of waste.

Next, I disaggregate waste flows into two types of waste—high-value and low-value—based on value-to-weight ratios of the 62 categories of waste. To construct the value-to-weight ratios, I calculate the ratio of the average dollar-value and average weight of trade in each category.

[4]To construct the FTA dummies, I utilize data on trade agreements that are listed as best known by the WTO: ASEAN, COMESA, EFTA, EU, MERCOSUR, and NAFTA.

Then, I divide the 62 categories into two types of waste: high-value, which corresponds to the top tercile, and low-value, which corresponds to the bottom two terciles of value-to-weight ratios (See Figure A.3). Figure 1 shows that while 75% of the materials in high-value waste are metallic in nature, low-value waste is a mix of different materials, including plastics and paper.[5]

Table 1 presents summary statistics on the two types of waste. Panel A shows that, on average, countries exporting high-value waste have similar levels of GDP per capita, GDP, and EPI, as countries exporting low-value waste. In contrast, countries importing high-value waste, on average, have higher GDP per capita, GDP, and EPI than countries importing low-value waste. Thus, the statistics reveal that importers of low-value waste, on average, have lower incomes, lower incomes per capita, and lower levels of environmental regulation than importers of high-value waste. Figures 2 and 3 depict a pattern that is consistent with these findings. As a share of GDP, high-income countries in the European and North American regions are the major importers of high-value waste. However, as a share of GDP, the major importers of low-value waste are primarily lower-income countries, such as Pakistan, Turkey, and Vietnam. Finally, the table shows that on average, a tonne of high-value waste is valued at \$2631.39, while a tonne of low-value waste is valued at \$264.82.

# 2 Stylized Facts

In this section, I present a series of stylized facts on international trade in waste to motivate the gravity setup of the model and the welfare calculations. I document these stylized facts based on reduced-form gravity regressions, where the value of bilateral trade from country $i$ to $j$, denoted by $X_{ij}$, is directly proportional to income levels, $Y_i$ and $Y_j$, and inversely related to trade barriers, $\tau_{ij}$:

$$X_{ij} = \exp\left(\beta_0 + \beta_1 \log Y_i + \beta_2 \log Y_j + \beta_3 \log \tau_{ij} + \boldsymbol{\beta_4} \mathbf{Z_i} + \boldsymbol{\beta_5} \mathbf{Z_j}\right) \times \eta_{ij}. \tag{1}$$

The term $\tau_{ij}$ comprises geographic barrier variables: distance, contiguity, and common language.[6] The vector $\mathbf{Z_i}$ includes logged exporter-level controls, exporter's EPI and GDP per unit of land, while $\mathbf{Z_j}$ includes analogous importer-level controls. Finally, $\eta_{ij}$ is the error term with $E[\eta_{ij}|Y_i, Y_j, \tau_{ij}, \mathbf{Z_i}, \mathbf{Z_j}] = 1$.

[5]Although metals and yarn are a part of both high- and low-value waste, the nature of the categories within these two broad classes is different. The metals and yarn that comprise high-value waste are chiefly precious objects, such as gold and silk.

[6]In principle, ratification of the Basel Convention could be an important determinant of waste trade. In practice, by 2015, the vast majority of countries ratified the Basel Convention, with the notable exception of the United States. Thus, this variable has little meaningful variation, and I do not include it in the analysis.

To estimate Equation (1), I use the Poisson pseudo-maximum likelihood (PPML) estimation technique, which yields consistent and efficient estimates (Silva and Tenreyro, 2006).[7] To account for unobservable heterogeneity at the country level, I also estimate a specification with exporter and importer fixed effects, $\mu_i$ and $\mu_j$, respectively.[8] Further, to study the choice between high-value and low-value waste across countries, I estimate a specification with the ratio of bilateral high-value to total waste trade as the dependent variable. Due to potential correlation between observations of the same trading partners, I cluster standard errors at the exporter-importer level for all specifications.

## 2.1 Aggregate Waste Flows

I begin by discussing the stylized facts on aggregate waste flows.

*Fact 1: Bilateral waste flows across countries are positively associated with exporters' and importers' income levels.*

Table 2 reports the elasticity of aggregate bilateral waste flows with respect to exporter's and importer's incomes. I find that the elasticity of the aggregate value of bilateral waste trade with respect to exporters' GDP is 0.552 and with respect to importers' GDP is 1.199, both significant at the 1% level. These results indicate that higher-income countries have larger overall production and consumption activity than lower-income countries. Therefore, they generate and export larger quantities of waste. Furthermore, higher-income countries likely have a greater capacity to recycle waste and a greater demand for secondary inputs in their manufacturing sector and, consequently, engage in more waste imports. I also find that waste trade is more sensitive to importer's income than to exporter's income. In contrast, for manufactured goods, trade is almost equally sensitive to both exporter's and importer's income levels, with elasticities in the 0.84-0.89 range (See Table A.2). In addition, waste

[7] I prefer the PPML method for two reasons. First, in the presence of heteroscedasticity, the mean of the log of the error term depends on higher-order moments of the error term, so it is not independent of the covariates. Thus, estimation of the log-linearized gravity equation via ordinary least squares (OLS) yields inconsistent estimates. However, the PPML estimator performs well under different specifications of heteroscedasticity. Second, bilateral trade data tend to have many zero observations. In my sample, 86-91% of observations across aggregate, high-value, and low-value waste flows are zero. Trade observations that are small, such as for distant country pairs or smaller countries, are more likely to suffer from a rounding error due to being recorded as zero during data collection. This rounding error is based on values of regressors. Thus, the zero observations in the dependent variable not only heavily reduce the sample size but also lead to inconsistent estimates while estimating the log-linearized Equation (1) via OLS. The PPML estimator is robust to this form of measurement error.

[8] Because the inclusion of country-level fixed effects absorbs any variation at that level, coefficients of the variables part of the vectors $\mathbf{Z_i}$ and $\mathbf{Z_j}$ can no longer be estimated.

trade is more sensitive to importer's income level and less sensitive to exporter's income level than trade in manufactured goods.

*Fact 2: Bilateral waste flows across countries are inversely related to trade barriers.*

Table 2 shows that waste trade and distance have an inverse relationship. Specifically, I find that the magnitude of the negative elasticity of waste trade with respect to distance is 0.681-0.911 and significant at the 1% level. In contrast, the negative elasticity of manufactured goods trade is 0.457-0.653, suggesting that waste trade is more sensitive to geographic barriers than manufactured goods trade (See Table A.2). Moreover, the coefficient on the geographic barrier variable, contiguity, is positive and significant at the 1% level. If two countries are contiguous, they trade 151-177% more in waste than noncontiguous country pairs, as opposed to manufactured goods, where they trade 68-92% more.[9] Since lesser benefits accrue from importing waste than manufactured goods for a country, waste trade is more sensitive to trade barriers. Lastly, Table 2 shows a positive, albeit not statistically significant, correlation between waste flows and the common language dummy.

Turning to the effects of environmental regulations, I find a positive elasticity of waste trade with respect to exporter's EPI, with magnitude 2.398, and a negative elasticity with respect to importer's EPI, with magnitude 3.880, both significant at the 1% level. Arguably, a country with greater environmental regulation finds it harder to dispose or recycle negative externality-generating waste and thus exports more and imports less of it. This finding suggests that countries with stricter environmental regulations that care more about the negative externality due to waste seek external avenues for waste management by exporting it to other countries with lax environmental regulations (Kellenberg, 2012).

## 2.2 Heterogeneity by Type of Waste

In this subsection, I discuss the stylized facts on the two types of waste. I replace the dollar-value of high-value and low-value waste flows as dependent variables while estimating Equation (1). Table 2 shows that high-value and low-value waste flows qualitatively conform with the empirical facts described for aggregate waste flows in Section 2.1. Next, I discuss additional stylized facts on heterogeneity by type of waste.

*Fact 3: Low-value waste is more sensitive to trade barriers than high-value waste.*

[9] The coefficient on Contiguity in waste trade regressions is in the range of 0.920-1.020. Since it is a log-level regression, I calculate the marginal percentage change in the dependent variable as $100 \times (e^{\beta} - 1)$, where $\beta$ is the coefficient on Contiguity.

Table 2 shows that the negative elasticity of low-value waste is larger in magnitude than the elasticity of high-value waste with respect to distance. Specifically, in columns 3 and 5, the elasticity of high-value waste with respect to distance is -0.535 as opposed to -0.781 for low-value waste, and the elasticity of low-value waste statistically significantly exceeds that for high-value waste at the 5% level. Similarly, in models with exporter- and importer-specific effects, in columns 4 and 6, the magnitude of the negative elasticity with respect to distance for high-value waste, 0.728, is statistically significantly smaller than that for low-value waste, 1.055, at the 1% level. This finding indicates greater benefits to importing high-value waste than low-value waste, so trade in this type of waste is not as sensitive to trade costs as low-value waste trade. The observed trade patterns appear to arise from differences in waste-processing technology available in different countries. Processing high-value waste likely requires technology that is available in only a select set of high-income countries. As a result, technological availability swamps trade costs in determining flows of high-value waste. Conversely, trade costs swamp technological considerations while determining the direction of low-value waste trade.

*Fact 4: As income increases, a greater share of a country's waste imports is high-value waste.*

To further understand the choice between importing the two types of waste by a country, I estimate a specification by replacing the ratio of high-value to total waste as the dependent variable. Table 3 reveals that importer's income per capita is positively associated with the fraction of spending on high-value waste in total waste imports. Specifically, the elasticity of fraction spent on high-value waste imports with respect to an importer's GDP per capita is 0.107 and significant at the 1% level. Thus, richer countries allocate a greater share of their expenditure to importing high-value waste than to importing low-value waste. Table Table A.3 shows that this result is robust to variance-stabilizing logit and inverse hyperbolic sine (IHS) transformations of the dependent variable.[10]

# 3 Model

I assume a world with $N$ countries. Country $j$ has $\bar{L}_j$ households, a manufacturing sector producing a continuum of goods $\nu_m \in [0, 1]$, a high-value waste management sector that processes a continuum of waste materials $\nu_h \in [0, 1]$ within high-value waste type, $h$, a low-value waste management sector that processes a continuum of waste materials $\nu_l \in [0, 1]$ within low-value waste type, $l$, and a recycling sector. I describe the individual sectors,

[10]While the logit transformation converts ratio to the $(-\infty, +\infty)$ scale, the IHS transformation prevents loss of its zero observations.

the relationships between them, and the modeling choices in greater detail in the rest of this section. Throughout the paper, I denote the value of a commodity by $X$, the sector—manufacturing, high-value waste management, or low-value waste management—using the subscript $s \in \{m, h, l\}$, a bilateral flow using two country subscripts such as $ij$, and the overall value of imports using one country subscript such as $j$.[11]

## 3.1 Preferences

Households consume two commodities, manufactured goods and the recycled good. To model consumption choices, I assume Cobb-Douglas preferences across the composite of manufactured goods and the recycled product. Thus, households allocate fixed fractions of their expenditure to the two commodities. The composite of manufactured goods takes a constant elasticity of substitution (CES) form with elasticity, $\sigma_m$. Households also experience a negative externality due to the portion of two types of waste—high-value and low-value—that is disposed of domestically. The utility function for a household in country $j$ takes the form:

$$U_j = \frac{Q_j^{\alpha} C_j^{1-\alpha}}{1 + \sum_{s=\{h,l\}} W_{sj}^2},$$

where

$$Q_j = \left[ \int_0^1 q_j(\nu_m)^{\frac{\sigma_m - 1}{\sigma_m}} d\nu_m \right]^{\frac{\sigma_m}{\sigma_m - 1}}, \qquad \sigma_m > 1.$$

The term $Q_j$ represents the composite of manufactured goods, where $q_j(\nu_m)$ denotes the consumption of good $\nu_m$, and $C_j$ denotes the consumption of the recycled good.

The term $\frac{1}{1+\sum_{s=\{h,l\}} W_{sj}^2}$ denotes the disutility from high-value and low-value waste that is disposed domestically. Each externality term:

$$W_{sn} = \mu_{sj} \times \chi_{sj} \times \xi_s \times \sum_i \frac{X_{sij}}{w_j \bar{L}_j}, \qquad s \in \{h, l\}, \tag{2}$$

is the product of an externality parameter, $\mu_{sj}$, the fraction of waste disposed, $\chi_{sj}$, and the total volume of waste accumulated via domestic production or imports, $\xi_s \times \sum_{i=1}^N (X_{sij}/w_j \bar{L}_j)$. Here, $X_{sij}$ is the dollar value of imports of waste type $s$ from country $i$, which is weighted by total income, i.e., the product of wage rate, $w_j$, and labor supply, $\bar{L}_j$. The term $\xi_s$ is a conversion factor that converts the dollar value of waste to tonnes (specific values provided in Section 1.3). The parameter $\mu_{sj}$ represents the social marginal cost of waste disposal that is allowed to vary by type of waste, $s$, and country, $j$.

Following Shapiro (2016), I model the externality as a pure externality, which households

[11] For instance, $X_{mij}$ represents the total value of exports from country $i$ to $j$ in sector $m$, while $X_{hj}$ represents the total value of imports of country $j$ in sector $h$.

take as given while making consumption decisions. The externality also does not influence the decisions of private firms about how much waste to trade. The quadratic form summarizes the exponential effect of waste disposal on the surrounding environment and the effect of the environment on utility. To keep the utility finite for cases with no disposal, I add one to the denominator.[12] I rely on the existing literature to quantify the willingness-to-pay to avoid waste disposal, which is summarized by the parameters $\mu_{sj}$, $\forall s \in \{h, l\}$. Thus, I calibrate parameter $\mu_{sj}$ so that one additional tonne of waste type, $s$, decreases the money-metric utility by the economic valuation of the externality provided by the literature.

Each household inelastically supplies one unit of labor. Thus, the social welfare of a country is given by its indirect utility:

$$V_j = \alpha^{\alpha}(1-\alpha)^{1-\alpha} \times \frac{Y_j}{P_j} \times \frac{1}{1 + \sum_s W_{sj}^2}, \tag{3}$$

which is the product of real income:

$$\frac{Y_j}{P_j} = \frac{w_j \bar{L}_j}{P_{mj}^{\alpha} p_{rj}^{1-\alpha}},$$

and the cost of externality. Here, $P_j = P_{mj}^{\alpha} p_{rj}^{1-\alpha}$, a composite of the price index for manufactured goods, $P_{mj}$, and price of recycled product, $p_{rj}$, is the overall price index in country $j$ (See Section 3.4.1).

## 3.2 Technology

Technology varies across goods, sectors, and countries. The efficiency of producing good $\nu_s$ in sector $s \in \{m, h, l\}$ in country $j$, $z_j(\nu_s)$, is drawn from a Fréchet distribution as in Eaton and Kortum (2002). For any $z$, the measure of goods $\nu_s \in [0, 1]$ such that the efficiency of producing these goods $z_j(\nu_s) \leq z$ is given by the cumulative distribution function of a Fréchet random variable:

$$F_{sj}(z) = \exp(-T_j z^{-\theta_s}),$$

where $\theta_s > 1$ is the shape parameter and $T_j > 0$ is the scale parameter. For a given $\theta_s$, the country-specific parameter $T_j$ determines the aggregate efficiency or absolute advantage of a country. The assumption that aggregate efficiency, $T_j$, is the same across all sectors within a country signifies that a country that is generally efficient at making goods in one sector is also efficient at making goods in another (Fieler, 2011).

The parameter $\theta_s$, which varies by sector but not by country, governs the comparative advantage not only across varieties *within* a sector but also *across* sectors (Fieler, 2011).

[12] My results are robust to adding another small number, 0.01, instead.

The variability in technological draws is inversely related to the parameter $\theta_s$. A greater variability in technological draws, i.e., a smaller $\theta_s$, generates greater price dispersion and thus a larger volume of trade in sector $s$. Thus, trade is more intense in goods of the sector with a smaller $\theta$. This parameter also governs comparative advantage across sectors. The aggregate efficiency in sector $s$ in country $j$ is $E(z_j(\nu_s)) \propto T_j^{\frac{1}{\theta_s}}$. Such a formulation drives the distribution of efficiencies in two sectors in two different countries away from each other. As a consequence, poor countries tend to specialize in sectors where $\theta_s$ is large, while the rich specialize in sectors where $\theta_s$ is small.[13]

## 3.3 Production, Waste Management, and Recycling

The manufacturing sector produces a continuum of goods, $\nu_m \in [0, 1]$. The production of each manufactured good also generates two byproducts, high-value and low-value waste. For simplicity, I model the two types of waste as inputs to the production of manufacturing output even though they are byproducts.[14] Assuming constant returns to scale, the unit cost of production is:

$$p_j(\nu_m) = \frac{w_j^{\beta} u_{hj}^{\gamma} u_{lj}^{1-\beta-\gamma}}{z_j(\nu_m)}, \tag{4}$$

where $p_j(\nu_m)$ is the price of manufactured good $\nu_m$, $w_j$ is the wage rate, and $u_{sj}$ is the unit price of collection of waste type $s$, exogenously set by the government. The term $z_j(\nu_m)$ is the efficiency of producing good $\nu_m$ in country $j$. Since the output of each manufactured good is increasing in its inputs, greater waste generation translates to more manufacturing production. Further, abatement of waste generation is possible because the three inputs are substitutable; a firm can maintain constant output by increasing its labor input and reducing its levels of waste generation. The revenue earned by the government via waste collection is given as a lump-sum subsidy to the domestic recycling sector.

The two types of waste—high-value and low-value—collected by the government are treated at a domestic waste-management sector that is specific to that kind of waste. Each waste-management sector, $s \in \{h, l\}$, sorts the waste into a continuum of materials, $\nu_s \in [0, 1]$.

[13] The expected unit cost of delivering goods from country $i$ to country $j$ relative to the expected unit cost of procuring it domestically is $\frac{E(p_{ij}(\nu_s))}{E(p_{jj}(\nu_s))} = \left(\frac{T_i}{T_j}\right)^{-\frac{1}{\theta_s}} \frac{\tau_{sij} w_i}{w_j}$, where $\tau_{sij}$ is the trade cost for exporting commodity $s$ from country $i$ to $j$. For a large $\theta_s$, the first term is small, so wages swamp technology in determining the costs. Since wages are low for a poor country, it specializes in goods with a high $\theta$. For a small $\theta$, technology swamps wages, so a high-income country, with high levels of aggregate efficiency, specializes in a sector with low $\theta$. See Fieler (2011) for details.

[14] Equivalently, one can model a joint production function of manufactured good, high-value waste, and low-value waste and then invert it so that the two types of waste become inputs to manufacturing output (See Copeland and Taylor (2004)). Instead, I simplify the production function to the regular Cobb-Douglas form with three inputs, two of which are high- and low-value waste.

The sector uses only one input, labor, to produce a sorted material. Assuming constant returns to scale, the unit cost of sorted material, $\nu_s$, within waste type $s$ is:

$$p_j(\nu_s) = \frac{w_j}{z_j(\nu_s)}, \qquad s \in \{h, l\} \tag{5}$$

where $z_j(\nu_s)$ is the efficiency of labor to produce the sorted material $\nu_s$ in country $j$. The manufacturing and waste-management markets are competitive.

The recycling sector uses the materials in the two types of waste—high-value and low-value—as inputs to produce a recycled product. The demand for material $\nu_s$ of waste type $s$ in country $j$ is denoted by $q_j(\nu_s)$. Following Fieler (2011), I employ a non-homothetic production function for the recycling sector:

$$\sum_{s \in \{h,l\}} \left[ \alpha_s^{\frac{1}{\sigma_s}} \frac{\sigma_s}{\sigma_s - 1} \int_0^1 q_j(\nu_s)^{\frac{\sigma_s - 1}{\sigma_s}} d\nu_s \right],$$

where $\alpha_s > 0$ is the weight, and $\sigma_s > 1$ governs the elasticity of substitution across varieties of type $s$. I normalize $\sum_{s \in \{h,l\}} \alpha^{\frac{1}{\sigma_s}} = 1$. The non-homothetic production function allows countries of different levels of recycling output to allocate different fractions of their expenditure to the two types of waste.

Solving the cost-minimization problem of the recycling sector, I find that the ratio of expenditure on high-value waste to low-value waste by this sector in country $j$ is:

$$\frac{X_{hj}}{X_{lj}} = \lambda_j^{\sigma_h - \sigma_l} \times \frac{\alpha_h P_{hj}^{1-\sigma_h}}{\alpha_l P_{lj}^{1-\sigma_l}} \tag{6}$$

where $P_{sj}$ is the CES price index of waste type $s \in \{h, l\}$, and $\lambda_j$ is the Lagrange multiplier associated with the cost-minimization problem. The demand for each type increases with the corresponding weight, $\alpha_s$, and decreases with the corresponding price index, $P_{sj}$.

The term $\lambda_j^{\sigma_h - \sigma_l}$ governs the ratio spent on the two types of waste $X_h/X_l$. Although the parameter $\sigma_s$ is typically associated with elasticity of substitution, here, it also governs the output elasticity of demand of inputs (Fieler, 2011). Since the shadow price of recycling output, $\lambda_j$, is increasing in the total output of the recycling sector, under the assumption that the elasticity of demand for high-value waste exceeds that for low-value waste, $\sigma_h > \sigma_l$, an increase in total output leads to a greater expenditure share for high-value waste. Further, the zero-profit condition of the recycling sector and the market-clearing condition of the recycled good, presented in Section 3.4.3, show that $\lambda_j$ is increasing in the income level of a country. Thus, a higher-income country allocates a greater fraction of its expenditure to high-value waste than low-value waste, consistent with *Fact 4* in Section 2.2. Essentially, I interpret the finding summarized as *Fact 4* as the assumption $\sigma_h > \sigma_l$ in my model. Figure 4 depicts the aforementioned links between all the sectors within a country.

## 3.4 Trade

In my framework, trade is subject to "iceberg" trade costs. To deliver one unit of variety $\nu_s$ of sector $s$ to country $j$, country $i$ needs to ship $\tau_{sij} > 1$ units. I normalize $\tau_{sjj} = 1 \; \forall j$, i.e., domestic shipping is free of trade barriers. The iceberg trade cost is allowed to vary by sector, as denoted by subscript $s$.

### 3.4.1 Price Indices

With perfect competition, the total price of good $\nu_s$ from country $i$ in country $j$ is the product of marginal cost of production and trade cost:

$$p_{ij}(\nu_s) = \frac{w_i \tau_{sij}}{z_i(\nu_s)}. \tag{7}$$

Assuming the two types of waste to be homogeneous for collection purposes, I set $u_{si} = w_i \; \forall s \in \{h, l\}$ in Equation (4). Hence, the term $w_i$ in Equation (7) represents the unit cost of production across all sectors, $s \in \{m, h, l\}$. A household in country $j$ buys from the lowest-cost supplier. Thus, the price of good $\nu_s$ in country $j$ is the lowest of the prices offered by all exporters:

$$p_j(\nu_s) = \min_k \{p_{kn}(\nu_s)\}. \tag{8}$$

The pricing rule combined with the technology distribution allows me to derive the price indices for all sectors in each country. As in Eaton and Kortum (2002), the CES price index for sector $s$ in country $j$ is:

$$P_{sj} = \left[\Gamma\left(\frac{\theta_s + 1 - \sigma_s}{\sigma_s}\right)\right]^{\frac{1}{1-\sigma_s}} \times \phi_{sj}^{-\frac{1}{\theta_s}}, \tag{9}$$

where $\Gamma$ is the gamma function, $\phi_{sj} = \sum_i T_i (w_n \tau_{sij})^{-\theta_s}$, and $\theta_s + 1 > \sigma_s$ is the necessary condition for a finite solution. The parameter $\phi_{sj}$ summarizes how aggregate technologies, input costs, and trade barriers from around the world govern prices in country $j$. In the presence of international trade, the effective technology in each country is enlarged due to access to technology discounted by input costs and trade barriers from other countries, leading to a decrease in prices (Eaton and Kortum, 2002).

### 3.4.2 Trade Flows

In this section, I elaborate how the distribution of prices and the demand structure determine trade flows in the three sectors for manufactured goods, high-value waste, and low-value waste. A typical household's problem yields the demand function for the composite of manufactured goods. The fraction of income allocated to manufactured goods, $m$, in country $j$ is:

$$X_{mj} = \alpha w_j \bar{L}_j. \tag{10}$$

Similarly, if the wages $w_n$ and trade barriers $\tau_{sij}$, $s \in \{h, l\}$, are given, then the distribution of technologies yields the distribution of prices in the two waste sectors. Given the prices, solving the recycling sector's problem yields the demand functions for the two inputs—high-value and low-value waste. The total expenditure on each type of waste is:

$$X_{sj} = \lambda_j^{\sigma_s} \alpha_s P_{sj}^{1-\sigma_s}, \qquad s \in \{h, l\}. \tag{11}$$

Thus, the total expenditure of country $j$ on commodities from country $i$ from sector $s$ is the product of the share spent on $i$'s goods or materials and the total expenditure on sector $s$ by country $j$:

$$X_{sij} = \frac{T_i (w_i \tau_{sij})^{-\theta_s}}{\phi_{sj}} X_{sj}, \qquad s \in \{m, h, l\}. \tag{12}$$

### 3.4.3 Market Clearing

The Lagrange multiplier associated with the recycling sector's cost-minimization problem, $\lambda$, is solved implicitly by combining the zero-profit condition and the market-clearing condition of the recycled good:

$$\sum_{s=\{h,l\}} X_{sj} = (1-\alpha) w_j \bar{L}_j, \qquad \forall j, \tag{13}$$

which is a continuous and strictly increasing function of income, $w_j \bar{L}_j$. Finally, equating labor supply with labor demand yields the $N$ labor market-clearing conditions:

$$\beta \sum_i X_{mji} + \sum_i X_{hji} + \sum_i X_{lji} = w_j \bar{L}_j. \qquad \forall j \tag{14}$$

This completes the statement of the model.

In summary, the world economy comprises $N$ countries, each with $\bar{L}_j$ households, aggregate productivity $T_j$, and trade costs that vary by sector, $\tau_{sij}$. Exports occur in three sectors—manufacturing, high-value waste and low-value waste—denoted by $s \in \{m, h, l\}$. The parameter $\alpha$ governs the fraction of expenditure by a household on manufactured goods,

$m$, and the recycled product; the parameters $\alpha_s$ and $\sigma_s$ govern the size and the income elasticity of demand of the two types of waste, $s \in \{h, l\}$; and the trade elasticities, $\theta_s$, govern the comparative advantage both *within* and *across* sectors. Given wages $w_j$, Equations (9) to (12) specify trade flows across the three sectors. The equilibrium is defined by the shadow prices, $\lambda \in \Delta(N)$, that solve recycled good market-clearing conditions (13), and wages, $w \in \Delta(N-1)$, that solve labor market-clearing conditions (14). Given $\sigma_h > \sigma_l$, higher-income countries allocate greater shares of expenditures to high-value waste. Further, lower-income countries specialize in goods with higher trade elasticities, i.e. low-value waste. Finally, within a sector, the fraction of expenditure on goods from a particular country depends on the technology discounted by input and trade costs.

Next, I discuss the implication behind Equation (2) that accounts for the disutility due to the externality from waste disposal. In reality, externalities from waste trade do not affect trading decisions for two main reasons. First, most developing countries have unregulated and informal recycling operations, which provide limited safeguards to protect against the ill effects on workers' health or the local environment (Vidal, 2014). Second, non-recyclable waste is often exported under the guise of recyclable waste (Gutierrez, 2016).[15] Imported recyclable waste that is commingled or soiled with non-recyclable waste is more difficult, or even impossible, to suitably reprocess by recycling firms. Waste that cannot be appropriately recycled inevitably generates a negative externality via disposal. The term in Equation (2) captures the externality from the portion of local waste, whether from local sources or imports, that countries end up having to dispose of.

## 3.5 Counterfactual Calculations

To measure the effect of a policy change on social welfare, I calculate the empirical analogue of the equivalent variation. The equivalent variation is the amount of money a country would accept at old prices to end up at the new utility obtained through a policy change. Following Dekle et al. (2008) and Shapiro (2016), I reformulate the equivalent variation in terms of a proportional change in indirect utility, $\hat{V}_n = V_j'/V_j$.[16] Thus, the equivalent variation for country $j$ is:

$$EV_j = w_j \bar{L}_j (\hat{V}_j - 1). \tag{15}$$

[15] A variety of reasons contribute to illegal exports of non-recyclables as recyclables ranging from varying definitions of non-recyclables across countries to coercion on lower-income countries due to the unequal nature of their relationship with the rich.

[16] To calculate the proportional change in indirect utility, I require the proportional change in price of recycled good $p_{rj}$. Comparing the first-order conditions from the cost-minimization and profit-maximization problems of the recycling sector shows that $p_{rj} = \lambda_j$, which is solved implicitly using Equation (13). I use this relationship to measure the proportional change in $p_{rj}$.

To measure the disposal intensity, $\chi_{sj}$, I require data on recycling rates for high-value and low-value waste. I obtain the recycling rate data for mixed waste for the countries in my sample from Kaza et al. (2018), predominantly from the 2012-2017 time period. I find that the recycling rate, in percentage terms, is positively correlated with the log of income, with a slope coefficient of 3.26 (s.e. = 1.04). Thus, a 1% increase in GDP is associated with a 0.03 percentage point (p.p.) increase in the recycling rate, suggesting that higher-income countries are better at recycling waste in the domestic economy.

To infer the recycling rates by type of waste, I supplement the overall recycling rate data with recycling rates for different materials in the U.S. for 2015 from United States Environmental Protection Agency (2020). Specifically, I use data on recycling rates for "Paper and Paperboard", "Ferrous Metals", "Aluminum", "Non-ferrous metals", "Plastics", "Lead-Acid Batteries", "Rubber and Leather", "Textiles", and "Wood". I assign each of these categories to either high-value waste or low-value waste by matching the classification in trade data.[17] Finally, to obtain an estimate of the recycling rates for the two types of waste in the U.S., I calculate the imports-value weighted average of recycling rates for the materials in each type. Following this procedure, I calculate the average recycling rates for high-value waste and low-value waste to be 52.56% and 33.17%, respectively.[18] The higher recycling rate for high-value waste is consistent with the argument that recycling high-value waste likely results in greater value-added to the economy than recycling low-value waste. Lastly, for other countries in my sample, I extrapolate the recycling rates by type of waste to be proportional to the overall recycling rates.[19] Figure 5 shows the distribution of recycling rates for both types of waste in my sample.

## 3.6 Calibration of the Externality Parameter

To quantify the externality costs from waste disposal, I calibrate the parameter $\mu_{sj}$, which represents the social marginal cost of disposal of waste type $s$. I rely on the existing estimates of external costs of waste from Bond et al. (2020) and McKinsey (2016) to measure $\mu_{sj}$. Bond et al. (2020) quantify the external costs from plastic waste to be \$1000/tonne from four aspects, namely, carbon dioxide emissions, air pollution, collection and sorting costs, and

[17] For example, "Textiles" maps to Yarn. Due to the lack of break-up of recycling rates for different metals, I assign the entire "Non-Ferrous Metals" category to high-value waste since 75% of these metals are part of high-value waste in trade data. Similarly, even though rubber is low-value and leather is high-value waste in trade data, I assign the entire category of "Rubber and Leather" to high-value waste.

[18] The average recycling rates for high- and low-value waste are robust to assigning "Rubber and Leather" to low-value waste instead—53.4% and 31.8%, respectively.

[19] I convert all rates to a scale of $[0, \infty)$ using the transformation $\frac{x}{100-x}$ before calculating the proportional rates for the two types of waste. In this way, the extrapolated rates asymptote above at 100.

ocean clean-up costs.[20] [21] This estimate is same as the European Union tax of \$1000/tonne on non-recycled plastic waste that is levied on member countries starting on January 1, 2021. Even though plastic waste comprises only 10% of the low-value waste in my sample, it is rampant in all activities of an economy. Thus, I use this estimate as the value the European Union places on disposal of mixed-waste. The McKinsey (2016) study calculates the external costs from mixed waste for five Southeast Asian countries to be \$375/tonne.[22]

To calibrate the parameter $\mu_{sj}\ \forall s$, I write the indirect utility function in Equation (3) in money-metric terms, $e_j(v, P, \{W_s\}_{s=h,l}) = V_n \times P_n \times (1 + \sum_s W_{sj}^2)$. Then, I differentiate the money-metric utility function with respect to the volume of waste disposed, $\chi_s \times \xi_s \times \sum_i X_{sij}$, and choose the value of $\mu_{sj}$ so that the marginal cost of disposed waste equals the economic valuation of the externality provided in the aforementioned studies. Specifically, I choose $\mu_{sj}$ so that one additional tonne of disposed waste, $s$, decreases the money-metric utility of country $j$ by a dollar-value proportional to its EPI.[23] Thus, the parameter $\mu_{sj}$ is isomorphic to the social marginal cost of disposal of waste type $s$ in country $j$. While the disposal intensity is larger for high-value waste than for low-value waste, which is decreasing in the income level of a country, the externality cost per unit of waste is increasing in income level. Figure 6 shows the social marginal cost of waste in dollars per tonne. Rich countries, mainly in the European and North American regions, have the highest social marginal costs of waste disposal, while lower-income countries such as India and China have the lowest social marginal costs of waste disposal. I also present the corresponding calibrated externality parameters for high- and low-value waste in Figures A.4 and A.5, respectively.

[20] A potential concern is that the \$1000/tonne partially captures external costs at the global rather than domestic level due to the carbon dioxide emissions from waste disposal. However, of the \$1000/tonne estimate, carbon dioxide emissions account for a share of only 37.5%. I find that my welfare estimates are robust to reducing the external cost for the European Union by this amount (See Section 5.5.

[21] Bond et al. (2020) include the collection and sorting costs in the external costs of plastics waste because much of the plastic waste stream is not collected and sorted. Thus, they assume the collection and sorting to be a part of unaccounted externality from disposal.

[22] The five Southeast Asian countries are China, Indonesia, the Philippines, Thailand, and Vietnam.

[23] I solve the following two equations in two unknowns:

$$log(917) = \beta_0 + \beta_1 EPI_{EU},$$

$$log(370) = \beta_0 + \beta_1 EPI_{SEA},$$

where $EPI_{EU}$ and $EPI_{SEA}$ are the average environmental performance indices for the EU and the relevant Southeast Asian (SEA) countries. Here, I use the inflation-adjusted estimates of the social marginal cost of waste disposal, \$ 917/tonne and \$370/tonne. I use the values of $\beta_0$ and $\beta_1$ to extrapolate economic valuation for the countries in my sample.

# 4 Estimation

In this section, I first present the estimation methodology and the results for trade elasticities in Section 4.1, followed by the estimation strategy for the other parameters in Section 4.2, and the fit between simulated flows and trade flows in the data in Section 4.3.

## 4.1 Trade Elasticities

The gravity equation (12) for sector $s$ relates bilateral trade with aggregate efficiency and input costs in the exporting country, prices and total expenditure on sector $s$ in the importing country, and the trade barrier between the two. After rearrangement and log-linearization, I write the equation as:[24]

$$\ln \frac{X_{sij}}{X_{sj}} = S_i - S_j - \theta_s \ln \tau_{sij}, \tag{16}$$

where $S_i \equiv \ln T_i - \theta_s \ln w_i$ is the measure of exporting country $i$'s technology discounted by input costs. The term $S_j \equiv \ln \phi_{sj}$ is a measure of importing country $j$'s prices.

To estimate the elasticities of trade flows with respect to trade barriers, one must disentangle trade costs from these trade elasticities. To do so, I use price data to construct a measure of trade barriers as in Eaton and Kortum (2002). The domestic price of any good, $\nu$, must be bounded above by the price at which a consumer can buy the good from another country $i$. Thus, for the producer of $\nu$ in country $j$ to stay competitive, the following no-arbitrage condition must hold:

$$p_j(\nu) \leq \tau_{ij} p_i(\nu).$$

Thus, the maximum relative price must also satisfy the above inequality:

$$\max_{\nu} \frac{p_j(\nu)}{p_i(\nu)} \leq \tau_{ij}.$$

To compute the measure of trade barriers, I use basic-heading-level price data from the 2017 cycle of the International Comparison Program (ICP). A basic-heading represents a group of similar and well-defined goods for which expenditure data in the participating economies are available (World Bank, 2020). Of the 155 basic-headings in the ICP data, I keep price data on 66 tradable commodities (Simonovska and Waugh, 2014). Table A.4 lists the 66 basic-headings. The data from 2017 are temporally the closest to the trade data in

[24]Note that Eaton and Kortum (2002) estimate the equation $\frac{X_{ij}/X_j}{X_{ii}/X_i} = \left(\frac{P_i \tau_{ij}}{P_j}\right)^{-\theta}$ using a proxy for $\left(\frac{P_i \tau_{in}}{P_j}\right)$ that is constructed using price data. This version of the gravity equation, however, requires imputed gross manufacturing production data to construct the dependent variable (Simonovska and Waugh (2014)). In contrast, I estimate Equation (12) using GDP data as a proxy for $X_{sj}$ and with country-specific effects.

my sample.[25] Thus, I exploit the disaggregated price data to obtain an approximate measure of trade barriers as follows:

$$\ln \hat{\tau}_{ij}^{1} = \max_{\nu}\{\ln(p_j(\nu)) - \ln(p_i(\nu))\}. \tag{17}$$

where the superscript denotes the first-order statistic. To estimate the trade elasticities across the three sectors $s \in \{m, h, l\}$, I estimate Equation (16) with exporter and importer fixed-effects, $S_i$ and $S_j$. Assuming that the trade costs vary by a fixed proportion among the three sectors irrespective of the country pair, the fixed effects would also absorb the unobservable heterogeneity by sector. The trade barrier measure suffers from measurement error due to the approximation and errors in the price data itself (Simonovska and Waugh, 2014). To address this, I perform a two-stage least squares (2SLS) estimation of Equation (16) with the geographic barrier variable, distance, as an instrument for $\hat{\tau}_{ij}$.

Since multiple methods to perform this estimation exist in the literature, some discussion is in order. The 2SLS procedure is used to alleviate an errors-in-variables issue when the measurement error is classical, i.e., mean zero (Simonovska and Waugh, 2014). However, Simonovska and Waugh (2014) show that Eaton and Kortum's measure of trade barriers, constructed using finite sample of prices, always *underestimates* the true trade costs. To address this issue, I modify the trade cost measure to the sum of first-order statistic with the difference between first- and second-order statistics, $2\hat{\tau}^1 - \hat{\tau}^2$. Robson and Whitlock (1964) show that this modified measure is as efficient as $\hat{\tau}^1$ but with less bias. Although the Robson and Whitlock (1964) approach is not based on explicit distributional assumptions like the simulated method of moments (SMM) approach suggested by Simonovska and Waugh (2014), I prefer this approach due to its computational simplicity.

### 4.1.1 Results

Table 4 reports the trade elasticity estimates in the three sectors: manufactured goods, high-value waste, and low-value waste. I find that the OLS estimates with origin- and destination-level effects have the expected negative sign and increase in magnitude when moving from manufacturing to low-value waste sector, consistent with the pattern in Tables 2 and A.2. However, the measurement error in the trade barrier variable can lead to attenuation bias in the OLS estimates. In support of this interpretation, I find that the negative 2SLS estimates are larger in magnitude, in the range of 7.260 to 9.831. As before,

[25] The 2017 cycle is the latest in the ICP and thus follows an updated methodology that provides more reliable data than the previous cycles. Two additional advantages of using the ICP price data are: first, the sampled goods in the data set span all categories of the GDP, reflecting a wide number of industries (Simonovska and Waugh, 2014), and second, the dataset extensively covers 216 economies, which is favorable to my country-level international trade framework.

the size of the estimates increases from manufactured goods to low-value waste. This finding implies that a 1% decrease in trade costs causes a 7.26% increase in manufacturing, a 7.29% increase in high-value waste, and a 9.83% increase in low-value waste flows. Since most countries accrue lesser benefits from importing low-value waste than from importing high-value waste or manufactured goods, the low-value waste flows are the most sensitive to trade costs.

The size of the gains from international trade depends inversely on the size of these trade elasticity estimates. For comparison, I also estimate the trade elasticities using $\hat{\tau}^2$ and $\hat{\tau}^1$ as measures of trade barrier. In Table A.5, I use $\hat{\tau}^2$ as the measure of trade barriers, as in Eaton and Kortum (2002). My 2SLS estimate 14.59 (s.e. = 0.65) for manufactured goods is close to Eaton and Kortum's estimate of 12.86 (s.e. = 1.64). However, consistent with the argument in Simonovska and Waugh (2014), the difference in estimates between Tables A.5 and A.6 reflects the downward bias in the trade barrier measure leading to upward biases in trade elasticity estimates. Thus, to estimate the other model parameters, I prefer the 2SLS estimates in Table 4. Additionally, the 2SLS estimate for manufactured goods in Table 4 is close to the median estimate of 8.28 in Eaton and Kortum (2002).

## 4.2 Price of Recycled Good, Technology, and Trade Costs

Equations (9) to (12) specify the value of trade flows from country $i$ to country $n$ in sector $s$:

$$
\begin{aligned}
X_{sij} = \frac{T_i(w_i\tau_{sij})^{-\theta_s}}{\phi_{sj}} X_{sj}, \qquad & s \in \{m,h,l\}, \\
X_{mj} = \alpha w_j \bar{L}_j&, \\
X_{sj} = \lambda_j^{\sigma_s}\alpha_s P_{sj}^{1-\sigma_s}, \qquad & s \in \{h,l\}, \\
P_{sj} = \left[\Gamma\left(\frac{\theta_s + 1 - \sigma_s}{\sigma_s}\right)\right]^{\frac{1}{1-\sigma_s}} \times \phi_{sj}^{-\frac{1}{\theta_s}}&, \\
\phi_{sj} = \sum_i T_i(w_j\tau_{sij})^{-\theta_s}&,
\end{aligned} \tag{18}
$$

where $\sum_{s\in\{h,l\}} \alpha_s^{1/\sigma_s} = 1$, the shadow prices of recycled good $\lambda_j$ are solved implicitly using Equation (13), and the technology parameters, $T_j$, are solved using Equation (14). The trade flows for the $N$ countries are a function of wages, $\{w_i\}_{i=1}^N$, population, $\{\bar{L}_i\}_{i=1}^N$, technology parameters, $\{T_i\}_{i=1}^N$, the shadow price of recycled goods, $\{\lambda_i\}_{i=1}^N$, trade barriers between all exporters $i$ and importers $j$, $\{\tau_{sij}\}_{s=\{m,h,l\}}$, the parameters $\{\theta_s\}_{s=\{m,h,l\}}$ controlling the spread of the distribution of technologies in the three sectors, the parameters $\{\sigma_s\}_{s=\{h,l\}}$ controlling the elasticity of demand for the two types of waste, and the weight of high-value waste in recycling sector production, $\alpha_h$.

My sample comprises data on 91 countries. Trade among countries within my sample accounts for 91% of world trade in manufactured goods, 95% of world trade in high-value waste, and 96% of world trade in low-value waste. To perform the estimation, I set $\alpha = 0.993$, the share of manufacturing trade in total trade in my sample, and $\alpha_h^{1/\sigma_h} = 0.456$, the share of high-value waste trade in total waste trade in my sample. I set $\sigma_m = 3$, $\sigma_h = 2.5$, and $\sigma_l = 2$ to meet the condition for finite solution $\sigma_s < \theta_s + 1$ and the condition $\sigma_h > \sigma_l$ that governs the fraction of expenditure allocated to the two kinds of waste in a country based on its income level. For simplicity, the parameter $\beta$ that governs the share of expenditure on inputs, labor and waste, by the manufacturing sector is set at 0.98 for all countries. This figure is one minus the share of expenditure on waste-management in overall income from manufacturing for the U.S. economy (Simmons, 2016).

**Stage I: Price of Recycled Good.** To estimate the shadow price of the recycled good, $\lambda_j$, I use the zero-profit condition for the recycling sector combined with the market-clearing condition for the recycled good: $\sum_{s=\{h,l\}} X_{sj} = (1-\alpha) w_j \bar{L}_j$. Given the parameters $\{\alpha, \alpha_h, \theta_m, \theta_h, \theta_l, \sigma_h, \sigma_l\}$, data on wages $\{w_j\}_j$, and population $\{\bar{L}_j\}_j$, for each guess of technology parameters $\{T_j\}_j$, I use the $N$ equations in Equation (13) to solve for the $N$ unknowns $\lambda_j$. Solving for the Lagrange multipliers in this way reduces the number of parameters to be estimated by 91.

**Stage II: Technology.** Given the parameters $\{\alpha, \alpha_h, \beta, \theta_m, \theta_h, \theta_l, \sigma_h, \sigma_l\}$, data on wages $\{w_j\}_j$ and population $\{\bar{L}_j\}_j$ and substituting the implicit solution for the Lagrange multipliers $\{\lambda_j\}_j$, Equation (14) describes $N$ labor market-clearing conditions in $N$ unknowns. For each guess of the trade costs $\{\tau_{sij}\}$, I simulate the whole economy to generate trade flows until I find the technology parameters $\{T_j\}_j$ that satisfy the market-clearing conditions in Equation (14). Solving for the technology parameters in this way further reduces the number of parameters to be estimated by 91.[26]

**Stage III: Trade Costs.** Substituting implicit solutions of $\{T_i\}_{i=1}^N$ and $\{\lambda_j\}_{j=1}^N$ into Equation (18) , which describes trade flows in the three sectors, I obtain the stochastic form of trade flow equations as:

$$X_{sij} = h(w, L; \alpha, \beta, \alpha_h, \theta_m, \theta_h, \theta_l, \sigma_h, \sigma_l, \{\tau_{mij}\}_{i,n=1}^N, \{\tau_{hij}\}_{i,n=1}^N, \{\tau_{lij}\}_{i,n=1}^N) + \epsilon_s \tag{19}$$

where $\epsilon_s$ is the error term. Under the restriction that the trade costs $\tau_{sij} \geq 1$ and $\tau_{sjj} = 1\ \forall s$, I

[26] Alvarez and Lucas (2007) prove the existence and uniqueness of an equilibrium for the model in Eaton and Kortum (2002). Further, Fieler (2011) argues that her model satisfies the conditions for existence and shows, through Monte Carlo simulations, that the parameters are well identified. The existence and uniqueness in Fieler's case suggests that the equilibrium for my model, which is an extension of her model, also exists and is unique.

solve $N(N-1)$ trade flow equations numerically to obtain $N(N-1)$ trade costs, $\{\tau_{sij}\}_{i,j=1,i\neq j}^{N}$, for each sector $s = \{m, h, l\}$. This procedure allows me to infer trade costs so that the trade flows fit almost perfectly.[27]

Similar to Fieler (2011), I simulate the whole economy to account for endogenous variables, including wages, and zero trade flows. However, in her case, she first assumes that trade costs are a deterministic function of observables such as distance, contiguity, common language, and trade agreement, and then estimates the corresponding parameters using non-linear least squares (NLLS). Not only is my approach analytically straightforward, but it also avoids solving an NLLS optimization problem using the polytope method, which runs into the issue of convergence to a local rather than global minima in multivariate cases (Judd, 1998).

A drawback of my approach, however, is that I cannot separately identify bilateral trade costs from heterogeneity at the country level (Costinot and Rodríguez-Clare, 2014), such as country-specific preferences towards different commodities. To verify that the trade cost estimates capture actual trade barriers at least to some degree, I check the extent to which rudimentary trade cost variables—the observable geographic barriers—explain the variation in these trade costs in the next section. Further, my estimation approach does not account for structural errors in trade costs that can affect trade flows via changes in technology parameters. However, Fieler (2011) demonstrates that the effects of these structural errors are small, as introducing large multiplicative shocks to trade costs leads to only small changes in equilibrium wages.

### 4.3 Goodness of Fit

In this section, I assess the goodness of fit of the model by comparing trade flows predicted by the model to the actual trade flows in data and checking whether the predicted flows align with facts in the data. Figure 7 plots the simulated trade flows at the estimated parameter values against the actual flows. Although I do not obtain a perfect fit between actual and simulated flows, the $R^2$ values are high: 92.02%, 93.27%, and 67.33% for manufactured goods, high-value waste, and low-value waste, respectively.[28] Thus, at first glance, the model fits the data well.

As a sanity check, I evaluate whether the observable trade barriers explain the variation

[27] I do not obtain a perfect fit because for each guess of trade costs, I first solve for the technology parameters and the Lagrange multipliers in Stages I & II. Although the trade costs are allowed to vary by sector, only one set of technology parameters and Lagrange multipliers solve the market-clearing conditions, leading to a trade-off in choosing trade costs for the three sectors. Further, I solve for the trade costs under the restriction, $\tau_{sij} \geq 1$.

[28] I experiment with different values of $\sigma_h$ and $\sigma_l$ satisfying $\sigma_s < \theta_s + 1$ and $\sigma_h > \sigma_l$ and find that the predicted flows and the $R^2$ do not change. However, estimating the trade costs under the reverse condition, $\sigma_l > \sigma_h$, worsens the model fit. Specifically, the $R^2$ are lower by at least 13%.

in the inferred trade costs from Stage III. To do so, I estimate the following equations:

$$\log(\hat{\tau}_{sij}) = \gamma_1 + \gamma_2 Distance_{ij} + \gamma_3 Distance_{ij}^2 + \boldsymbol{\delta}\mathbf{D_{ij}} + \varepsilon_{sij}, \qquad s \in \{m, h, l\} \tag{20}$$

where $\hat{\tau}_{sij}$ are the inferred trade costs from Stage III, and $\mathbf{D_{ij}}$ is a vector that includes bilateral dummy variables. The dummies for manufactured goods include contiguity, common language, and free trade agreement. For high- and low-value waste, I only include the dummies for contiguity and common language. Table 5 shows that the $\bar{R}^2$ for the three sectors is in the range of 4.3-9.4%. Even though the $R^2$ are relatively low because I exclude country- and sector-specific trade barriers for this sanity check, they suggest that the estimated trade costs capture variation due to geographic barriers. In addition, since the coefficient on $Distance$ is positive and significant while the coefficient on $Distance^2$ is negative and significant, the estimated trade costs are a concave function of distance. Thus, the positive marginal effect of distance on trade costs is decreasing with distance. The signs on the rest of the dummies—contiguity, common language, and free trade agreement—are consistent with the stylized facts obtained from the raw data.

Figure 8 shows that the residuals are larger for higher-income countries. Table 6 shows that–as a percentage of GDP, trade among the 30 richest countries in the sample is 12.558% for the manufacturing sector, 0.048% for high-value waste, and 0.047% for low-value waste. The model closely predicts these shares to be 12.396%, 0.050%, and 0.040%, respectively. Unlike the Eaton and Kortum (2002) model, which underestimates trade flows in general, the model captures trade among rich countries well. Consistent with Fieler (2011), this finding is robust to the choice of weights, as the dependent variable $X_{ij}$ in Stage III places higher weights on larger countries.[29] Thus, even though the residuals are higher for larger countries, the model adequately captures trade among them. Further, the fact that the model underpredicts low-value waste trade for the rich, who trade relatively less in this sector explains the finding that the $R^2$ for this sector in Figure 7 is lower than that for the other two.

The model's prediction for trade among the rest of the countries is also close—5.513%, 0.011%, and 0.023% against 6.137%, 0.011%, and 0.022% in the data. Thus, the model captures the empirical fact that rich countries trade more in all three sectors than lower-income countries. Additionally, it accounts for the fact that the rich trade more in high-value waste than low-value waste, while the lower-income countries trade more in low-value waste than high-value waste.

Figure 9 illustrates the choice between the two types of waste. The data show an increasing and statistically significant relationship between the share of imports of high-value waste in

[29] Silva and Tenreyro (2006) argue that the choice of weights depends on the pattern of heteroscedasticity and is thus an empirical question. Even though the observations for larger countries have more information, they are also noisier, while the observations for smaller countries are prone to measurement error.

total waste and income, and the model correctly predicts this relationship. Panel A in Table 7 shows that the model also captures the increasing relationship between the sector-specific share of total trade in GDP, which I henceforth refer to as "openness" for that sector, and income per capita. While the data show a positive and statistically significant relationship between openness and income per capita for the manufacturing and high-value waste sectors, the model captures the positive relationship across all three sectors, which is not statistically significant in any sector.

Panel B in Table 7 replaces income per capita with total income in the regressions. In the data, the slopes of the regression lines are negative for all three sectors and statistically insignificant for two. Similarly, the slopes are negative according to the model. The size of a country presents two opposing forces. On the one hand, trade is a small fraction of a large country's total income. On the other hand, higher-income countries trade more because they have higher incomes per capita. Thus, middle-income countries tend to have larger variability in trade shares (Fieler, 2011), which is also a fact that the model captures well.

# 5 Counterfactuals

In this section, I analyze a set of counterfactuals. Since the counterfactuals related to waste trade policies are novel exercises, I first present the results from the standard autarky counterfactual as a benchmark in Section 5.1. Then, I present the results from the waste-autarky counterfactual in which all waste trade is shut down in Section 5.2. In Section 5.3, I present results from China's ban on certain categories of waste imports, and in Section 5.4, I discuss the welfare implications of the Basel Ban amendment that bans all exports of hazardous waste from developed to developing countries.

For each policy change, I change the relevant set of trade costs and solve the market-clearing conditions (13) and (14) for the new equilibrium recycled good prices and wages. Then, I substitute the indirect utility at the new equilibrium along with that at the old equilibrium into Equation (15) to calculate the effect of the policy change. When calculating the externality costs at the new equilibrium using Equation (2), only the organization of trade, $\sum_i X_{sij}$, changes while the disposal intensity, $\chi_{sj}$, remains constant.[30] Thus, the *technique* of disposal remains unchanged, but the *composition* of waste changes as buyers change the volumes and varieties of waste types to buy from different countries.

[30]One can endogenize disposal intensity to change with trade policies to capture second-order effects on externality costs. With trade, countries could become more efficient at recycling, leading to less disposal and lower environmental costs. However, in this paper, I focus on the primary effects of trade policies from changes in the overall volume and composition of waste generation.

## 5.1 Autarky

In the autarky counterfactual, trade in all commodities—manufactured goods, high-value waste, and low-value waste—is shut down, i.e., $\tau_{sin} \to \infty \; \forall i \neq n \; \forall s \in \{m, h, l\}$. Prohibiting all trade is an extreme measure to tackle the issue of international trade in waste. However, since the counterfactuals related to waste trade policies are novel exercises, it is imperative to measure gains to waste trade relative to gains to overall trade. The autarky counterfactual provides welfare implications from not only shutting down all trade but also from changes in overall volumes of production in every sector that ensue from this policy change. Thus, trade in manufactured goods, which account for considerable generation of waste, has the potential to adversely affect local environments in countries via changes in the scale of production.

Panel A in Table 8 presents the gross benefits and environmental costs of shutting down all trade. The rich countries have the largest gains to trade of 3.25% of GDP. Countries, such as Belgium and Singapore, that are relatively open to trade have among the highest benefits, while countries that are relatively closed to trade, such as the United States, have among the lowest benefits to trade (See Table A.7). A host of modeling assumptions on the supply-side—market structure, firm-level heterogeneity, one sector, multiple sectors, intermediate goods, and multiple factors of production—and the demand side—CES utility—play a role in explaining the modest size of these benefits (Costinot and Rodríguez-Clare, 2014). Being an extension of the work-horse Eaton and Kortum (2002) framework, the size of the gains to trade from my model is consistent with their estimates.

On the environmental costs side, middle-income countries disproportionately bear externality costs due to trade of 0.49% of GDP. This finding reflects that middle-income countries spend a higher fraction of their GDP on disposal-intensive low-value waste. Although poor countries also allocate greater fractions of their GDP to low-value waste, middle-income countries have higher social marginal costs of waste disposal than those countries. At the country level, I find that although most countries incur larger environmental costs from opening up to trade, some smaller-sized countries, such as the Seychelles and Moldova, incur smaller costs too. Such smaller economies have limited domestic capacity to recycle and thus rely primarily on exports to deal with waste. Since waste trade accounts for only 0.07% of overall international trade in commodities, the small environmental costs due to waste, approximately 0.13% of gross benefits, are unsurprising.

## 5.2 Waste-Autarky

In the waste-autarky counterfactual, trade in both high-value and low-value waste is shut down, i.e., $\tau_{sin} \to \infty \; \forall i \neq n \; \forall s \in \{h, l\}$. On the one hand, in the autarky counterfactual, access to technology from the rest of the world declines, leading to a fall in labor efficiency and wages. On the other hand, in the waste-autarky counterfactual, wages rise due to substitution away from waste inputs and toward labor in the manufacturing sector. This counterfactual provides the effect of shutting down trade in waste and the changes in production volumes in all sectors that result from this policy change.

Panel B in Table 8 reports the gross benefits and environmental costs of prohibiting trade in waste. Column 2 shows that the global gains to trade in waste are 0.013% of GDP, which is 0.43% of the global gains to overall trade.[31] Differentiating by income group, I find that poor countries disproportionately benefit from trade in waste, at 0.021% of GDP. In addition, the volume of high-value waste rises by 12.25%, while the volume of low-value waste declines by 0.73%. Equation (11) shows that the changes in the prices of the two inputs to recycling, i.e., high- and low-value waste, relative to the price of recycled output are sufficient to explain the changes in overall volumes of waste generation. Thus, a rise in the price of low-value waste and a fall in the price of high-value waste relative to the price of recycling output explain the volume changes. Since low-income countries specialize in low-value waste, the relative price increase for this input benefits them the most.

Columns 4-5 show that allowing waste trade decreases the environmental costs for all country groups, with poor countries experiencing the largest decrease. Poor countries allocate a larger share of their income to disposal-intensive low-value waste, whose overall generation volume is declining. Thus, all country groups are better off with waste trade even after accounting for its environmental costs. I find that high-value waste trade creates welfare effects that are qualitatively similar to the overall waste trade. However, rich countries, which specialize in high-value waste exports and disproportionately use it as an input in their recycling, gain the most—0.012% of GDP—and incur the largest decline in environmental costs—0.037% of GDP—due to high-value waste trade (Panel C in Table 8). In contrast, with low-value waste trade, the direction of changes in the volume of generation of the two types of waste flips; high-value waste generation decreases while low-value waste generation increases. Thus, even though trade in low-value waste makes the middle-income group worse off, it still makes the rich and low-income countries better off (Panel D in Table 8).

I also report country-level estimates of the gross benefits and costs of imposing waste-autarky in Table A.8. On the benefits side, countries more open to trade in waste, such as Belgium and Vietnam, experience the largest gains to waste trade, while countries relatively closed to waste trade, such as the United States and Brazil, experience the lowest benefits. Some countries, such as the Seychelles and Zambia, experience negative gains and positive externality costs to waste trade. Such countries that are reliant on exports to deal with waste increase the volume of generation of both waste types as more options become available with allowing waste trade. In addition, the price of recycled good increases relative to wages,

[31] The size of these gains is also commensurate with increasing trade costs in all sectors by 0.081%.

leading to a decrease in their real incomes.

Lastly, I find that shutting down trade in waste reorganizes manufacturing production across countries. Rich countries see a fall in production volumes by 0.002% while middle and poor countries see a rise of 0.003% and 0.0003%, respectively. Rich countries are major producers and exporters of high-value waste input to manufacturing. Thus, as the overall volumes of this major input fall, manufacturing production by rich countries is also adversely affected.

## 5.3 China Ban

In 2018, China imposed an import ban on 24 categories of waste that included types of plastics, paper, and yarn. Over the next two years, it expanded the banned categories to include scrap metal, old ships, slag, stainless steel, and timber (You, 2018). Since the banned categories have substantial overlap with low-value waste in my sample, I shut down imports of low-value waste by China, which is a major importer of this type of waste to study the effects of the ban. Table A.9 shows that the policy helps China on both fronts, with an increase in gross benefits and a decrease in environmental costs, while also helping other low-income countries, such as India and the Philippines, in the same manner.

Panel E in Table 8 presents the impacts on gross benefits and environmental costs aggregated by income level. Column 2 shows that rich countries lose 0.002% of GDP, while poor countries gain 0.002% of GDP as a result of the ban. Since poor countries are major buyers of low-value waste, they experience positive benefits from this policy change, explained by the decrease in price of low-value waste relative to wages. I also find that the overall volume of high-value waste increases by 0.46%, while that of low-value waste decreases by 0.11%, *qualitatively* similar to low-value waste autarky. Since middle-income and poor countries allocate a greater fraction of their income to low-value waste than to high-value waste, their environmental costs also decrease. In contrast, the rich allocate a greater share to high-value waste, so their environmental costs increase. Thus, in terms of net benefits, the rich are worse off, while the middle- and poor-income countries are better off.

Finally, the Chinese ban also reorganizes the production of manufactured goods globally in accordance with the generation volume changes in the two types of waste. While rich and the poor countries see a decrease of 0.001% in manufacturing production, middle income countries see a rise of 0.002%.

## 5.4 Ban Amendment

The Ban amendment to the Basel Convention, which came into force in 2019, is an agreement among parties to the Convention to prohibit exports of all hazardous waste from the

Organization of Economic Cooperation and Development (OECD), the EU, and Liechtenstein to other countries that primarily include developing countries (Basel Action Network and International Pollutants Elimination Network, 2019). According to the amendment, Annex VII countries that have ratified the amendment are prohibited from exporting hazardous waste to any Non-Annex VII country, regardless of whether they ratified the amendment or not. Similarly, the Non-Annex VII countries that have ratified the amendment are prohibited from accepting imports of hazardous waste from any Annex VII country. The amendment also bans trade in non-hazardous waste that is contaminated with hazardous substances and defers to country definitions of hazardous waste in several cases. Since all waste can, arguably, have some degree of hazardous content (Kellenberg and Levinson, 2014), I impose the Ban amendment by shutting all waste exports from Annex VII countries that ratified the amendment to all Non-Annex VII countries and all waste imports of Non-Annex VII countries that ratified the amendment from all Annex VII countries. Table A.10 lists the 36 Annex VII countries, of which 29 ratified the amendment, and the 52 Non-Annex VII countries, of which 29 ratified the amendment within the sample.

Panel F in Table 8 reports the gross benefits and environmental costs of the Ban amendment. I find that the results are qualitatively similar to the waste-autarky counterfactual, albeit the magnitudes are lower. The welfare effects of imposing the Ban amendment are 22-23% of the effects of imposing an overall waste trade ban. Surprisingly, my estimates reveal that this policy that is meant to favor the developing countries that ratified the amendment is most harmful to them, similar to an overall waste trade ban, which is also most harmful to poor and developing countries.

## 5.5 Robustness Checks

I test the robustness of my welfare estimates to a variety of alternatives, including the functional form of the externality, estimates of the social marginal cost of waste disposal, and estimates of the trade elasticities. In all cases, my main results continue to hold: existing patterns of waste trade make countries of all income levels better off, but low-value waste trade makes middle-income countries worse off. In addition, the China ban makes lower-income countries, including China, better-off.

First, I test the robustness of my environmental cost estimates to a new nested CES formulation of the utility across the Cobb-Douglas composite of manufactured goods and recycled product and the volume of waste disposed domestically. The indirect utility is as follows:[32]

[32]To measure the effect of a policy change, I calculate the empirical analogues of the equivalent variation: $EV_j = w_j \bar{L}_j \times [\{(\hat{Y}_j/\hat{P}_j)^\rho - ((\sum_s W'_{sj})^\rho - (\sum_s W_{sj})^\rho)/(\alpha^\alpha(1-\alpha)^{1-\alpha} \times Y_j/P_j)^\rho\}^{1/\rho} - 1]$.

$$V_j = \left(\frac{Y_j}{P_j}\right)^\rho - \mu(\sum_{s=\{h,l\}} W_{sj})^\rho,$$

where $W_{sj} = \xi_s \times \chi_{sj} \times \sum_i X_{sij}$ is the volume of waste disposed, the parameter $\rho = (\sigma - 1)/\sigma$ is the substitution parameter, and $\mu$ is the weight on externality. I calibrate the two parameters, $\mu$ and $\rho$, using estimates of social marginal cost of waste disposal for the EU and Southeast Asia, \$1000/tonne and \$375/tonne, respectively. Specifically, I solve for $\mu$ and $\rho$ such that the willingness-to-pay for a EU country to avoid one additional tonne of waste disposal is \$1000, and that for a SEA country is \$375. Panel A in Table A.12 shows the externality cost estimates by income group under each counterfactual. I find that with these environmental cost estimates, which are smaller than those obtained using the baseline functional form, the qualitative conclusions still hold. My estimate of $\rho = 0.1225$ translates to an elasticity of substitution, $\sigma > 1$. Since the substitution across goods and the externality is more sensitive to price changes than in the baseline formulation, the environmental costs are lower. The robustness of the estimates suggests that rather than the functional form of the externality, the social marginal cost of disposed waste and the general equilibrium changes from a policy drive the results.

Another potential concern in the calculation of externality costs is the choice of estimates for the social marginal cost of disposed waste. In particular, the costs from carbon dioxide emissions from waste disposal are borne by the world as a whole. Therefore, the estimate of \$1000/tonne from Bond et al. (2020) partially accounts for external effects at the global rather than domestic level. Of the \$1000/tonne estimate, carbon dioxide emissions account for a share of only 37.5%. I check the robustness of my welfare estimates to reducing the social marginal cost for the European Union to \$625. Panel B shows that the external costs for poor countries increase by 16-32%, while for rich and middle-income countries they decrease by 6-36% across counterfactuals. The decrease in the variance of social marginal cost from 320.52 to 134.50, which drives this change, also reaffirms the main conclusions of the paper.

I also assess the robustness of my results to alternative trade elasticity estimates. Specifically, Simonovska and Waugh (2014) show that the true trade elasticity estimates for manufactured goods are roughly half of the estimates using Eaton and Kortum's 2SLS approach. Commensurate with their finding, I set the trade elasticities $\theta_m = 4.85$, $\theta_h = 4.95$, and $\theta_l = 6.58$, which are half of the 2SLS estimates in Table A.6. Table A.13 shows the welfare estimates across counterfactuals. As the variability in labor efficiencies increases, i.e., the size of the trade elasticity estimates decreases, the size of welfare gains increases across all counterfactuals (Simonovska and Waugh, 2014; Shapiro, 2016). However, the qualitative conclusions of the paper are robust to these changes.

Finally, I also use the model to calibrate social marginal costs of waste disposal for use in the counterfactual calculations, as explained in Appendix A. In this case, I find that countries have larger willingness-to-pay to avoid one additional tonne of low-value waste from being disposed than calculated in the existing literature. Consequently, even though existing patterns of waste trade still make all income groups better off, low-value waste trade makes them worse off. The China ban still makes richer countries worse off while the poorer countries, including China, are better off. Overall, the conclusion that low-value waste is the worse of the two types of waste to trade passes muster with the enlarged social marginal costs that I infer from the model.

# 6 Conclusion

I quantify the welfare implications of international trade in waste. To this end, I build a structural gravity model with the generation of waste micro-founded as a by-product of manufacturing. To assess heterogeneity in welfare by type of waste, I decompose waste flows into low- and high-value waste and estimate separate trade elasticities for both types along with for manufactured goods. This setup also allows the externality costs, which depend on the ease of recycling different materials, to vary by type of waste. The key finding through counterfactual simulations is that existing patterns of waste trade make all countries better off. However, the low-value waste trade makes middle-income countries worse off.

The non-recyclable portion of waste imports by countries inevitably generates a negative externality that is not accounted for by private players while making trading decisions. Hence, one would expect that restricting international trade in waste would reduce externality costs due to waste disposal. In contrast, my results demonstrate that accounting for general equilibrium changes in the scale and composition of waste generation that ensue from this policy change can increase the environmental costs across countries. Combined with a decrease in gross benefits, the increase in environmental costs makes all countries worse off. However, shutting down the low-value waste trade makes middle-income countries, which are major importers of this waste type, better off. Depending on the type of waste that countries specialize in, their manufacturing production is also adversely affected.

Thus, my analysis can inform policy decisions on the type of waste to target while regulating trade flows. Kaza et al. (2018) asserts that global waste generation will grow by 69% by 2050, with most of the increase coming from lower-income countries whose incomes are rising. These countries have much higher open dumping rates that contribute to the environmental costs from waste. This paper shows that although relocation of waste to countries with higher recycling capacity creates gross benefits, it also imposes local environmental costs on importing countries. I show that targeted regulation of waste flows can influence the scale and composition and thus the environmental costs of waste disposal.

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# 7 Figures

Figure 1: Composition of High- and Low-Value Waste

This figure shows the categories in Table A.1 that comprise two types of waste—high- and low-value waste. High-value waste comprises categories that fall under the top tercile of value-to-weight ratios, while low-value waste includes the rest of the categories. Metals comprise a major share in both high- and low-value waste in my sample. However, metals part of high-value waste are mainly precious metals, Gold, Copper, Nickel, Aluminum, Tungsten, Molybdenum, Tantalum, Magnesium, Cobalt, Bismuth, Cadmium, Titanium, Zirconium, and Antimony. Metals part of low-value waste are mainly ferrous in nature—Steel and Iron, Lead, Zinc, Tin, Beryllium, and Chromium. Yarn also is a part of both types of waste. As a part of high-value waste, yarn mainly comprises precious fibers including silk, wool, and fine animal hair, while as a part of low-value waste it comprises coarse animal hair, cotton, and synthetic fibers.

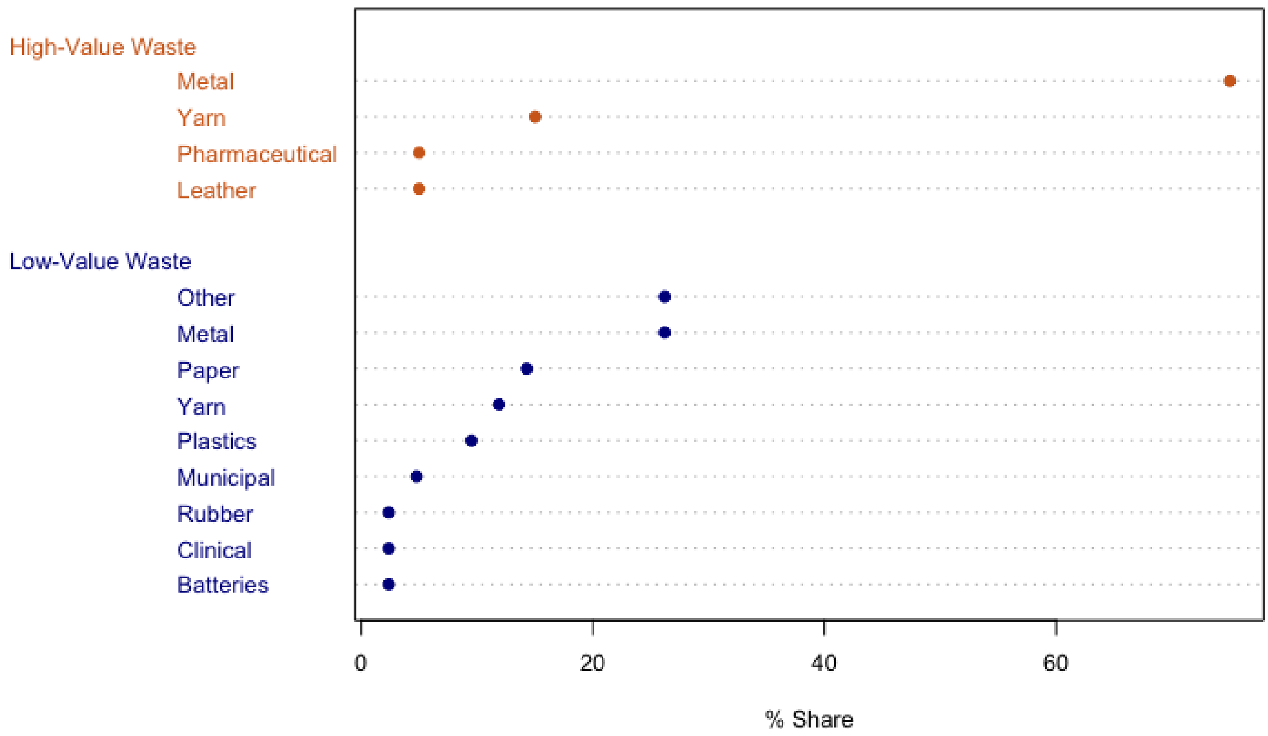


Figure 2: High-Value Waste Imports (as % of GDP)

High-value waste comprises categories in Table A.1 that fall under the top tercile of value-to-weight ratios. This figure shows the dollar-value of high-value waste imports of a country as a percentage of its GDP. The darker the color, the larger is the country's high-value waste imports as a share of its income. White represents missing data.

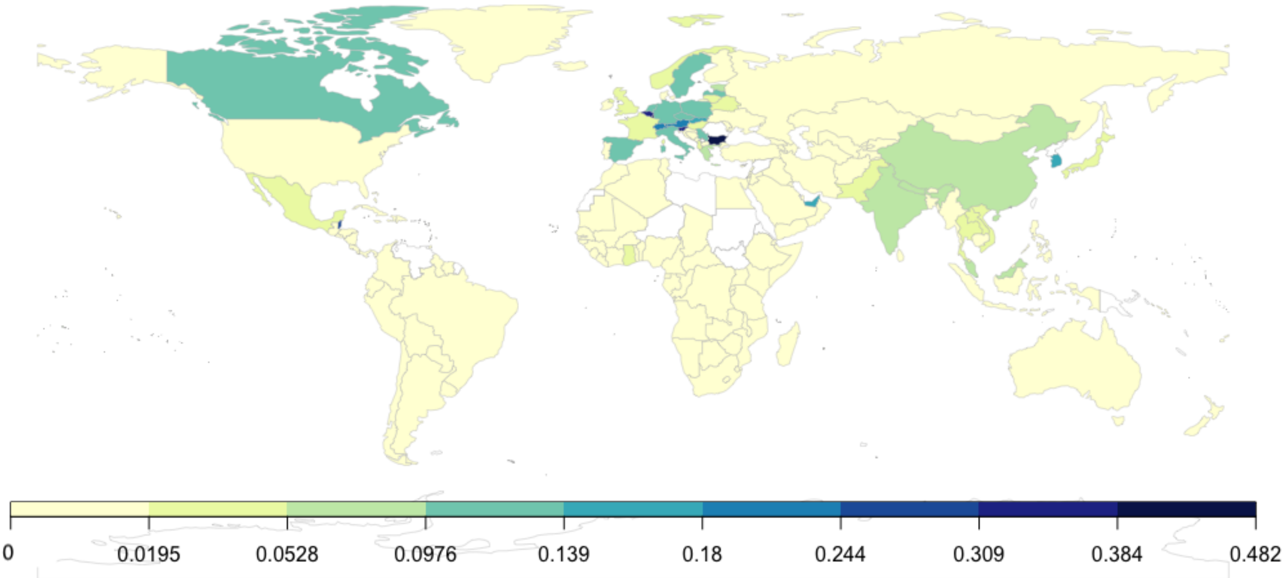



Figure 3: Low-Value Waste Imports (as % of GDP)

Low-value waste comprises categories in Table A.1 that fall under the bottom-two terciles of value-to-weight ratios. This figure shows the dollar-value of low-value waste imports of a country as a percentage of its GDP. The darker the color, the larger is the country's low-value waste imports as a share of its income. White represents missing data.

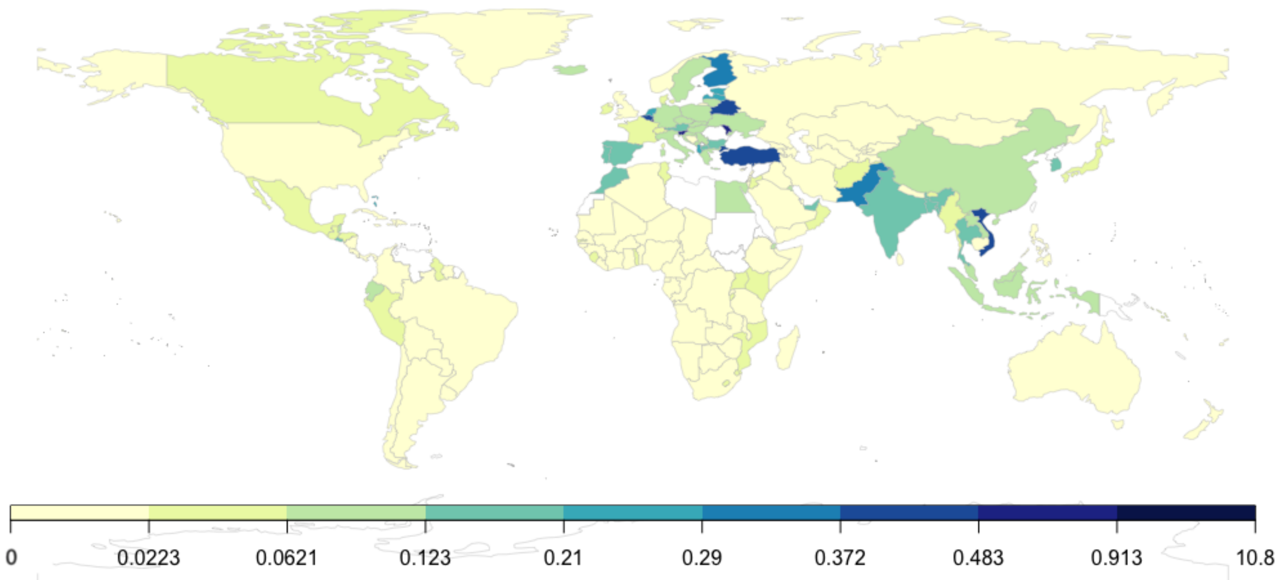


Figure 4: Flow of Goods and Services between Sectors in a Country

This figure shows the links between sectors in the general equilibrium model described in Section 3. Specifically, the figure depicts the flow of inputs, labor and two types of waste, to the production and waste-management sectors, and the flow of manufactured output and recycled product to households for final consumption. The black arrows represent the flows that can take place only domestically. The orange arrows represent the flows that can take place both domestically and across borders. See Section 3 for further details.

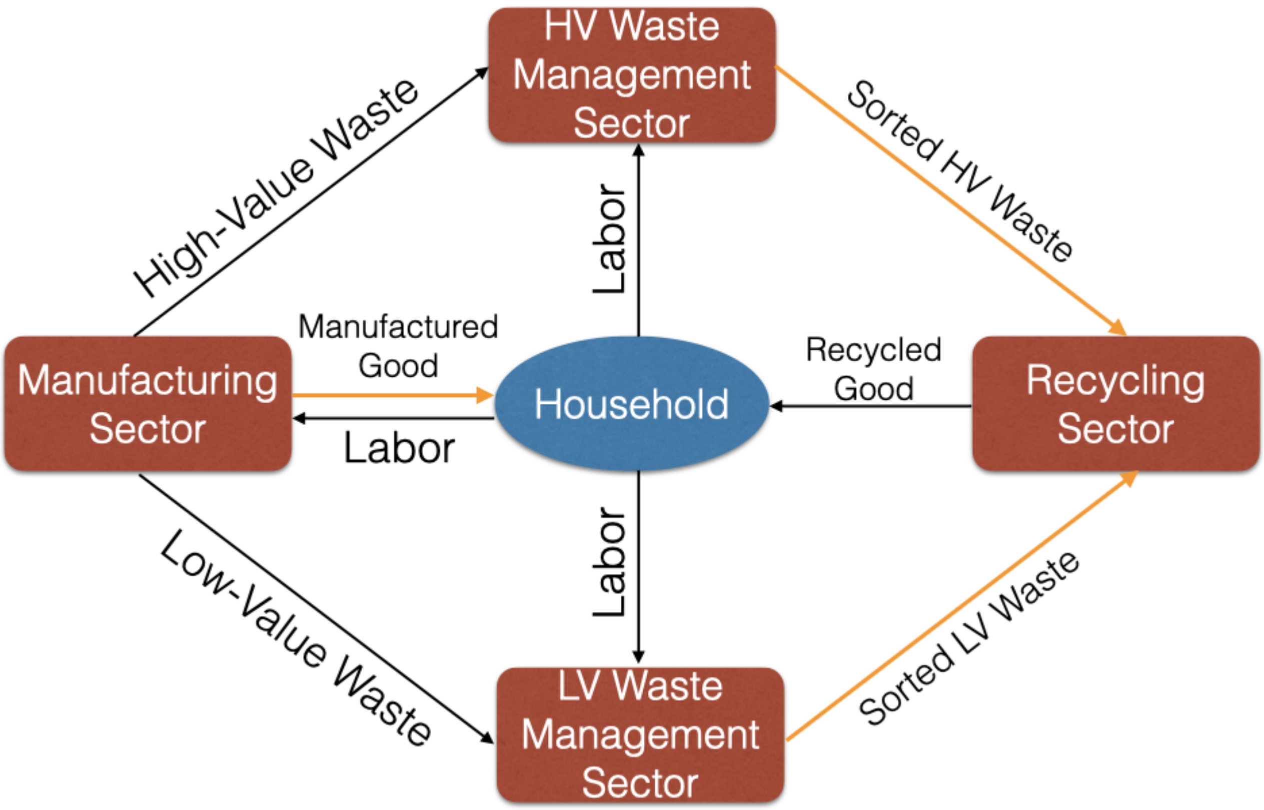


Figure 5: Recycling Rates by Type of Waste

This figure shows the extrapolated recycling rates for high- and low-value waste for the 91 countries in my sample. The "grey" dots represent the recycling rates for mixed waste from Kaza et al. (2018). The "orange" dots represent the recycling rates for high-value waste extrapolated to be proportional to overall recycling rates (grey dots) using the recycling rates for different materials under high-value waste for the USA from United States Environmental Protection Agency (2020). The "blue" dots are the analogous extrapolated recycling rates for low-value waste. See Section 3.5 for details.

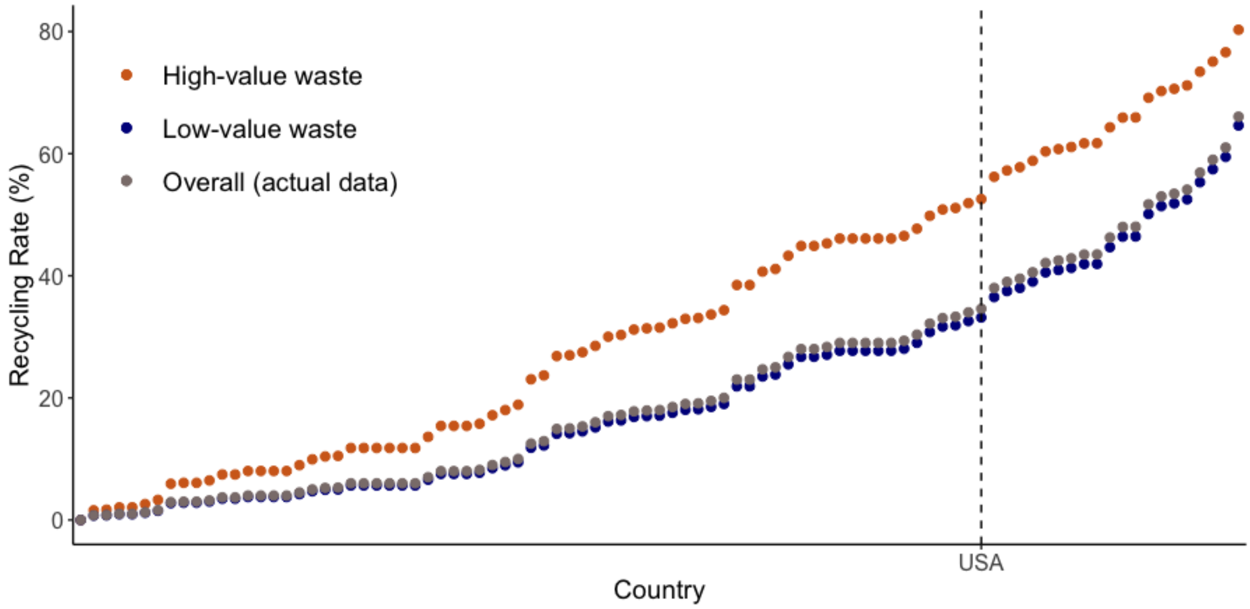



Figure 6: Social Marginal Cost of Waste ($/tonne)

This figure shows the extrapolated social marginal costs of waste disposal for each country in my sample. I use the values of $1000/tonne from Bond et al. (2020) and $375/tonne from McKinsey (2016) for the European Union and Southeast Asia, respectively, to extrapolate the social marginal costs to the countries in my sample based on their Enviornmental Performance Indices. Section 3.6 describes the extrapolation methodology in detail.

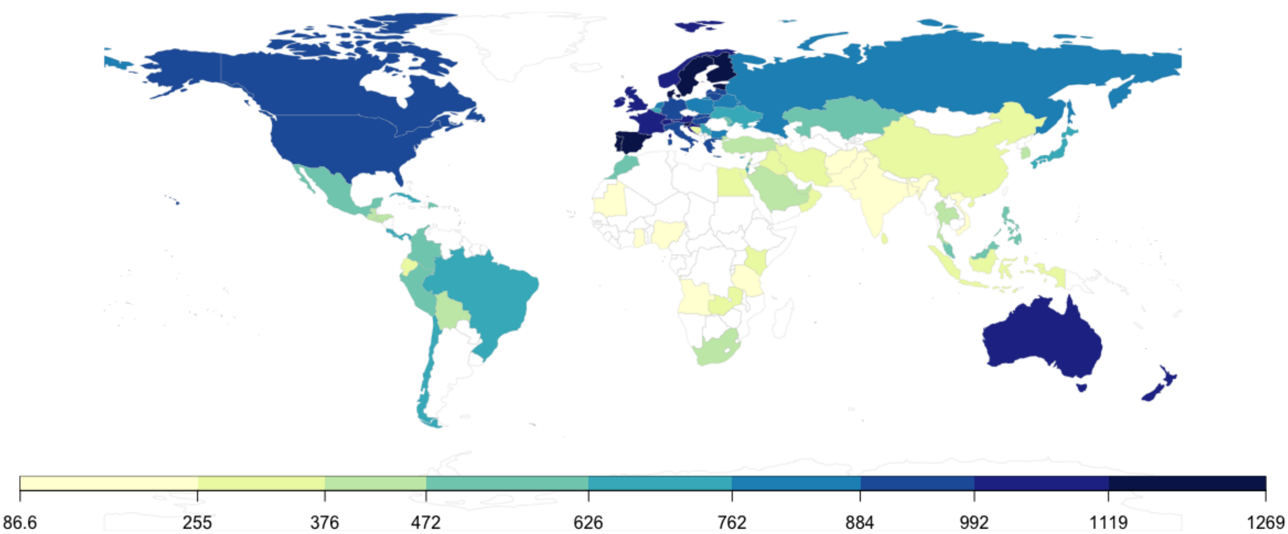


Figure 7: Goodness of Fit-Trade Flows

This figure shows the simulated flows at the estimated parameter values from Sections 4.1 and 4.2 against the actual flows in the data for the three sectors—manufactured goods, high-value waste and low-value waste. The graphs also report the $R^2$s from the OLS regression of actual flows on simulated flows.

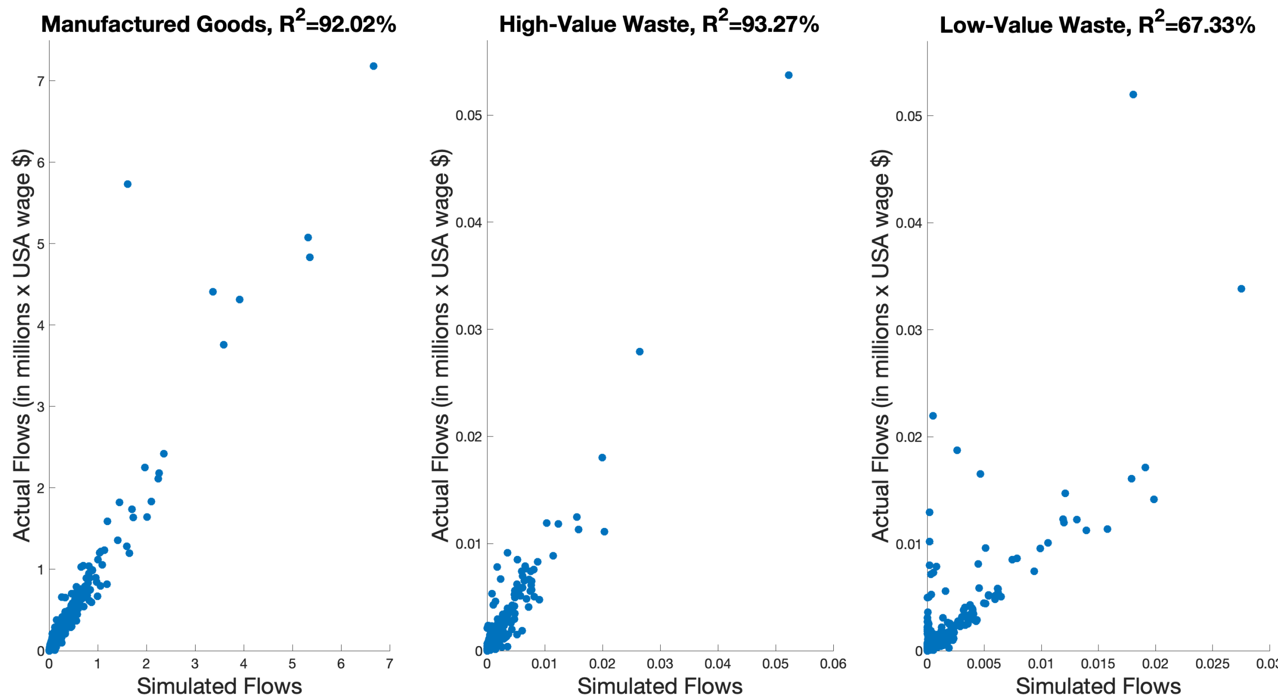


Figure 8: Goodness of Fit-Sum of Square Residuals by Importer

This figure shows the sum of squared residuals by importing country from the OLS regression of actual flows on simulated flows at estimated parameter values from Sections 4.1 and 4.2.

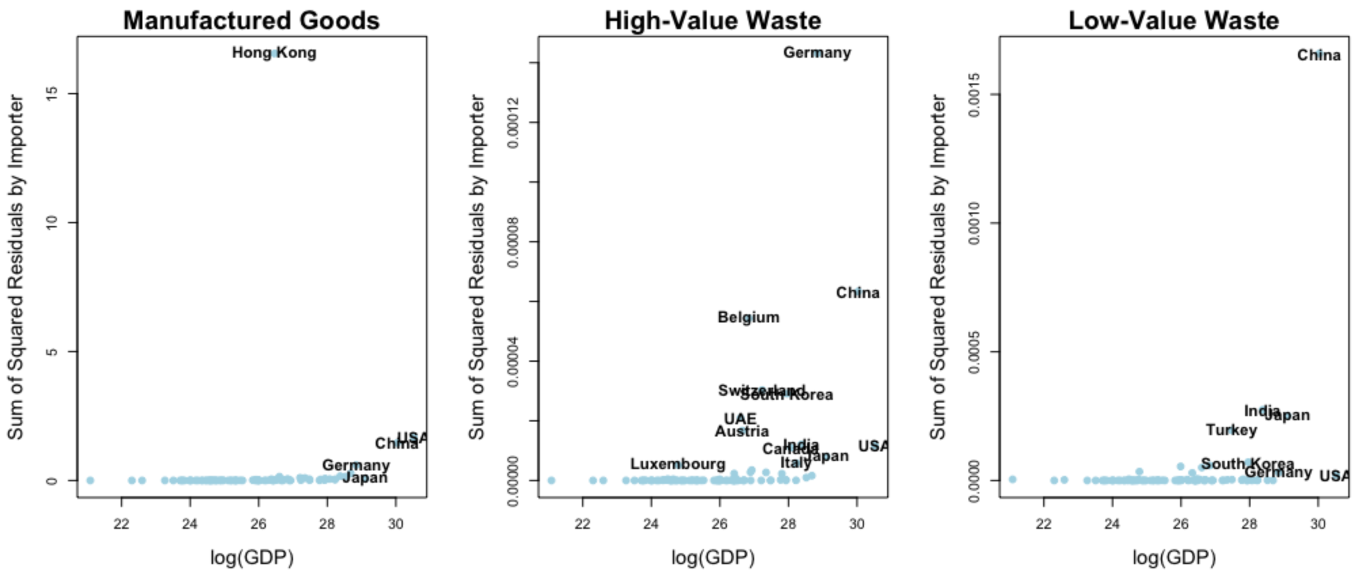
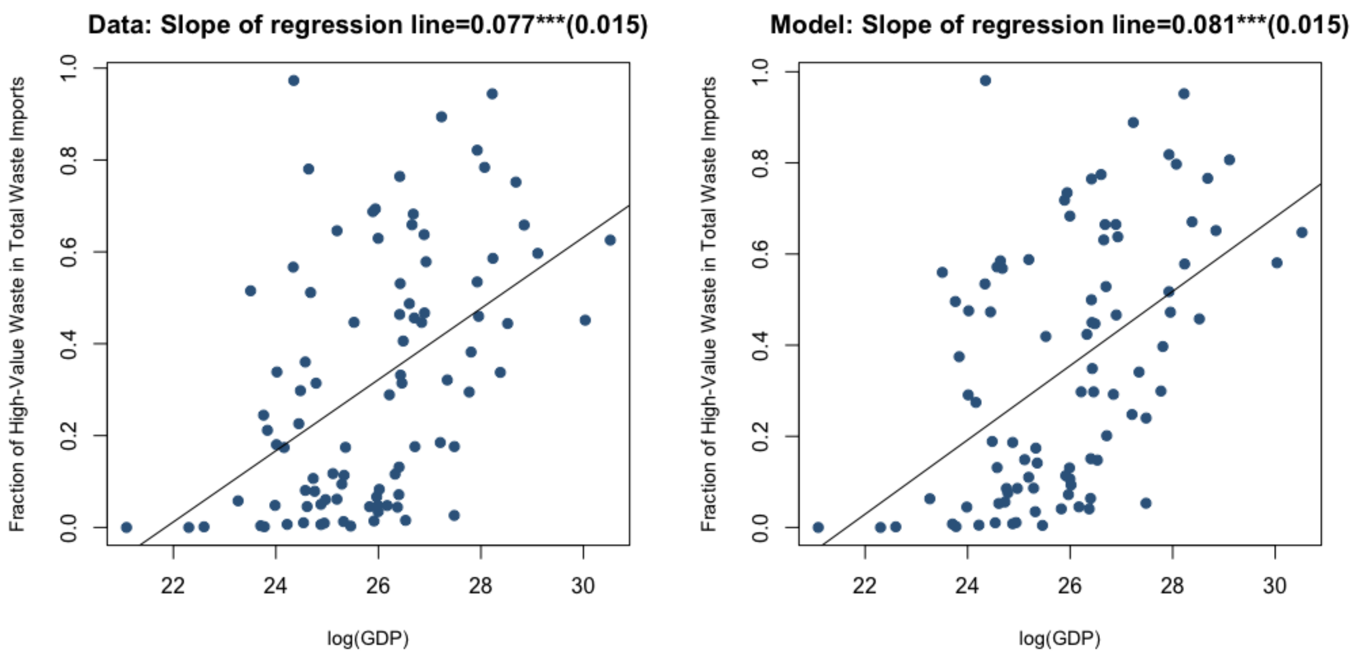



Figure 9: Goodness of Fit-Fraction of High-Value Waste in Total Waste Imports

This figure shows the scatter plots of fraction of dollar-value of high-value waste in total value of waste imports for the countries in my sample. The left panel is the plot for actual data while the right panel is for the simulated flows at estimated parameter values for the model. I also report the slopes from OLS regression of fraction of expenditure on high-value waste on $log(GDP)$.



# 8 Tables

Table 1: Summary Statistics by Type of Waste

This table reports the summary statistics for the two types of waste. Panel A reports the summary statistics for the exporter- and importer-specific variables. Panel B reports the summary statistics for the bilateral variables.

| *Panel A:* | *Exporter:* | | *Importer:* | |
|---|---|---|---|---|
| | High-Value Waste | Low-Value Waste | High-Value Waste | Low-Value Waste |
| GDP/capita | 22,790 | 22,575 | 24,932 | 20,380 |
| GDP (billion \$) | 1,367 | 1,365 | 1,630 | 1,159 |
| GDP/Land (1000 \$/sq. km) | 13,388 | 12,950 | 19,501 | 16,624 |
| EPI | 75.39 | 75.19 | 75.93 | 72.63 |

| *Panel B:* | High-Value Waste | Low-Value Waste |
|---|---|---|
| Weight (1000 kgs) | 4,091 | 30,503 |
| Value (1000 \$) | 10,766 | 8,079 |
| Distance | 5,878 | 6,113 |

Table 2: Gravity Equation Estimations for Waste Flows

This table reports the results from estimation of Equation (1). Columns 1 and 2 report the results with aggregate bilateral waste flows, Columns 3 and 4 with bilateral high-value waste flows, and Columns 5 and 6 with bilateral low-value waste flows as the dependent variables. See Section 2 for a description of the regression specification and the estimation methodology. Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Aggregate Waste | | High-Value Waste | | Low-Value Waste | |
|---|---|---|---|---|---|---|
| log(Exporter's GDP) | 0.552*** | | 0.477*** | | 0.551*** | |
| | (0.0781) | | (0.107) | | (0.0912) | |
| log(Importer's GDP) | 1.199*** | | 1.331*** | | 1.092*** | |
| | (0.0703) | | (0.106) | | (0.0706) | |
| log(Exporter's EPI) | 2.785*** | | 2.668*** | | 2.685*** | |
| | (0.743) | | (0.805) | | (0.749) | |
| log(Importer's EPI) | -3.910*** | | -2.798*** | | -4.447*** | |
| | (0.459) | | (0.674) | | (0.438) | |
| log(Exporter's GDP/Land) | 0.102** | | 0.0394 | | 0.143*** | |
| | (0.0409) | | (0.0391) | | (0.0554) | |
| log(Importer's GDP/Land) | 0.249*** | | 0.329*** | | 0.198*** | |
| | (0.0437) | | (0.0722) | | (0.0480) | |
| log(Distance) | -0.681*** | -0.911*** | -0.535*** | -0.728*** | -0.781*** | -1.055*** |
| | (0.0814) | (0.0722) | (0.0757) | (0.0937) | (0.105) | (0.0801) |
| Contiguity | 0.920*** | 1.020*** | 0.999*** | 1.019*** | 0.798*** | 1.082*** |
| | (0.241) | (0.204) | (0.236) | (0.254) | (0.261) | (0.211) |
| Common Language | 0.0909 | 0.0751 | 0.195 | -0.0988 | 0.0510 | 0.370** |
| | (0.150) | (0.178) | (0.161) | (0.212) | (0.172) | (0.172) |
| Constant | -26.46*** | 25.72*** | -34.48*** | 23.74*** | -20.26*** | 26.21*** |
| | (4.351) | (0.613) | (4.537) | (0.798) | (4.196) | (0.666) |
| Exporter FE | | Y | | Y | | Y |
| Importer FE | | Y | | Y | | Y |
| R-squared | 0.515 | | 0.458 | | 0.423 | |
| Observations | 28,056 | 42,435 | 28,390 | 38,802 | 28,390 | 42,851 |

Table 3: Choice between High- and Low-Value Waste by Income of a Country

This table reports the results from estimation of Equation (1) with the dependent variable replaced by "Ratio". The dependent variable, Ratio, is the ratio of dollar-values of bilateral high-value waste flows to total waste flows. See Section 2 for a description of the regression specification and the estimation methodology. Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Ratio | |
|---|---|---|
| log(Exporter's GDP/capita) | -0.0256 | |
| | (0.0261) | |
| log(Importer's GDP/capita) | 0.107*** | |
| | (0.0268) | |
| log(Exporter's EPI) | -0.0624 | |
| | (0.145) | |
| log(Importer's EPI) | 1.181*** | |
| | (0.176) | |
| log(Exporter's GDP/Land) | -0.0126 | |
| | (0.0145) | |
| log(Exporter's GDP/Land) | 0.0692*** | |
| | (0.0135) | |
| log(Distance) | 0.0285 | -0.0211 |
| | (0.0188) | (0.0245) |
| Contiguity | -0.0305 | -0.175** |
| | (0.0865) | (0.0819) |
| Common Language | -0.109** | 0.105** |
| | (0.0470) | (0.0470) |
| Constant | -7.775*** | -0.699*** |
| | (0.861) | (0.208) |
| Exporter FE | | Y |
| Importer FE | | Y |
| R-squared | 0.111 | |
| Observations | 6,117 | 6,740 |

Table 4: Estimating Trade Elasticities with Trade Barrier= $2\hat{\tau}^1_{in} - \hat{\tau}^2_{in}$

This table reports the results from estimation of Equation (16). Columns 1, 2 and 3 report the results with bilateral manufactured good flows, Columns 4, 5, and 6 with bilateral high-value waste flows, and Columns 7, 8, and 9 with bilateral low-value waste flows as the dependent variables. For each sector, the first column reports the OLS estimates, the second column reports the first-stage estimates, and the last one reports 2SLS estimates. See Section 4.1 for a discussion on the construction of measure of trade barriers and the regression specification. In all three sectors, the test for weak instruments yields robust F-statistics ranging from 294-510, above the cutoff of 104 (Lee et al., 2020). Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Manufactured Goods | | | High-Value Waste | | | Low-Value Waste | | |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | FS | 2SLS | OLS | FS | 2SLS | OLS | FS | 2SLS |
| Trade Barrier | -1.170*** | | -7.260*** | -1.361*** | | -7.290*** | -1.501*** | | -9.831*** |
| | (0.0794) | | (0.338) | (0.140) | | (0.428) | (0.123) | | (0.527) |
| log(Distance) | | 0.252*** | | | 0.250*** | | | 0.231*** | |
| | | (0.011) | | | (0.015) | | | (0.012) | |
| Exporter FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| R-squared | 0.947 | 0.986 | | 0.924 | 0.987 | | 0.919 | 0.987 | |
| Observations | 6,932 | 6932 | 6,932 | 2,470 | 2470 | 2,470 | 3,411 | 3411 | 3,411 |

Table 5: Goodness of Fit-Estimated Trade Costs and Geographic Barriers

This table presents the results from estimation of Equation (20). The dependent variables are the log of estimated trade costs from Section 4.2 for the three sectors in my model. See Section 4.3 for a description of the regression specification. I exclude the observations where trade flows are zero. Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

| | Manufactured Goods Trade Costs | High-Value Waste Trade Costs | Low-Value Waste Trade Costs |
|---|---|---|---|
| Distance | $0.052^{***}$ | $0.058^{***}$ | $0.047^{***}$ |
| | (0.006) | (0.007) | (0.005) |
| Distance$^2$ | $-0.002^{***}$ | $-0.002^{***}$ | $-0.002^{***}$ |
| | (0.0003) | (0.0004) | (0.0003) |
| Contiguity | 0.215 | $-0.102^{*}$ | $-0.140^{**}$ |
| | (0.176) | (0.055) | (0.068) |
| Common Language | $-0.038$ | $-0.055^{*}$ | 0.001 |
| | (0.039) | (0.033) | (0.028) |
| Free Trade Agreement | $-0.148^{***}$ | | |
| | (0.019) | | |
| Constant | $0.969^{***}$ | $0.649^{***}$ | $0.767^{***}$ |
| | (0.023) | (0.026) | (0.017) |
| $R^2$ | 0.095 | 0.052 | 0.044 |
| Adjusted $R^2$ | 0.094 | 0.050 | 0.043 |
| Observations | 7,862 | 2,594 | 3,623 |

Table 6: Goodness of Fit-Trade as a % of GDP

This table reports the share of trade as a percentage of GDP. Column 1 reports the shares for the actual flows in the data while Column 2 reports the shares for the simulated flows at estimated parameter values for the model. Each panel represents the trade shares for the three sectors in the model.

| Countries | Data | Model |
|---|---|---|
| | **Panel A: Manufactured Goods** | |
| 30 Richest | 12.558% | 12.396% |
| Rest | 6.137% | 5.513% |
| | **Panel B: High-Value Waste** | |
| 30 Richest | 0.048% | 0.050% |
| Rest | 0.011% | 0.011% |
| | **Panel C: Low-Value Waste** | |
| 30 Richest | 0.047% | 0.040% |
| Rest | 0.022% | 0.023% |

Table 7: Goodness of Fit-Openness by GDP per capita and GDP

This table shows the estimated slopes from OLS regressions of openness $(Exports + Imports)/GDP$ on $log(GDP/capita)$ in Panel A and on $log(GDP)$ in Panel B, for the three sectors. The second column is for actual flows while the third is for the simulated flows at estimated parameter values for the model. Standard errors are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| Sector | Data | Model |
|---|---|---|
| | **Panel A: Openness on log(GDP/capita)** | |
| Manufactured Goods | $0.063^{*}(0.036)$ | $0.049(0.030)$ |
| High-Value Waste | $0.0002^{**}(0.0001)$ | $0.0002(0.0001)$ |
| Low-Value Waste | $0.001(0.002)$ | $0.0004(0.002)$ |
| | **Panel B: Openness on log(GDP)** | |
| Manufactured Goods | $-0.038(0.027)$ | $-0.043^{*}(0.022)$ |
| High-Value Waste | $-0.0002(0.0001)$ | $-0.0002^{*}(0.0001)$ |
| Low-Value Waste | $-0.004^{***}(0.001)$ | $-0.003^{***}(0.001)$ |

Table 8: Counterfactual Results

Each panel in this table reports the results from a counterfactual exercise. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The $\Delta$ Gross Benefits are calculated in terms of proportional changes in real income, $w_j\bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$, and $\Delta$ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. See Sections 3.5 and 5 for further details.

| | Δ Gross Benefits | | Δ Environmental Costs | |
|---|---|---|---|---|
| Income Group | (%GDP) | (billions \$) | (%GDP) | (billions \$) |
| | **Panel A: Autarky** | | | |
| Global | -3.05 | -2168 | -0.39 | -274 |
| Rich | -3.25 | -1480 | -0.35 | -159 |
| Middle | -2.63 | -589 | -0.49 | -109 |
| Poor | -3.21 | -99 | -0.19 | -6 |
| | **Panel B: Waste-Autarky** | | | |
| Global | -0.013 | -9 | 0.018 | 13 |
| Rich | -0.014 | -6 | 0.019 | 8 |
| Middle | -0.009 | -2 | 0.016 | 4 |
| Poor | -0.021 | -0.6 | 0.024 | 0.8 |
| | **Panel C: High-Value Waste-Autarky** | | | |
| Global | -0.01 | -7 | 0.030 | 21 |
| Rich | -0.012 | -6 | 0.037 | 17 |
| Middle | -0.007 | -2 | 0.019 | 4 |
| Poor | -0.001 | -0.04 | 0.004 | 0.1 |
| | **Panel D: Low-Value Waste-Autarky** | | | |
| Global | -0.004 | -3 | -0.005 | -4 |
| Rich | -0.006 | -3 | -0.003 | -1 |
| Middle | 0.001 | 0.2 | -0.012 | -3 |
| Poor | -0.004 | -0.1 | 0.002 | 0.06 |
| | **Panel E: China Ban** | | | |
| Global | -0.002 | -1 | 0.003 | 2 |
| Rich | -0.002 | -1 | 0.006 | 3 |
| Middle | -0.0001 | -0.03 | -0.003 | -0.6 |
| Poor | 0.002 | 0.06 | -0.006 | -0.2 |
| | **Panel F: Ban Amendment** | | | |
| Global | -0.003 | -2 | 0.004 | 3 |
| Rich | -0.003 | -2 | 0.003 | 1 |
| Middle | -0.002 | -0.4 | 0.007 | 2 |
| Poor | -0.010 | -0.3 | 0.013 | 0.4 |

**Online Appendix to**
**"Welfare Effects of International Trade in Waste"**

Prakrati Thakur
University of Illinois

# A Social Marginal Cost of Waste Disposal

I use the model to calibrate social marginal cost of waste disposal for use in the counterfactual calculations. To do so, I calibrate a lower bound of the social marginal cost of low-value waste disposal for countries that implemented the Ban amendment. Assuming that this policy is good for the countries that ratified it, I use the Ban amendment counterfactual to solve for estimates of the social marginal cost of low-value waste such that the net benefits from the policy change are zero. Since I aim to capture lower bounds on the economic valuation of only low-value waste, I set the externality parameter for high-value waste, $\mu_{hn} = 0$, and focus on countries whose gross benefits and environmental costs both decrease with the policy change.[33] Consequently, I infer the externality parameter and the corresponding social marginal cost of low-value waste for four countries: Belgium, Finland, UK, and Zambia. Then, I extrapolate social marginal cost and the corresponding externality parameters to the rest of the countries in my sample based on log incomes. In this way, I use the model to get a lower bound of the social marginal cost of disposed low-value waste for each country to use for the calculation of environmental costs in the counterfactuals.

Panel C in Table A.12 shows the results with these alternative estimates of social marginal costs of disposed waste. I find that the results are *qualitatively* similar, i.e., the direction of change in the environmental costs holds, but *quantitatively* larger than with the baseline social marginal cost estimates. These results suggest that the changes in scale and composition of waste disposal are the same, but the willingness-to-pay to avoid waste disposal is higher. One caveat of this approach to estimating social marginal costs of waste disposal is that ratifying countries likely only considered the waste re-location effects of the policy while the social marginal costs that I infer from the model are accounting for its general equilibrium effects. Thus, the values I infer from the model are higher than the true valuation placed by countries on the externality due to disposed waste. Even in this case, existing patterns of waste trade still make all income groups better off, while low-value waste trade makes them worse-off.

[33] For countries where gross benefits decrease and environmental costs increase, the net benefits are always negative, and for countries where gross benefits increase and environmental costs decrease, the net benefits are always positive. For countries where both increase, the net benefits can be positive or negative depending on the size of the social marginal cost of disposed waste. For such countries, solving for the externality parameter such that net benefits are zero gives an upper bound on the social marginal cost of disposed waste rather than a lower bound.

The China ban still makes the richer countries worse-off while the poorer countries including China are better off. Overall, the conclusion that low-value waste is worse of the two types of waste to trade passes muster the test with enlarged social marginal costs that I infer from the model.

Figure A.1: Aggregate Waste Exports (as % of GDP)

This figure shows the dollar-value of overall waste exports of a country as a percentage of its GDP. The darker the color, the larger are the country's waste exports as a share of its income. The waste categories part of my sample are in Table A.1. White represents missing data.

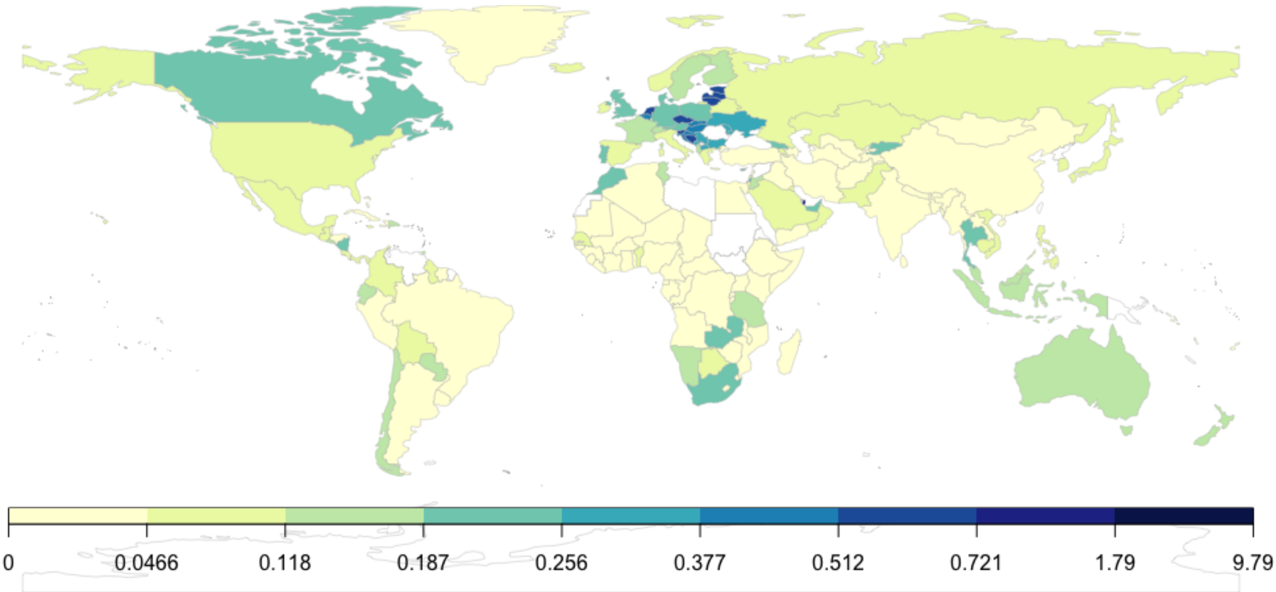



Figure A.2: Aggregate Waste Imports (as % of GDP)

This figure shows the dollar-value of overall waste imports of a country as a percentage of its GDP. The darker the color, the larger is the country's waste imports as a share of its income. The waste categories part of my sample are in Table A.1. White represents missing data.

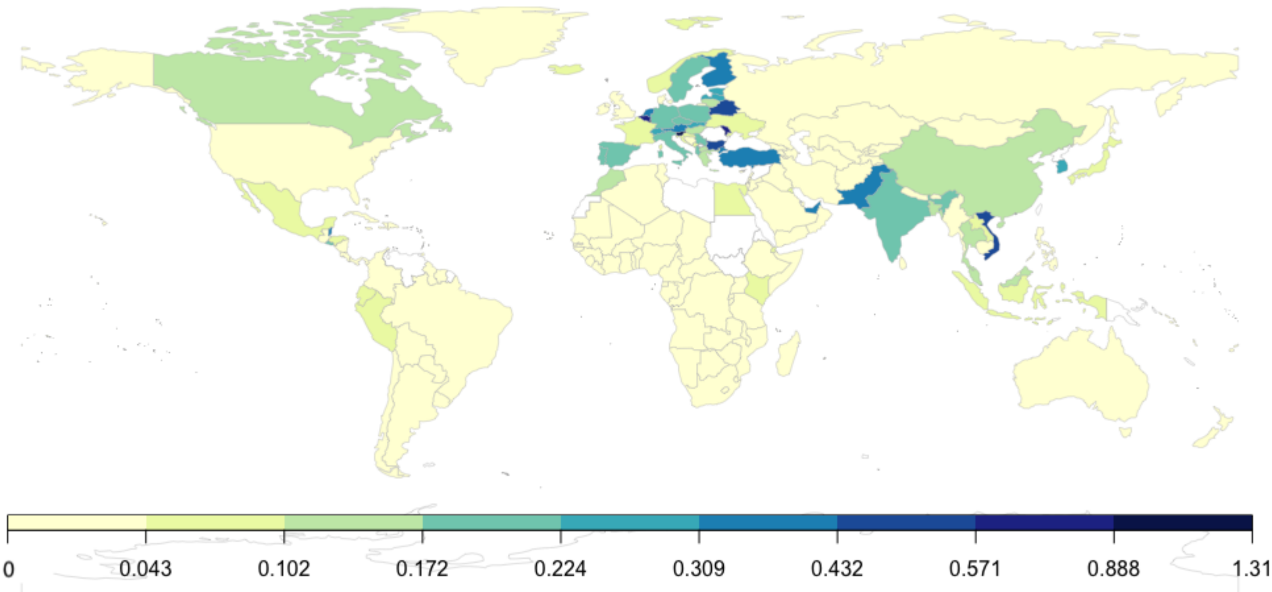


Figure A.3: Value-to-weight Ratios for Waste Categories

This figure presents the value-to-weight ratios across the 62 six-digit HS categories of waste. To construct the value-to-weight ratios, I calculate the average dollar-value and average weight of trade in each category, and take the ratio of the subsequent quantities. I exclude the outlier HS category 810330-Tantalum waste, which has a value-to-weight ratio of \$63/kg, from the figure. The dotted line represents the separation between high-value and low-value waste in my sample.

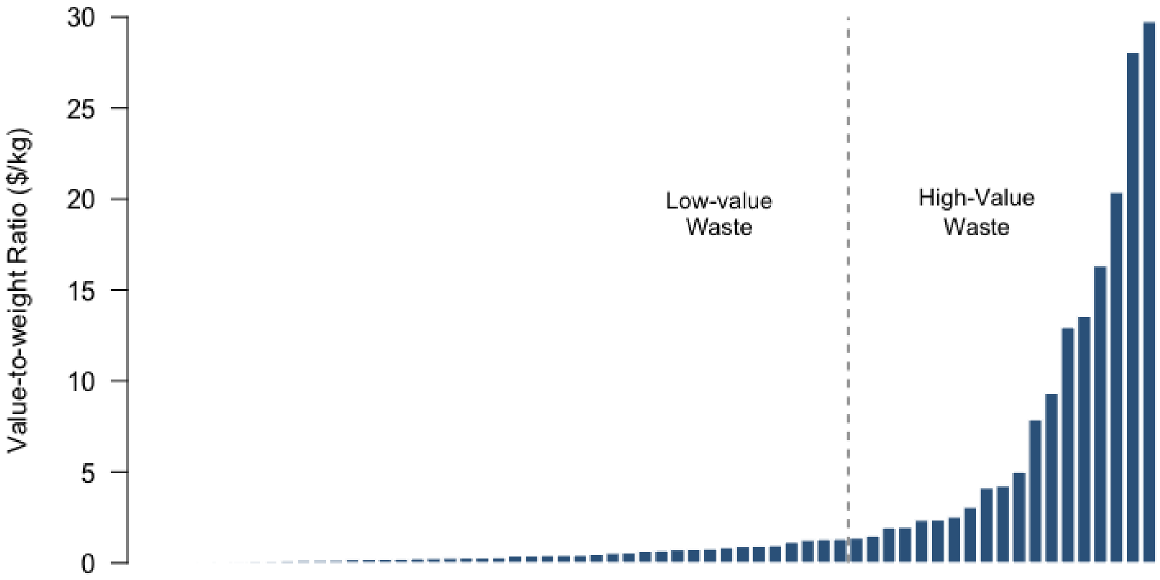



Figure A.4: Externality Parameter for High-Value Waste, $\mu_h$

This figure shows the calibrated externality parameters for high-value waste for each country in my sample. See Section 3.6 for details on the calibration methodology.

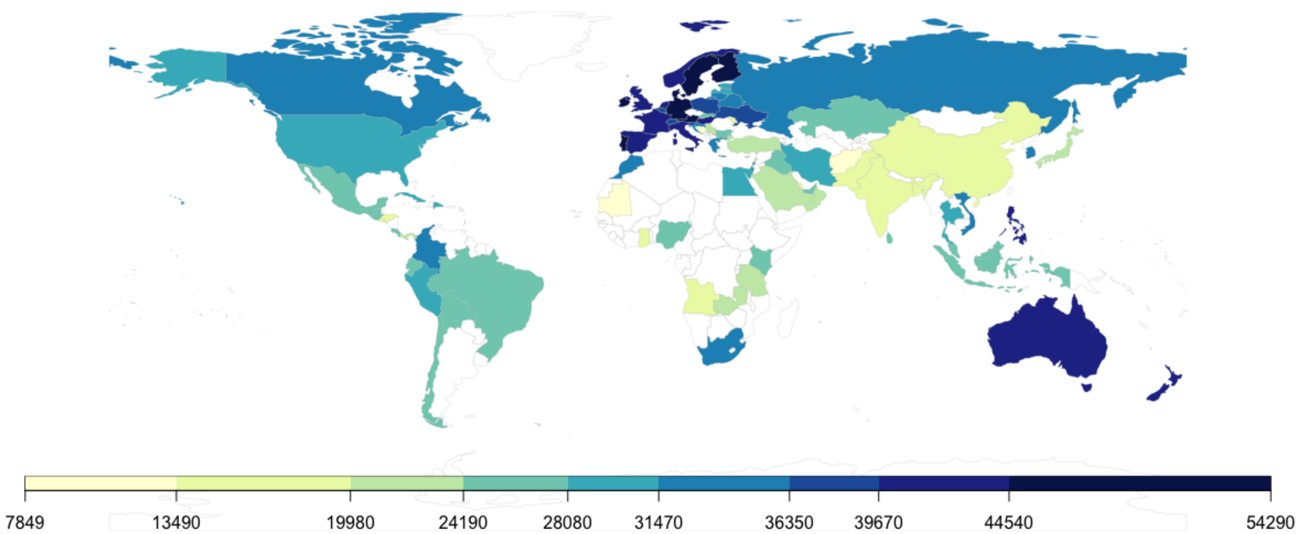


Figure A.5: Externality Parameter for Low-Value Waste, $\mu_l$

This figure shows the calibrated externality parameters for low-value waste for each country in my sample. See Section 3.6 for details on the calibration methodology.

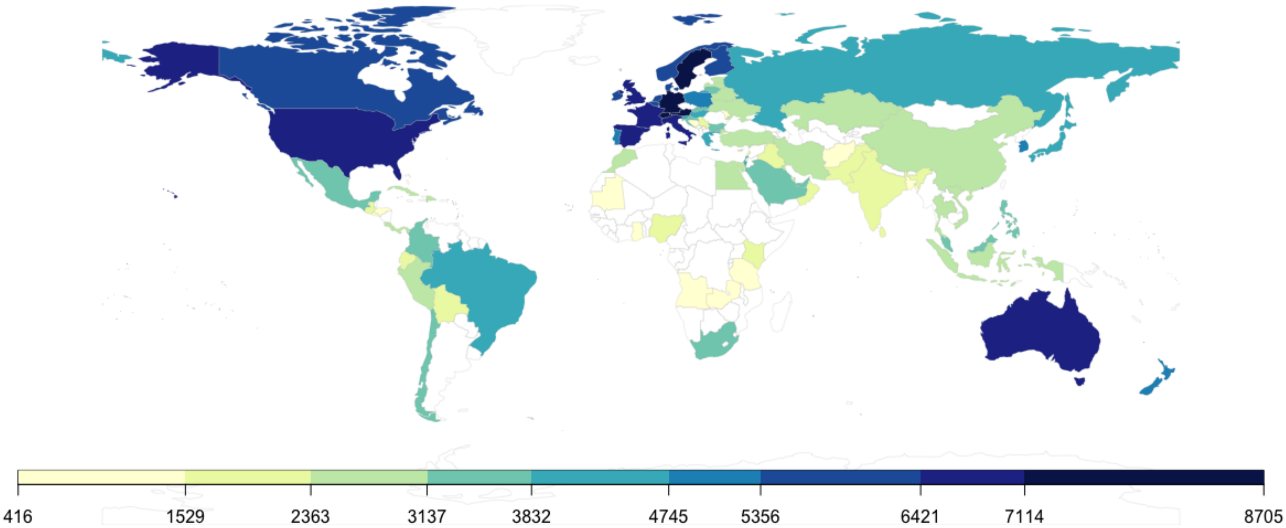


Table A.1: Harmonized System (HS) Categories of Waste

This table lists the 62 six-digit HS categories of waste in my sample, picked following Kellenberg (2012).

| HS Code | Commodity Description | HS Code | Commodity Description |
|---|---|---|---|
| 251720 | Macadam of slag/dross/sim. industrial waste | 520210 | Yarn waste (incl. thread waste), of cotton |
| 252530 | Mica waste | 520299 | Cotton waste other than yarn waste |
| 261900 | Slag, dross (excl. granulated slag), scalings, and other waste from mfr. | 550510 | Waste (incl. noils, yarn waste and garnetted stock) of synth. fibers |
| 262110 | Ash and residues from the incineration of municipal waste | 550520 | Waste (incl. noils, yarn waste and garnetted stock) of art. fibers |
| 271091 | Waste oils cont. polychlorinated biphenyls (PCBs) | 711291 | Waste and scrap of gold incl. metal clad with gold |
| 271099 | Waste oils other than those cont. PCBs | 711299 | Waste and scrap of precious metal/metal clad with precious metal |
| 300680 | Waste pharmaceuticals | 720410 | Waste and scrap of cast iron |
| 382510 | Municipal waste | 720421 | Waste and scrap of stainless steel |
| 382530 | Clinical waste | 720429 | Waste and scrap of alloy steel other than stainless steel |
| 382541 | Halogenated waste organic solvents | 720430 | Waste and scrap of tinned iron/steel |
| 382549 | Waste organic solvents other than halogenated waste organic solvents | 720441 | Ferrous turnings, shavings, chips, milling waste, sawdust filings |
| 382550 | Wastes of metal pickling liquors,hydraulic fluids, brake fluids, etc | 720449 | Ferrous waste and scrap (excl. 720410-720441) |
| 382561 | Wastes from chem./allied industries mainly cont. organic constituents | 740400 | Copper waste and scrap |
| 382569 | Wastes from chem./allied industries n.e.s. in Ch. 38 | 750300 | Nickel waste and scrap |
| 382590 | Residual prods. of chem./allied industries n.e.s. in Ch. 38 | 760200 | Aluminum waste and scrap |
| 391510 | Waste, parings, and scrap of polymers of ethylene | 780200 | Lead waste and scrap |
| 391520 | Waste, parings, and scrap of polymers of strene | 790200 | Zinc waste and scrap |
| 391530 | Waste, parings, and scrap of polymers of vinyl chloride | 800200 | Tin waste and scrap |
| 391590 | Waste, parings, and scrap of plastics n.e.s. 39.15 | 810197 | Tungsten waste and scrap |
| 400400 | Waste, parings, and scrap of rubber (excl. hard rubber) | 810297 | Molybdenum waste and scrap |
| 411520 | Parings and oth. waste of leather/composition leather not suit. for mfr. | 810330 | Tantalum waste and scrap |
| 440130 | Sawdust and wood waste and scrap | 810420 | Magnesium waste and scrap |
| 450190 | Waste cork; crushed/granulated/ground cork | 810530 | Cobalt waste and scrap |
| 470710 | Recovered (waste and scrap) unbleached kraft paper/paperboard | 810600 | Bismuth and arts. thereof, incl. waste and scrap |
| 470720 | Recovered (waste and scrap) paper/paperboard mainly of bleached chem. | 810730 | Cadmium waste and scrap |
| 470730 | Recovered (waste and scrap) paper/paperboard made mainly of mech. pulp | 810830 | Titanium waste and scrap |
| 470790 | Recovered (waste and scrap) paper/paperboard (excl. of 470710-470730) | 810930 | Zirconium waste and scrap |
| 500310 | Silk waste (incl. cocoons unsuit. for reeling, yarn waste and garnetted stock) | 811020 | Antimony waste and scrap |
| 500390 | Silk waste (incl. cocoons suit. for reeling, yarn waste and garnetted stock) | 811213 | Beryllium waste and scrap |
| 510320 | Waste of wool/of fine animal hair, incl. yarn waste | 811222 | Chromium waste and scrap |
| 510330 | Waste of coarse animal hair | 854810 | Waste and scrap of primary cells, primary batteries |

Table A.2: Gravity Equation Estimations for Manufactured Good Flows

This table reports the results from estimation of Equation (1). The dependent variable is bilateral manufactured good flows. See Section 2 for a description of the regression specification and the estimation methodology. Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Manufactured Goods | |
|---|---|---|
| log(Exporter's GDP) | 0.878*** | |
| | (0.0224) | |
| log(Importer's GDP) | 0.836*** | |
| | (0.0255) | |
| log(Exporter's EPI) | -1.319*** | |
| | (0.289) | |
| log(Importer's EPI) | -0.450* | |
| | (0.245) | |
| log(Exporter's GDP/Land) | 0.120*** | |
| | (0.0214) | |
| log(Importer's GDP/Land) | 0.0587*** | |
| | (0.0204) | |
| log(Distance) | -0.457*** | -0.653*** |
| | (0.0716) | (0.0327) |
| Contiguity | 0.650*** | 0.517*** |
| | (0.209) | (0.109) |
| Common Language | 0.0801 | 0.191** |
| | (0.125) | (0.0920) |
| Free Trade Agreement | 0.640*** | 0.506*** |
| | (0.128) | (0.0687) |
| Constant | -16.86*** | 28.09*** |
| | (1.750) | (0.288) |
| Exporter FE | | Y |
| Importer FE | | Y |
| Observations | 28,056 | 45,156 |
| R-squared | 0.725 | |

Table A.3: Robustness Check: Choice between High- and Low-Value Waste

This table reports the results from estimation of Equation (1) with the dependent variable replaced by logit and inverse hyperbolic sine transformations of "Ratio". Ratio is the ratio of dollar-values of bilateral high-value waste flows to total waste flows. See Section 2 for a description of the regression specification and the estimation methodology. Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Logit | Inverse Hyperbolic Sine |
|---|---|---|
| log(Exporter's GDP/capita) | -0.149 | -0.00689 |
| | (0.107) | (0.00748) |
| log(Importer's GDP/capita) | 0.224* | 0.0313*** |
| | (0.122) | (0.00703) |
| log(Exporter's EPI) | 0.0453 | -0.0190 |
| | (0.672) | (0.0423) |
| log(Exporter's EPI) | 2.419*** | 0.196*** |
| | (0.692) | (0.0381) |
| log(Exporter's GDP/Land) | -0.0472 | -0.00269 |
| | (0.0543) | (0.00415) |
| log(Importer's GDP/Land) | 0.160** | 0.0216*** |
| | (0.0720) | (0.00386) |
| log(Distance) | 0.189** | 0.00544 |
| | (0.0786) | (0.00541) |
| Contiguity | -0.952*** | -0.00547 |
| | (0.355) | (0.0205) |
| Common Language | 0.167 | -0.0240** |
| | (0.180) | (0.0118) |
| Constant | -14.95*** | -0.994*** |
| | (3.587) | (0.204) |
| Observations | 2,855 | 6,117 |
| R-squared | 0.090 | 0.106 |

The dependent variable is ratio of high-value to total waste flows.
Standard errors clustered by exporter-importer pairs in parentheses.
Significance codes: *** p<0.01, ** p<0.05, * p<0.1

Table A.4: ICP Price Data

This table lists the 66 tradable basic headings for which I have purchasing power parity (PPP) data from ICP's 2017 cycle. I use the price data to estimate trade elasticities in my model. See Section 4.1 for a discussion on the choice of basic-headings.

| Product Name | Product Name |
|---|---|
| Rice | Clothing materials, other articles of clothing and clothing accessories |
| Other cereals, flour and other cereal products | Garments |
| Bread | Shoes and other footwear |
| Other bakery products | Furniture and furnishings |
| Pasta products and couscous | Carpets and other floor coverings |
| Beef and veal | Repair of furniture, furnishings and floor coverings |
| Pork | Household textiles |
| Lamb, mutton and goat | Major household appliances whether electric or not |
| Poultry | Small electric household appliances |
| Other meats and meat preparations | Glassware, tableware and household utensils |
| Fresh, chilled or frozen fish and seafood | Major tools and equipment |
| Preserved or processed fish and seafood | Small tools and miscellaneous accessories |
| Fresh milk | Non-durable household goods |
| Preserved milk and other milk products | Pharmaceutical products |
| Cheese and curd | Other medical products |
| Eggs and egg-based products | Therapeutic appliances and equipment |
| Butter and margarine | Motor cars |
| Other edible oils and fats | Motor cycles |
| Fresh or chilled fruit | Bicycles |
| Frozen, preserved or processed fruit and fruit-based products | Telephone and telefax equipment |
| Fresh or chilled vegetables, other than potatoes and other tuber vegetables | Audio-visual, photographic and information processing equipment |
| Fresh or chilled potatoes and other tuber vegetables | Recording media |
| Frozen, preserved or processed vegetables and vegetable-based products | Major durables for outdoor and indoor recreation |
| Sugar | Other recreational items and equipment |
| Jams, marmalades and honey | Newspapers, books and stationery |
| Confectionery, chocolate and ice cream | Appliances, articles and products for personal care |
| Food products n.e.c. | Jewellery, clocks and watches |
| Coffee, tea and cocoa | Fabricated metal products, except machinery and equipment |
| Mineral waters, soft drinks, fruit and vegetable juices | Electrical and optical equipment |
| Spirits | General purpose machinery |
| Wine | Special purpose machinery |
| Beer | Road transport equipment |
| Tobacco | Other transport equipment |

Table A.5: Estimating Trade Elasticities with Trade Barrier= $\hat{\tau}^2_{in}$

This table reports the results from estimation of Equation (16). Columns 1, 2 and 3 report the results with bilateral manufactured good flows, Columns 4, 5, and 6 with bilateral high-value waste flows, and Columns 7, 8, and 9 with bilateral low-value waste flows as the dependent variables. For each sector, the first column reports the OLS estimates, the second column reports the first-stage estimates, and the last one reports 2SLS estimates. See Section 4.1 for a discussion on the construction of measure of trade barriers and the regression specification. In all three sectors, the test for weak instruments yields robust F-statistics ranging from 336-517, above the cutoff of 104 (Lee et al., 2020). Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Manufactured Goods | | | High-Value Waste | | | Low-Value Waste | | |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | FS | 2SLS | OLS | FS | 2SLS | OLS | FS | 2SLS |
| Trade Barrier | -3.936*** | | -14.59*** | -4.209*** | | -15.39*** | -4.523*** | | -19.91*** |
| | (0.206) | | (0.651) | (0.380) | | (0.851) | (0.329) | | (0.989) |
| log(Distance) | | 0.126*** | | | 0.118*** | | | 0.114*** | |
| | | (0.006) | | | (0.006) | | | (0.005) | |
| Exporter FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| R-squared | 0.950 | 0.998 | | 0.926 | 0.998 | | 0.921 | 0.998 | |
| Observations | 6,932 | 6932 | 6,932 | 2470 | 2,470 | 2,470 | 3,411 | 3,411 | 3411 |

Table A.6: Estimating Trade Elasticities with Trade Barrier= $\hat{\tau}^1_{in}$

This table reports the results from estimation of Equation (16). Columns 1, 2 and 3 report the results with bilateral manufactured good flows, Columns 4, 5, and 6 with bilateral high-value waste flows, and Columns 7, 8, and 9 with bilateral low-value waste flows as the dependent variables. For each sector, the first column reports the OLS estimates, the second column reports the first-stage estimates, and the last one reports 2SLS estimates. See Section 4.1 for a discussion on the construction of measure of trade barriers and the regression specification. In all three sectors, the test for weak instruments yields robust F-statistics ranging from 354-575, above the cutoff of 104 (Lee et al., 2020). Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

| | Manufactured Goods | | | High-Value Waste | | | Low-Value Waste | | |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | FS | 2SLS | OLS | FS | 2SLS | OLS | FS | 2SLS |
| Trade Barrier | -2.322*** | | -9.695*** | -2.555*** | | -9.894*** | -2.848*** | | -13.16*** |
| | (0.132) | | (0.423) | (0.228) | | (0.534) | (0.201) | | (0.640) |
| log(Distance) | | 0.189*** | | | 0.184*** | | | 0.172*** | |
| | | (0.008) | | | (0.010) | | | (0.008) | |
| Exporter FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Importer FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| R-squared | 0.949 | 0.995 | | 0.925 | 0.995 | | 0.921 | 0.995 | |
| Observations | 6,932 | 6932 | 6,932 | 2,470 | 2470 | 2,470 | 3,411 | 3411 | 3,411 |

Table A.7: Country-by-Country Impacts in Autarky Counterfactual

This table reports the country-level results of the Autarky counterfactual (See Section 5.1). All figures are in % of 2015 GDP.

| Country | ΔGross Benefits | ΔEnvironmental Costs | Country | ΔGross Benefits | ΔEnvironmental Costs |
|---|---|---|---|---|---|
| China, Hong Kong SAR | -45.500 | -0.342 | El Salvador | -3.46 | 0.144 |
| Viet Nam | -19.200 | -0.170 | Chile | -3.27 | -0.92 |
| Singapore | -18.700 | -0.393 | Angola | -3.25 | -0.209 |
| Belgium | -14.700 | -0.336 | Israel | -3.19 | -0.668 |
| Hungary | -12.700 | -0.780 | Spain | -3.18 | -0.852 |
| Estonia | -12.100 | 0.464 | Norway | -3.17 | -0.733 |
| Slovakia | -11.500 | -0.861 | Italy | -3.13 | -0.525 |
| Slovenia | -11.300 | -0.153 | South Africa | -2.97 | -0.425 |
| Latvia | -11.200 | 0.229 | France | -2.93 | -0.725 |
| Netherlands | -10.700 | -0.429 | Kazakhstan | -2.78 | -0.73 |
| Malaysia | -10.500 | -0.555 | Bolivia | -2.71 | -0.189 |
| Lithuania | -8.710 | -0.406 | Bangladesh | -2.66 | -0.143 |
| Honduras | -7.690 | 0.223 | United Kingdom | -2.51 | -0.628 |
| Mauritania | -7.250 | 0.671 | Turkey | -2.43 | -0.473 |
| Bulgaria | -7.090 | -0.441 | Russian Federation | -2.4 | -0.975 |
| Bahrain | -6.920 | -0.054 | Indonesia | -2.38 | -0.411 |
| Oman | -6.510 | -0.227 | Sri Lanka | -2.36 | -0.455 |
| Panama | -6.400 | -0.639 | Costa Rica | -2.32 | -0.817 |
| Thailand | -6.360 | -0.478 | Kenya | -2.3 | -0.316 |
| United Arab Emirates | -6.270 | -0.341 | China, Macao SAR | -2.26 | -0.54 |
| Poland | -5.830 | -0.556 | Guatemala | -2.23 | -0.483 |
| Belarus | -5.540 | -0.934 | Peru | -2.17 | -0.7 |
| Bosnia Herzegovina | -5.530 | 0.654 | Lebanon | -2.15 | -0.259 |
| Austria | -5.380 | -0.466 | Greece | -2.14 | -1.05 |
| Seychelles | -5.300 | 41.500 | Occ. Palestinian Terr. | -2.14 | 1 |
| Serbia | -5.160 | -0.199 | Dominican Rep. | -2.05 | -0.519 |
| Mexico | -4.940 | -0.603 | Ecuador | -2.05 | -0.407 |
| Ukraine | -4.850 | -0.880 | China | -2.04 | -0.353 |
| Ghana | -4.790 | -0.211 | Iran | -1.98 | -0.412 |
| Rep. of Korea | -4.740 | -0.196 | Saudi Arabia | -1.91 | -0.419 |
| Ireland | -4.680 | -0.761 | Colombia | -1.9 | -0.725 |
| Germany | -4.620 | -0.298 | India | -1.9 | -0.184 |
| Switzerland | -4.600 | -0.491 | New Zealand | -1.83 | -1.03 |
| Croatia | -4.560 | -0.910 | Japan | -1.79 | -0.728 |
| Luxembourg | -4.280 | -0.534 | Cyprus | -1.78 | 0.0297 |
| Qatar | -4.280 | -0.587 | Afghanistan | -1.75 | 0.068 |
| Philippines | -4.230 | -0.559 | Australia | -1.74 | -0.647 |
| Rep. of Moldova | -4.210 | 4.080 | Kuwait | -1.68 | -0.31 |
| Zambia | -4.180 | 0.125 | Pakistan | -1.66 | -0.206 |
| Portugal | -4.160 | -1.160 | United States of America | -1.66 | 0.00535 |
| Iraq | -4.150 | -0.437 | United Rep. of Tanzania | -1.64 | -0.226 |
| Sweden | -3.890 | -0.746 | Egypt | -1.48 | -0.39 |
| Finland | -3.690 | -1.020 | Nigeria | -1.47 | -0.297 |
| Canada | -3.670 | -0.724 | Brazil | -1.3 | -0.83 |
| Denmark | -3.670 | -0.842 | Cuba | -0.661 | -1.02 |
| Morocco | -3.630 | -0.634 | | | |

Table A.8: Country-by-Country Impacts in Waste-Autarky Counterfactual

This table reports the country-level results of the Waste-Autarky counterfactual (See Section 5.2). All figures are in % of 2015 GDP.

| Country | ΔGross Benefits | ΔEnvironmental Costs | Country | ΔGross Benefits | ΔEnvironmental Costs |
|---|---|---|---|---|---|
| Luxembourg | -0.187 | -0.023 | France | -0.016 | 0.0118 |
| Lebanon | -0.107 | 0.131 | India | -0.0149 | 0.018 |
| Belgium | -0.094 | 0.066 | Israel | -0.0147 | 0.0416 |
| Viet Nam | -0.080 | 0.071 | Russian Federation | -0.0142 | 0.0525 |
| Austria | -0.077 | 0.239 | Italy | -0.0141 | 0.0422 |
| Latvia | -0.076 | 0.106 | Ireland | -0.0132 | 0.0755 |
| Cyprus | -0.068 | 0.260 | United Kingdom | -0.012 | -0.0129 |
| Panama | -0.067 | 0.178 | China, Hong Kong SAR | -0.011 | 0.17 |
| United Rep. of Tanzania | -0.060 | 0.099 | Indonesia | -0.00804 | -0.00622 |
| Bosnia Herzegovina | -0.059 | 0.014 | China | -0.00769 | 0.0211 |
| El Salvador | -0.057 | 0.086 | Mexico | -0.00736 | -0.00668 |
| United Arab Emirates | -0.053 | 0.072 | United States of America | -0.00718 | 0.00583 |
| Netherlands | -0.050 | -0.029 | Norway | -0.00707 | 0.00152 |
| Hungary | -0.049 | 0.149 | Bulgaria | -0.00702 | 0.0929 |
| Occ. Palestinian Terr. | -0.047 | 0.148 | Turkey | -0.00679 | 0.00732 |
| South Africa | -0.046 | 0.082 | Kuwait | -0.00648 | -0.00397 |
| Poland | -0.042 | 0.092 | Chile | -0.00552 | -0.0433 |
| Guatemala | -0.040 | 0.171 | New Zealand | -0.00513 | -0.03 |
| Ukraine | -0.037 | 0.092 | Japan | -0.00494 | 0.00357 |
| Switzerland | -0.037 | 0.135 | China, Macao SAR | -0.00475 | -0.0867 |
| Ecuador | -0.036 | 0.090 | Rep. of Korea | -0.0047 | 0.0128 |
| Sweden | -0.035 | 0.161 | Philippines | -0.00409 | -0.00715 |
| Bolivia | -0.035 | 0.248 | Spain | -0.00309 | -0.0224 |
| Singapore | -0.033 | 0.113 | Brazil | -0.00247 | 0.00933 |
| Slovakia | -0.033 | 0.304 | Mauritania | -0.00221 | 0.016 |
| Kenya | -0.031 | 0.088 | Afghanistan | 0.00279 | -0.0935 |
| Serbia | -0.031 | 0.204 | Costa Rica | 0.00299 | -0.253 |
| Greece | -0.030 | 0.237 | Cuba | 0.00329 | -0.0958 |
| Ghana | -0.030 | 0.133 | Qatar | 0.00363 | -0.0429 |
| Germany | -0.028 | 0.044 | Finland | 0.0053 | -0.114 |
| Dominican Rep. | -0.028 | 0.085 | Denmark | 0.00769 | -0.119 |
| Estonia | -0.028 | 0.500 | Bahrain | 0.00778 | -0.0375 |
| Lithuania | -0.027 | 0.032 | Colombia | 0.0136 | -0.0974 |
| Honduras | -0.025 | -0.174 | Angola | 0.0149 | -0.0239 |
| Croatia | -0.025 | -0.322 | Peru | 0.0162 | -0.0873 |
| Egypt | -0.024 | 0.055 | Iraq | 0.018 | -0.0422 |
| Saudi Arabia | -0.024 | 0.026 | Sri Lanka | 0.018 | -0.0935 |
| Bangladesh | -0.024 | 0.020 | Portugal | 0.0183 | -0.211 |
| Nigeria | -0.022 | 0.038 | Iran | 0.0203 | -0.0444 |
| Morocco | -0.022 | 0.033 | Thailand | 0.0232 | -0.0959 |
| Kazakhstan | -0.020 | 0.078 | Oman | 0.0242 | -0.00202 |
| Canada | -0.019 | 0.043 | Zambia | 0.0431 | -0.31 |
| Pakistan | -0.018 | 0.020 | Belarus | 0.045 | -0.217 |
| Malaysia | -0.018 | 0.022 | Rep. of Moldova | 0.247 | 0.319 |
| Slovenia | -0.017 | 0.155 | Seychelles | 0.479 | -0.886 |
| Australia | -0.016 | 0.032 | | | |

Table A.9: Country-by-Country Impacts in China Ban Counterfactual

This table reports the country-level results of the China Ban counterfactual (See Section 5.3). All figures are in % of 2015 GDP.

| Country | ΔGross Benefits | ΔEnvironmental Costs | Country | ΔGross Benefits | ΔEnvironmental Costs |
|---|---|---|---|---|---|
| Dominican Rep. | -0.036 | 0.291 | Poland | -0.000517 | -0.0015 |
| Viet Nam | -0.034 | 0.032 | United States of America | -0.000442 | -0.000392 |
| Indonesia | -0.030 | 0.077 | Israel | -0.000287 | -0.000725 |
| Nigeria | -0.029 | 0.053 | China | 0.000239 | -0.00186 |
| Bangladesh | -0.027 | 0.029 | Bulgaria | 0.000251 | -0.00141 |
| Lebanon | -0.024 | 0.149 | Iraq | 0.000517 | -0.00674 |
| Italy | -0.024 | 0.076 | Russian Federation | 0.0017 | -0.0118 |
| United Arab Emirates | -0.022 | 0.052 | Rep. of Moldova | 0.00183 | -0.0963 |
| Angola | -0.022 | 0.050 | Saudi Arabia | 0.00201 | -0.00683 |
| Serbia | -0.021 | 0.333 | Slovakia | 0.00224 | -0.028 |
| Austria | -0.021 | 0.069 | Kazakhstan | 0.00236 | -0.0141 |
| Canada | -0.020 | 0.078 | Qatar | 0.00287 | -0.015 |
| Latvia | -0.019 | 0.365 | Turkey | 0.00298 | -0.00949 |
| Cyprus | -0.019 | 0.324 | Chile | 0.00351 | -0.019 |
| Ireland | -0.018 | 0.094 | Bolivia | 0.0046 | -0.0403 |
| Iran | -0.017 | 0.045 | Oman | 0.00502 | 0.00449 |
| Morocco | -0.017 | 0.094 | Denmark | 0.00515 | -0.0247 |
| Belgium | -0.015 | 0.033 | Belarus | 0.00517 | -0.0826 |
| Singapore | -0.014 | 0.042 | United Rep. of Tanzania | 0.00554 | -0.028 |
| Pakistan | -0.013 | 0.015 | China, Macao SAR | 0.00574 | -0.0985 |
| Finland | -0.012 | 0.078 | Ukraine | 0.00587 | -0.0435 |
| Hungary | -0.011 | 0.083 | Ghana | 0.0063 | -0.0463 |
| Estonia | -0.011 | 0.251 | Sweden | 0.00664 | -0.0339 |
| South Africa | -0.009 | 0.025 | Mauritania | 0.00685 | -0.156 |
| Guatemala | -0.009 | 0.054 | Thailand | 0.00735 | -0.0313 |
| Lithuania | -0.009 | 0.127 | Zambia | 0.00826 | -0.115 |
| Slovenia | -0.008 | 0.019 | India | 0.00934 | -0.0103 |
| Kuwait | -0.008 | 0.023 | Norway | 0.00997 | -0.0456 |
| Bahrain | -0.008 | 0.071 | Rep. of Korea | 0.01 | -0.0121 |
| Honduras | -0.007 | -0.005 | Luxembourg | 0.01 | -0.0866 |
| Panama | -0.006 | 0.054 | Occ. Palestinian Terr. | 0.0104 | -0.15 |
| Germany | -0.006 | 0.010 | Peru | 0.0109 | -0.0503 |
| Ecuador | -0.005 | 0.024 | Greece | 0.0111 | -0.0889 |
| Spain | -0.005 | 0.013 | China, Hong Kong SAR | 0.0122 | -0.0127 |
| New Zealand | -0.004 | 0.019 | Croatia | 0.0124 | -0.189 |
| Bosnia Herzegovina | -0.004 | 0.013 | El Salvador | 0.0151 | -0.17 |
| Costa Rica | -0.002 | 0.002 | Colombia | 0.0155 | -0.0652 |
| Egypt | -0.002 | 0.005 | Malaysia | 0.0159 | -0.072 |
| Seychelles | -0.002 | -0.001 | Philippines | 0.0166 | -0.0617 |
| Japan | -0.002 | -0.002 | Portugal | 0.0173 | -0.135 |
| Kenya | -0.002 | 0.006 | Switzerland | 0.0194 | -0.0543 |
| Netherlands | -0.002 | -0.009 | Cuba | 0.0215 | -0.177 |
| United Kingdom | -0.001 | -0.003 | Sri Lanka | 0.0226 | -0.0951 |
| France | -0.001 | 0.005 | Mexico | 0.0248 | -0.0877 |
| Brazil | -0.001 | 0.010 | Afghanistan | 0.0258 | -0.0776 |
| Australia | -0.001 | -0.002 | | | |

Table A.10: Ban Amendment Ratification Status of Within-Sample Countries

This table reports the Basel Ban amendment ratification status of the countries in my sample, as reported in Basel Action Network and International Pollutants Elimination Network (2019).

| Ratified | | Not-Ratified | |
|---|---|---|---|
| Annex VII | Non-Annex VII | Annex VII | Non-Annex VII |
| Austria | Bahrain | Australia | Afghanistan |
| Belgium | Bolivia | Canada | Angola |
| Bulgaria | China | Japan | Bangladesh |
| Chile | Colombia | Mexico | Belarus |
| Croatia | Ecuador | New Zealand | Bosnia and Herzegovina |
| Cyprus | Egypt | South Korea | Brazil |
| Denmark | El Salvador | United States of America | Cuba |
| Estonia | Ghana | | Dominican Republic |
| Finland | Guatemala | | Honduras |
| France | Indonesia | | India |
| Germany | Iran | | Iraq |
| Greece | Kenya | | Israel |
| Hungary | Kuwait | | Kazakhstan |
| Ireland | Lebanon | | Mauritania |
| Italy | Malaysia | | Pakistan |
| Latvia | Moldova | | Philippines |
| Lithuania | Morocco | | Russian Federation |
| Luxembourg | Nigeria | | Singapore |
| Netherlands | Oman | | State of Palestine |
| Norway | Panama | | Thailand |
| Poland | Peru | | Ukraine |
| Portugal | Qatar | | United Arab Emirates |
| Slovakia | Saudi Arabia | | Viet Nam |
| Slovenia | Serbia | | |
| Spain | Seychelles | | |
| Sweden | South Africa | | |
| Switzerland | Sri Lanka | | |
| Turkey | Tanzania | | |
| United Kingdom | Zambia | | |

Table A.11: Country-by-Country Impacts in Ban Amendment Counterfactual

This table reports the country-level results of the Ban Amendment counterfactual (See Section 5.4). All figures are in % of 2015 GDP.

| Country | ΔGross Benefits | ΔEnvironmental Costs | Country | ΔGross Benefits | ΔEnvironmental Costs |
|---|---|---|---|---|---|
| Egypt | -0.034 | 0.089 | Finland | -0.00162 | -0.00822 |
| Latvia | -0.028 | 0.245 | Singapore | -0.00116 | 0.0243 |
| Pakistan | -0.026 | 0.036 | Morocco | -0.00114 | 0.0527 |
| Indonesia | -0.025 | 0.067 | Zambia | -0.000513 | -0.0486 |
| Guatemala | -0.024 | 0.175 | Rep. of Korea | 0.000751 | -0.00127 |
| Angola | -0.022 | 0.050 | Bahrain | 0.000786 | -0.0194 |
| United Rep. of Tanzania | -0.022 | 0.108 | United Arab Emirates | 0.00114 | 0.00975 |
| Cyprus | -0.021 | 0.200 | Rep. of Moldova | 0.00121 | 0.164 |
| New Zealand | -0.021 | 0.133 | Serbia | 0.00123 | 0.193 |
| South Africa | -0.021 | 0.063 | Luxembourg | 0.0013 | -0.0143 |
| Dominican Rep. | -0.020 | 0.202 | Seychelles | 0.00276 | 0.00352 |
| Austria | -0.020 | 0.064 | Occ. Palestinian Terr. | 0.00357 | -0.0697 |
| Hungary | -0.019 | 0.108 | Qatar | 0.00367 | -0.00882 |
| Netherlands | -0.019 | 0.007 | China, Macao SAR | 0.00369 | -0.0274 |
| Russian Federation | -0.019 | 0.111 | Lithuania | 0.0042 | -0.12 |
| Greece | -0.018 | 0.097 | Mauritania | 0.00446 | 0.021 |
| Slovenia | -0.017 | 0.069 | Sweden | 0.00491 | -0.0303 |
| Estonia | -0.016 | 0.257 | France | 0.00502 | -0.0235 |
| Turkey | -0.015 | 0.040 | Iran | 0.00623 | -0.0134 |
| Bangladesh | -0.015 | 0.013 | Slovakia | 0.00633 | -0.0962 |
| Lebanon | -0.015 | 0.121 | Kazakhstan | 0.0085 | -0.0512 |
| Viet Nam | -0.014 | -0.004 | Kenya | 0.00885 | -0.0383 |
| Ukraine | -0.014 | 0.147 | Peru | 0.009 | -0.0273 |
| Iraq | -0.014 | 0.047 | Honduras | 0.00903 | -0.165 |
| Italy | -0.012 | 0.034 | El Salvador | 0.0104 | -0.0246 |
| Spain | -0.012 | 0.043 | Bulgaria | 0.0105 | -0.145 |
| Saudi Arabia | -0.012 | 0.039 | Brazil | 0.0107 | -0.0436 |
| Ecuador | -0.012 | 0.110 | Israel | 0.0111 | -0.0462 |
| Kuwait | -0.012 | 0.045 | Malaysia | 0.012 | -0.0188 |
| Philippines | -0.010 | 0.037 | China, Hong Kong SAR | 0.0128 | 0.0193 |
| Norway | -0.009 | 0.043 | Ghana | 0.014 | -0.0747 |
| Ireland | -0.009 | 0.051 | Switzerland | 0.0144 | -0.0405 |
| India | -0.009 | 0.010 | Mexico | 0.0144 | -0.0607 |
| Bolivia | -0.007 | 0.088 | Oman | 0.0145 | -0.00559 |
| Nigeria | -0.006 | 0.008 | Portugal | 0.0153 | -0.127 |
| Belgium | -0.006 | -0.001 | Afghanistan | 0.0165 | -0.0435 |
| Croatia | -0.006 | 0.036 | Poland | 0.0177 | -0.0663 |
| Germany | -0.005 | 0.008 | Cuba | 0.0178 | -0.136 |
| United Kingdom | -0.005 | -0.003 | Chile | 0.0181 | -0.155 |
| Panama | -0.005 | 0.097 | Thailand | 0.0185 | -0.0542 |
| Japan | -0.004 | 0.002 | Costa Rica | 0.0189 | -0.212 |
| Canada | -0.004 | 0.001 | Denmark | 0.0227 | -0.119 |
| Australia | -0.004 | 0.003 | Sri Lanka | 0.0237 | -0.0999 |
| United States of America | -0.003 | 0.0002 | Colombia | 0.0343 | -0.129 |
| China | -0.003 | 0.010 | Belarus | 0.0389 | -0.446 |
| Bosnia Herzegovina | -0.003 | 0.146 | | | |

Table A.12: Robustness Checks

Each panel in this table reports the change in environmental costs from a robustness check exercise for each counterfactual. Panel B presents estimates from excluding the $CO_2$ component from social marginal cost of waste disposal while Panel C presents estimates using alternative measures of social marginal cost of waste disposal that I back out from the model. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The $\Delta$ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. All figures are % of 2015 GDP. See Section 5.5 for details on the methodology.

| | Δ Environmental Costs (% of GDP) | | | |
|---|---|---|---|---|
| | Autarky | Waste-Autarky | China Ban | Ban Amendment |
| | **Panel A: Externality Functional Form** | | | |
| Rich | -0.65 | 0.003 | 0.001 | 0.0004 |
| Middle | -0.35 | 0.003 | -0.0001 | 0.002 |
| Poor | -0.85 | 0.009 | -0.001 | 0.005 |
| | **Panel B: Social Marginal Cost of Disposed Waste** | | | |
| Rich | -0.23 | 0.012 | 0.004 | 0.002 |
| Middle | -0.43 | 0.015 | -0.002 | 0.007 |
| Poor | -0.25 | 0.031 | -0.007 | 0.016 |
| | **Panel C: Social Marginal Costs from the Model** | | | |
| Rich | -0.76 | 0.048 | 0.013 | 0.009 |
| Middle | -1.61 | 0.049 | 0.009 | 0.033 |
| Poor | -1.55 | 0.16 | -0.065 | 0.093 |

Table A.13: Robustness Checks–Alternative Estimates for Trade Elasticities

Each panel in this table reports the results from a counterfactual exercise. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The Δ Gross Benefits are calculated in terms of proportional changes in real income, $w_j \bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$, and Δ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP.

| | Δ Gross Benefits | | Δ Environmental Costs | |
|---|---|---|---|---|
| Income Group | (%GDP) | (billions \$) | (%GDP) | (billions \$) |
| | **Panel A: Autarky** | | | |
| Global | -4.39 | -3118 | -0.38 | -268 |
| Rich | -4.70 | -2140 | -0.34 | -155 |
| Middle | -3.74 | -838 | -0.48 | -107 |
| Poor | -4.51 | -139 | -0.19 | -6 |
| | **Panel B: Waste-Autarky** | | | |
| Global | -0.029 | -21 | 0.046 | 33 |
| Rich | -0.037 | -17 | 0.062 | 28 |
| Middle | -0.014 | -3 | 0.018 | 4 |
| Poor | -0.019 | -0.59 | 0.024 | 0.74 |
| | **Panel C: High-Value Waste-Autarky** | | | |
| Global | -0.018 | -13 | 0.051 | 36 |
| Rich | -0.021 | -10 | 0.062 | 28 |
| Middle | -0.013 | -3 | 0.035 | 8 |
| Poor | -0.006 | -0.2 | 0.011 | 0.33 |
| | **Panel D: Low-Value Waste-Autarky** | | | |
| Global | -0.008 | -6 | -0.010 | -7 |
| Rich | -0.012 | -6 | -0.011 | -5 |
| Middle | -0.003 | -0.6 | -0.007 | -2 |
| Poor | 0.009 | 0.3 | -0.021 | -0.7 |
| | **Panel E: China Ban** | | | |
| Global | -0.001 | -0.8 | 0.0002 | 0.2 |
| Rich | -0.002 | -1 | 0.002 | 1 |
| Middle | 0.0005 | 0.1 | -0.003 | -0.7 |
| Poor | 0.008 | 0.2 | -0.003 | -0.1 |
| | **Panel F: Ban Amendment** | | | |
| Global | -0.007 | -5 | 0.012 | 8 |
| Rich | -0.007 | -3 | 0.008 | 4 |
| Middle | -0.007 | -2 | 0.019 | 4 |
| Poor | -0.007 | -0.2 | 0.015 | 0.5 |