Economic Impact of International Waste Flows*

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Abstract

I quantify the economic impact of international trade in waste. I build a structural gravity model in which waste is a byproduct of manufacturing and an input to recycling while waste flows are governed by both comparative advantage and the pollution haven effect. Although existing patterns of waste trade make countries of all income levels better off, low-value waste trade makes middle-income countries worse off. China's 2018 ban on low-value waste imports made China and several lower-income countries better off. The economic loss in lower-income countries due to low-value waste trade is attributed to the pollution haven effect.

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JEL Classification: F18, F64, H23, Q56

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International trade in waste has experienced considerable growth over the past three decades. Notably, waste trade saw a five-fold increase in volume from 34 million tons in 1988 to 157 million tons in 2015. Despite countries' active participation, waste trade is highly contentious as its economic and environmental ramifications on all trading partners are unclear. While waste trade can create negative externalities locally in importing countries via the health and environmental hazards posed by disposal of the nonrecyclable portion of waste (Kirby, 1994), it also creates benefits similar to regular trade like cheaper recycled materials, which can be used in manufacturing production, increased employment opportunities, and additional income. The environmental considerations have led countries to impose a range of controls on waste trade, from multilateral agreements, such as the Basel Convention in 1992, to the unilateral ban on imports of select waste types by China in 2018. Recent work by Li and Takeuchi (2021); Unfried and Wang (2022), Shi and Zhang (2022), and Sigman and Strowe (2024) quantifies the environmental costs of China's 2018 ban through the impact on air pollution and waste-management. However, a full assessment of the impact of waste trade and the associated regulations is only possible through a quantification of their gross economic benefits, which then facilitates a comparison with the environmental costs of waste trade.

I quantify the economic benefits of international trade in waste across countries. To this end, I extend the Ricardian model of trade by Eaton and Kortum (2002) by adding the generation of waste as a byproduct of manufacturing, whereafter waste itself is input to recycling. In the presence of negative externalities, both comparative advantage, due to technological differences, and the *pollution haven effect*, due to differences in environmental regulations, govern the direction of waste flows across countries. I assess heterogeneity in economic gains by waste type by allowing differences in abilities of countries to generate and reprocess two kinds of waste—high-value and low-value waste. Rich countries like the US, which are technologically superior, specialize in high-value waste like metals. In contrast, lower-income countries like India, with abundant cheap labor, specialize in low-value waste, comprising a mix of materials like plastics that require manual sorting.

My model also captures the pollution haven effect in relative flows of the two types of waste. Specifically, I capture the empirical fact that richer countries, which are also high environmental regulation countries, import a larger share of high-value waste than low-value waste by formulating *non-homothetic* production in a country's recycling sector that uses both types of waste to produce a recycled good. To my knowledge, mine is the first paper to formulate a structural gravity framework providing microfoundations for waste generation and waste flows as well as quantifying its economic effects.

The size of gains to trade hinges on the elasticity of the trade flows with respect to trade barriers. A challenge in estimating the model parameters in a structural gravity framework is disentangling the effect of trade elasticities from that of trade costs. In my framework, the *simultaneous* estimation of the parameters for the two waste sectors and manufactured goods presents an additional challenge. My solution is to perform the estimation sequentially. I first estimate the trade elasticities using model predictions to construct an economic measure of trade barriers for which the geographic barrier variables serve as instruments. Then, I estimate the rest of the key parameters of the model, including trade costs, by simulating the world economy. I use cross-sectional trade data on manufactured goods, high-value waste, and low-value waste that represents over 90% of world trade for the estimation. I find that low-value waste is more sensitive to trade barriers than high-value waste and manufactured goods. Specifically, a 1% decrease in trade costs causes a 7.3% increase in manufactured goods and high-value waste, and a 9.8% increase in low-value waste flows. To my knowledge, mine is also the first paper to provide estimates of the trade elasticities for international waste flows.

Another contribution of my paper is to consider a variety of counterfactual simulations to quantify the economic consequences of waste trade. The global gains to waste trade comprise 0.43% of gains to all trade while waste trade accounts for 0.7% of overall trade by value. Thus, per unit of trade value, waste trade generates only about 60% of the gains of regular trade. Differentiating the gains to waste trade by income level, I find that poor countries see the largest gains of 0.021% of GDP. Allowing trade in waste shifts the demand by recycling sectors across countries from low-value waste to high-value waste leading to a *rise* in the price of low-value waste relative to recycling. As lower-income countries specialize in low-value waste, this income group of countries disproportionately benefit from the price increase. While waste trade accounts for only a small portion of global trade in commodities, its general equilibrium effects are non-negligible for certain smaller-sized, developing economies.

I also study heterogeneity in gains by type of waste. While high-value waste trade creates economic effects qualitatively similar to the overall waste trade, low-value waste trade hurts middle-income countries. Allowing only low-value waste trade increases the scale of generation of low-value waste while its relative price *falls*. This price decrease makes middle-income countries, which specialize in low-value waste, worse off. Imposing regulation akin to China's 2018 import ban on select waste materials has effects qualitatively similar to a ban on all low-value waste trade. Like an overall low-value waste trade ban, the scale of low-value waste generation declines, making lower-income countries better off. Not only does the policy serve the lower-income countries in aggregate, but it also achieves its intended goal by increasing China's gross benefits. This finding supports the evidence in Sigman and Strowe (2024) that the Chinese policy resulted in countries reducing low-value plastic waste exports not only to China but also to other lower income countries. The main qualitative conclusions in my paper are robust to considering alternative estimates of trade elasticities, recycled good as an intermediate input to manufacturing, and a range of externality costs of waste disposal. On eliminating the pollution haven effect, however, even low-value waste trade makes the lower-income countries better off.

This paper contributes to studies on factors determining international trade in waste by providing theoretical microfoundations for waste generation and international waste flows. Papers in this line of research either use a reduced-form approach to test for *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 for landfilling (Copeland, 1991). However, a major source of economic incentives to import waste is the demand for recycled waste in local manufacturing production. Hence, in my framework, I abstract away from land-filling while allowing demand for waste by a country to arise in its recycling sector for "productive" reasons rather than for final disposal.

A limited literature studies the effects of waste trade regulations, such as the Basel Convention (Kellenberg and Levinson, 2014) and China's 2013 Operation Green Fence rejecting highly contaminated waste imports (Sun, 2019; Balkevicius et al., 2020), on international waste trade using the difference-in-differences approach. Recent work by Li and Takeuchi (2021); Unfried and Wang (2022), Shi and Zhang (2022), and Sigman and Strowe (2024) studies the more local impacts of China's 2018 ban on air pollution and waste-management. My use of a structural framework allows me to incorporate general equilibrium forces, to consider a richer set of counterfactuals, and to explicitly quantify economic gains, all of which is infeasible with a reduced-form framework. I also contribute to the literature on the *pollution haven hypothesis* (Copeland and Taylor, 1994, 2004; Antweiler et al., 2001), which posits migration of dirty industries to low environmental regulation countries with trade liberalization, by considering a separate channel through which trade can affect the environment, i.e., via movement of waste residue itself.

My paper also speaks to the relationship between trade imbalance, unit trade costs, and the quality-mix of exports in Hummels and Skiba (2004) and Lee et al. (2020b). Hummels and Skiba (2004) show that smaller unit costs of transportation deteriorate the quality-mix of exports, leading to exports of heavier goods or waste, as the relative price of high-quality goods increases. Further, Lee et al. (2020b) show that such decreases in unit trade costs are generated by a trade surplus in the importing country, while overlooking the role of environmental regulations in governing waste flows. In contrast, I show that even after controlling for the bilateral trade imbalances, comparative advantage and pollution haven effect play a key role in determining the pattern of waste trade. As in my paper, Lee et al. (2020b) establish that the externality costs of waste trade may exceed its economic benefits in certain cases. However, I am further able to distinguish between the effects of different waste types by using weight-to-value ratios to divide the waste categories into high- and low-value waste as a close approximation to waste that is readily recyclable and relatively unrecyclable.

My paper contributes to the literature studying the welfare effects of trade in goods using a structural gravity framework by endogenizing the generation of waste in manufacturing. Shapiro (2016) also builds a structural gravity model to quantify the effects of international trade on CO_2 emissions, where the emissions depend directly on equilibrium production and consumption decisions. By contrast, my formulation allows for a rich interaction between manufacturing production, waste generation, and trade that plays out in the counterfactual simulations. I also contribute to this literature methodologically by proposing a sequential estimation approach for the model parameters.

The paper is organized as follows: Sections 2 and 3 present the data and the empirical facts on international waste flows, respectively. Section 4 presents the theoretical framework and the strategy for counterfactual calculations. Section 5 presents the estimation strategy and estimates of model parameters while Section 6 presents the results from the counterfactuals. Section 7 concludes.

2 Data

With the goal of quantifying the economic gains from waste trade in a static framework, I use cross-sectional bilateral 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 those 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 value in U.S. dollars and weight in kilograms (kg) of bilateral flows is available. Since industrial waste represents 94-97% of global waste (Liboiron, 2016; Kaza et al., 2018) and the waste in my sample is primarily industrial in nature, I also obtain data on bilateral trade in manufactured goods, codes 1-8 under SITC.Rev4.[1]

Other variables of interest include income levels and wage rate. Thus, I obtain data,

[1] 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.

in current USD, on gross domestic product (GDP) and GDP per capita, used as a proxy for wage rate, from the World Development Indicators database. 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). I also use their bilateral indicators for contiguity and common official language. Further, I construct bilateral indicators for countries that share a free trade agreement (FTA) using data from the World Trade Organization.[2]

To control for the relationship between trade imbalance and the quality composition of trade (Hummels and Skiba, 2004; Lee et al., 2020b), I construct a measure of bilateral trade surplus from the importing country's perspective. To do so, I first gather the bilateral trade volume data on those commodities that can be shipped in the same transport vessels as waste, i.e., I exclude trade data on animal and food products as well as mineral oils and gases (HS codes: 01-24 and 2705-2713), which require special shipping containers. Then, I construct the trade surplus from the importing country's perspective as the ratio of its total export volume to import volume to use as control in all my specifications.

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).[3] The EPI quantifies the environmental performance of a country's policies by combining different indicators on the protection of human health and ecosystem vitality. While EPI may be an imperfect measure of the stringency of environmental policies of a country, it is the only measure in my knowledge that provides this information on a comprehensive list of countries. I further use population and output per unit of land, constructed using data on land area in square kilometres, from the WDI.

To gather the empirical facts, I use waste trade data among 224 countries and territories. Aggregating the flows across 62 categories of waste in my sample for each exporter-importer pair and assuming that missing trade flows are actually zero trade flows, I obtain 49952 observations (for 224×223 country pairs). 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 are among the major importers of waste (See Figures A.1 and A.2).

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

[3] Starting in 2006, the EPI Report is published every other year, so the EPIs for 2015 were unavailable.

To capture the heterogeneity in waste flows by recyclability, and therefore, their value and environmental damage, I disaggregate waste flows into two types—high-value and low-value—as a close approximation to relatively recyclable and unrecyclable waste. To do so, I construct the value-to-weight ratios of the 62 categories as the ratio of the average dollar value and average weight of trade in each category. 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.6). Figure 1 shows that while 75% of the categories in high-value waste are metals, low-value waste is a mix of different materials, including plastics and paper.[4] The categories within low-value waste also overlap substantially with the categories banned by China in 2018, arguably making these categories more environmentally damaging. While the empirical facts are robust to an alternative above- and below-median split, I prefer the top- and bothom-tercile split as the baseline as it matches closely with China's banned categories.

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 (See Figures A.3 and A.4). Therefore, the combined evidence in Figure A.1 to A.4 seems to support a pollution haven effect in relative rather than aggregate waste flows.

3 Empirical Facts

In this section, I present a series of empirical facts motivating the presence of the two forces—comparative advantage and the pollution haven effect—that govern the pattern of waste flows across countries. I document these empirical facts based on reduced-form gravity regressions, where the value of bilateral trade from country i to j in waste type s, denoted by X_{sij}, is directly proportional to income levels, Y_i and Y_j, and inversely related to trade barriers, τ_{ij}:

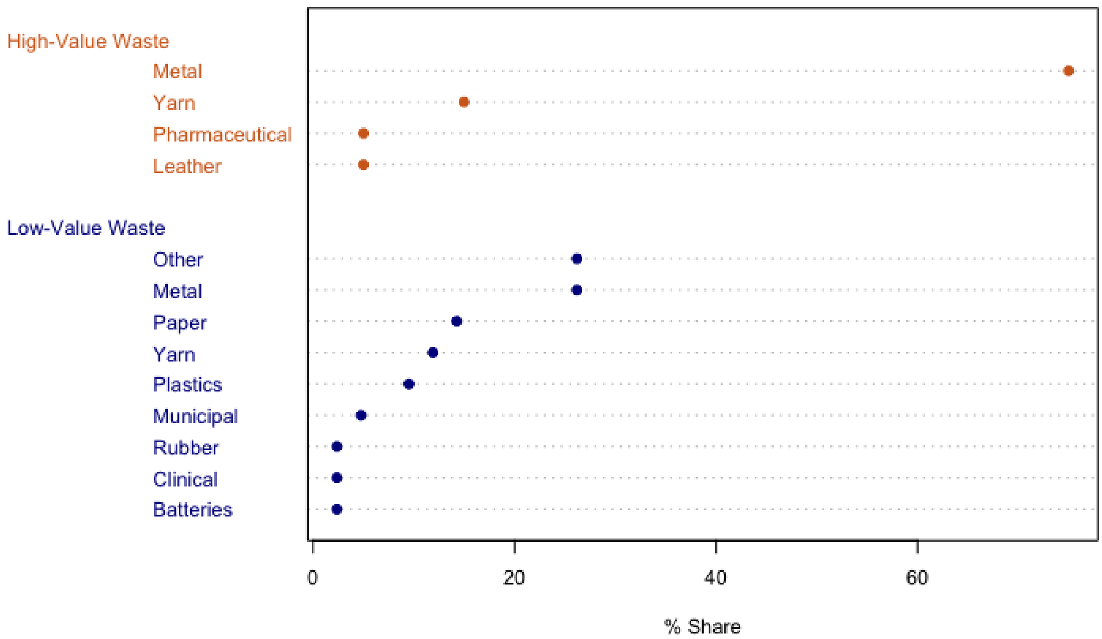
$$X_{sij} = \exp\left(\beta_0 + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_{3s} \ln \tau_{ij} + \boldsymbol{\beta_4} \mathbf{Z_i} + \boldsymbol{\beta_5} \mathbf{Z_j}\right) \times \eta_{ij}. \tag{1}$$

The term τ_{ij} comprises geographic barrier variables: distance, contiguity, and common language.[5] The vector $\mathbf{Z_i}$ includes logged exporter controls, exporter's level of environ-

[4] 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.

[5] 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

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 the high-value waste is 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 the high-value waste, yarn mainly comprises precious fibres including silk, wool, and fine animal hair, while as a part of the low-value waste, it comprises coarse animal hair, cotton, and synthetic fibres.

mental regulation, population, and GDP per unit of land, while $\mathbf{Z_j}$ includes analogous importer-level controls. Finally, η_{ij} is the error term with $E[\eta_{ij}|Y_i, Y_j, \tau_{ij}, \mathbf{Z_i}, \mathbf{Z_j}] = 1$. Allowing β_3 to vary by waste type, as denoted by subscript s, I capture heterogeneity across types in the sensitivity of trade flows to trade barriers. To estimate Equation (1), I use the Poisson pseudo-maximum likelihood (PPML) method, which yields consistent and efficient estimates (Silva and Tenreyro, 2006). To account for unobservable heterogeneity at the country level, I also estimate a specification with exporter and importer effects.

Further, to study the choice between high-value and low-value waste across countries, I estimate the following specification:

$$arcsinh(Ratio_{ij}) = \beta_0 + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 \ln \tau_{ij} + \boldsymbol{\beta_4}\mathbf{Z_i} + \boldsymbol{\beta_5}\mathbf{Z_j} + \varepsilon_{\mathbf{ij}}, \qquad (2)$$

exception of the United States. Thus, this variable has little meaningful variation, and I do not include it in the analysis.

where, $Ratio_{ij}$ is the fraction of total bilateral waste flows that are high-value and Y_i and Y_j are the exporter's and importer's per capita incomes, respectively. Since the dependent variable is a proportion, I adopt the variance-stabilizing inverse hyperbolic sine (IHS) transformation. Due to the prevalence of many zeros in the dependent variable, estimating this specification in log- or logit-form would result in the loss of those observations. Hence, I estimate the specification with an inverse hyperbolic sine transformation, which closely tracks the log function but is defined at zero (Bellégo et al., 2022).[6] Alternatively, I use the beta regression technique for modelling rates and proportions from Ferrari and Cribari-Neto (2004).[7] Due to the potential correlation between observations of the same trading partners, I cluster standard errors at the exporter-importer level in all specifications.

Before I discuss empirical facts by type of waste, note that even trade in waste conforms with the gravity model of international trade, i.e. waste flows are positively associated with incomes of trading partners and negatively associated with trade barriers, as shown in Table 1

Fact 1: Low-value waste is more sensitive to trade barriers than high-value waste.

Table 1 shows that the negative elasticity of low-value waste trade is larger in magnitude than that of high-value waste trade with respect to distance. Specifically, in columns 3-4, the coefficient on the interaction between logged-distance and low-value waste indicator is negative and statistically significant at 1% level. High-value waste is arguably more easily recyclable, and thus, valuable, than low-value waste. Thus, trade in this type of waste is not as sensitive to trade costs as low-value waste trade. The observed trade pattern may also be owing to differences in waste-processing technology in different countries. Processing high-value waste likely requires technology that is available in only select 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, which require more manual sorting. Thus, comparative advantage not only governs the scale of waste trade but also relative trade in the two types of waste across countries.

[6] The formula for the inverse hyperbolic sine is $\text{arcsinh}(x) = \ln(x + \sqrt{x^2+1})$. The function $\text{arcsinh}(x) - \ln(2)$ tracks $\ln(x)$ very closely for all positive integers, much closer than $\ln(x+1)$. Thus, except for an intercept shift of $\ln(2)$, the coefficients are comparable to using the log transformation if all values of $Ratio_{ij}$ were positive.

[7] Actually, beta regression is used in modelling continuous variable y that lies in the open standard unit interval $(0, 1)$. In my sample, since some observations lie at the extremes 0 and 1, I apply the standard transformation $(y(n-1)+0.5)/n$, with sample size n, following Smithson and Verkulien (2006) and Cribari-Neto and Zeileis (2010).

Table 1: Gravity Equation Estimates 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 and Columns 3 and 4 with bilateral flows by two types of waste, high- and low-value waste. Although I include trade flows among 224 countries or territories in all specifications, the number of observations varies by specification due to a large number of missing values in covariates, singletons for a trade partner, or observations separated by fixed effects. See Section 3 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.

	Total Waste Flows		Waste Flows by Type	
log(Exporter's GDP)	1.129***		1.129***	
	(0.172)		(0.172)	
log(Importer's GDP)	0.788***		0.788***	
	(0.0987)		(0.0991)	
Low-value			1.880***	1.645***
			(0.549)	(0.562)
log(Distance)	-0.667***	-0.881***	-0.567***	-0.799***
	(0.0782)	(0.0673)	(0.0771)	(0.0829)
log(Distance)×Low-value			-0.150**	-0.121*
			(0.0683)	(0.0682)
Contiguity	0.929***	0.984***	1.012***	1.028***
	(0.238)	(0.197)	(0.234)	(0.225)
Contiguity×Low-value			-0.125	-0.0663
			(0.174)	(0.201)
Common Language	0.0123	0.150	0.0295	0.115
	(0.157)	(0.167)	(0.172)	(0.223)
Common Language×Low-value			-0.0255	0.0524
			(0.235)	(0.237)
Constant	-20.87***	25.44***	-22.75***	23.70***
	(4.917)	(0.573)	(4.898)	(0.697)
Controls	Y	N	Y	N
Exporter FE	N	Y	N	Y
Importer FE	N	Y	N	Y
Pseudo-R^2	0.788	0.899	0.752	0.860
Observations	28,392	43,059	56,784	86,118

Fact 2: As income increases, a greater share of a country's waste imports is of high value.

To further understand the factors influencing the choice between importing the two types of waste by a country, I estimate Equation (2), where the dependent variable is the fraction of high-value waste traded. Columns 1-2 in Table 2 reveal that controlling for other factors, the importer's per capita income is positively and statistically significantly associated with the fraction of spending on high-value waste in total waste imports. Thus, richer countries allocate a greater share of their expenditure to importing high-value waste than to importing low-value waste. However, this choice between the two types of waste could be driven by price differences between high- and low-value waste.

Table 2: Choice between Two Types of Waste

This table reports the results from estimation of Equation (2) and with Ratio as the dependent variable in Beta regressions. In columns 1 and 2, Ratio is the fraction of dollar-value of total waste flows that is high-value while in columns 3 and 4, it is the fraction of weight of total waste flows that is high-value. As total waste flows contain many zero observations, this ratio contains several undefined values that are dropped from the regression, reducing the number of observations dramatically. See Section 3 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 (by Value)		Ratio (by Weight)	
	IHS	Beta	IHS	Beta
log(Exporter's GDP per capita)	-0.00505	0.0296	-0.0158***	-0.00383
	(0.00641)	(0.0199)	(0.00559)	(0.0178)
log(Importer's GDP per capita)	0.0457***	0.131***	0.0170***	0.0835***
	(0.00610)	(0.0182)	(0.00508)	(0.0158)
log(Distance)	-0.00278	-0.0742***	0.0187***	-0.0296**
	(0.00455)	(0.0137)	(0.00366)	(0.0115)
Contiguity	-0.0304**	-0.00889	-0.0427***	-0.0458
	(0.0148)	(0.0460)	(0.0113)	(0.0368)
Common Language	-0.0118	-0.00247	-0.0159*	-0.0173
	(0.00967)	(0.0292)	(0.00819)	(0.0255)
Constant	-1.705***	-7.623***	-0.820***	-6.143***
	(0.177)	(0.535)	(0.149)	(0.463)
Controls	Y	Y	Y	Y
R^2	0.125		0.076	
Observations	6,135	6,135	6,075	6,075

Hence, I assess the robustness of my results to using the ratios constructed based on the weight of waste traded rather than value. Columns 3-4 show that my results are robust to this change, indicating that a larger share of high-value waste in imports of richer countries is due to the volumes traded and not price differences. As richer countries are also higher environmental regulation countries, this finding points towards the presence of a pollution haven effect in the choice between high- and low-value waste in addition to the comparative advantage forces above. I find that all my reduced-form estimates pertaining to Facts 1-2 are robust to the inclusion of bilateral trade imbalance as a control, which rules out differences in unit trade costs driving the results above.

4 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 modeling of comparative advantage and pollution haven effect in the rest of this section.

4.1 Preferences

Households consume two commodities, manufactured goods and the recycled good. Assuming Cobb-Douglas preferences across the composite of manufactured goods and the recycled product, 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, σ_m. The utility function for a household in country j is:

$$U_j = Q_j^{\alpha} C_j^{1-\alpha},$$

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 ν_m, and C_j denotes the consumption of the recycled good. Each household inelastically supplies one unit of labor. Thus, the social welfare of a country is given by its indirect utility:

$$V_j = \alpha^{\alpha}(1-\alpha)^{1-\alpha} \frac{Y_j}{P_j}, \tag{3}$$

where

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

is the real income. 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 4.4.1), and w_j is the wage rate.

4.2 Technology

Technology varies across goods, sectors, and countries. The efficiency of producing good ν_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 θ_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). In principle, one can parameterize T_j as a function of level of environmental regulation in a country to account for the pollution haven effect in overall waste flows. However, this country effect is absorbed by fixed effects when estimating the trade elasticities. Further, although I do not explicitly model the scale effects due to differences in environmental regulation across countries, they are subsumed by changes in T_j in policy counterfactuals.

The parameter θ_s, which varies by sector but not by country, governs the comparative advantage across varieties *within* a sector. The variability in technological draws is inversely related to the parameter θ_s. A greater variability in technological draws, i.e., a smaller θ_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 θ. This parameter also governs comparative advantage *across* sectors (Fieler, 2011). 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 θ_s is large, i.e. low-value waste, while the rich specialize in sectors where θ_s is small, i.e. manufactured goods.[8] Together, the parameters T_j and θ_s, which I structurally estimate, characterize comparative advantage in overall and relative flows in two types of waste. Estimates in Section 5.1 reveal that

[8] 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 τ_{sij} is the trade cost for exporting commodity s from country i to j. For a large θ_s, the first term is small, so wages swamp technological ability in determining the costs. Since wages are low for a poor country, it specializes in goods with a high θ. For a small θ, technology swamps wages, so a high-income country, with high levels of aggregate efficiency, specializes in a sector with low θ. See Fieler (2011) for details.

low-value waste flows are indeed more sensitive to trade barriers than high-value waste flows, consistent with *Fact 1* in Section 3.

4.3 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. Considering an alternative framework where the recycled product is an intermediate input to manufacturing, the main qualitative conclusions of the paper continue to hold (See Appendix A). For simplicity, I model the two types of waste as inputs to production even though they are byproducts.[9] 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 ν_m, w_j is the wage rate, and u_{sj} is the unit price of collection of waste type s. The government may not necessarily internalize the external cost of waste generation by setting this price, u_{sj}, exogenously. Depending on whether the waste byproduct is valuable, this price of waste may be positive or negative for the manufacturer. If waste is not valuable, the manufacturer would *pay* a positive price or tax on waste generation and collection. If waste is valuable, this value is probably negligible relative to the value of final output unless the waste is appropriately managed or treated, in which case too the manufacturer pays a positive price for waste collection.

The term $z_j(\nu_m)$ is the efficiency of producing good ν_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 waste generation. The revenue earned by the government via waste collection is given as a lump-sum subsidy to domestic recycling.

Modeling the source of comparative advantage for a commodity (waste) which is both a byproduct of manufacturing and an input to recycling presents a challenge in my framework. To quantify the source of comparative advantage in waste trade separately from manufacturing trade, I allow the waste flow from manufacturing to recycling by way of a waste management sector. The two types of waste—high-value and low-value—collected by the government are converted to usable form in a domestic waste-management sector

[9] 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.

that is specific to that kind of waste. Each waste-management sector, $s \in \{h, l\}$, sorts the waste into a continuum of materials, $\nu_s \in [0, 1]$. The sector uses only one input, labor, to produce a sorted material. Assuming constant returns to scale, the unit cost of sorted material, ν_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 ν_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 ν_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 income 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 λ_j is the Lagrange multiplier associated with the cost-minimization problem. The demand for each type increases with the corresponding weight, α_s, and decreases with the corresponding price index, P_{sj}.

The term $\lambda_j^{\sigma_h - \sigma_l}$ determines the ratio of spending on the two types of waste, X_h and X_l. In this context, σ_s not only represents the elasticity of substitution but also the output elasticity of demand for inputs (Fieler, 2011). The more output the recycling sector produces, the higher the shadow price of recycled output, λ_j. Assuming that the elasticity of demand for high-value waste exceeds that of low-value waste ($\sigma_h > \sigma_l$), an increase in total output leads to a greater expenditure share for high-value waste. Additionally, λ_j increases with the income level of a country, as shown by the zero-profit condition of the recycling sector and the market-clearing condition of the recycled good in Section 4.4.3. Thus, a higher-income country allocates a larger proportion of its expenditure to high-value waste than low-value waste. As richer countries are also higher environmental regulation countries, the country- and waste-specific term, $\lambda_j^{\sigma_h - \sigma_l}$, captures the pollution haven effect in relative flows of high- and low-value waste across countries (See *Fact 2* in Section 3). Figure A.5 depicts the aforementioned connections between all the sectors within a country.

4.4 Trade

The categories of waste I consider are largely non-hazardous, industrial in nature.[10] Therefore, such waste holds a positive value to an importer.[11] In my framework, trade is subject to "iceberg" trade costs. To deliver one unit of variety ν_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.

4.4.1 Price Indices

With perfect competition, the total price of good ν_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 and its price equivalent to the price of a unit of labor, 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 ν_s in country j is the lowest of the prices offered by all exporters:

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

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:

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

[10] International trade in hazardous waste is regulated under the Basel Convention.

[11] The externality, however, may come from *volume* of this imported waste that ends up being unrecyclable and having to be disposed of. I consider such externality costs from waste trade in Appendix B.

where Γ is the gamma function, $\phi_{sj} = \sum_i T_i(w_i\tau_{sij})^{-\theta_s}$, and $\theta_s + 1 > \sigma_s$ is the necessary condition for a finite solution. The parameter ϕ_{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).

4.4.2 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_j and trade barriers τ_{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 in 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:

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

4.4.3 Market Clearing

The Lagrange multiplier associated with the recycling sector's cost-minimization problem, λ, 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:

$$\beta \sum_i X_{mji} + \sum_{s=\{h,l\}} \sum_i X_{sji} = w_j \bar{L}_j. \qquad \forall j \tag{14}$$

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 sector-specific trade costs, τ_{sij}. The three export sectors are manufacturing, high-value waste, and low-value waste, denoted by $s \in \{m, h, l\}$. The parameter α governs the fraction of household expenditure on manufactured goods and the recycled product; the parameters α_s and σ_s govern the size and the income elasticity of demand of the two types of waste, $s \in \{h, l\}$; and the trade elasticities, θ_s, govern the comparative advantage both *within* and *across* sectors. Given wages w_j, Equations (9) and (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). Higher-income countries allocate greater shares of expenditures to high-value waste due to $\sigma_h > \sigma_l$, and lower-income countries specialize in low-value waste due to higher trade elasticities (consistent with *Facts 1* and *2* in Section 3). The standard comparative advantage forces and the pollution haven effect determine waste trade patterns in the same direction. Low-value waste flows disproportionately toward lower income countries not only because of their cost advantage but also because of their lax environmental policy. Finally, the fraction of expenditure on goods from a particular country within a sector depends on technology discounted by input and trade costs.

4.5 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), I reformulate the equivalent variation in terms of a proportional change in real income, $\hat{Y}_j/\hat{P}_j$.[12] Thus, the equivalent variation for country j is:

$$EV_j = w_j \bar{L}_j \left(\frac{\hat{Y}_j}{\hat{P}_j} - 1 \right). \tag{15}$$

[12] To calculate the proportional change in real income, I require the proportional change in the 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}.

In Appendix B, I consider an extension where households also face externality costs from the volume of traded waste that is disposed of while in Section 6.4, I present a plausible range of environmental costs from waste trade for comparison against its benefits.

5 Estimation

In this section, I present the estimation methodology and the results for trade elasticities in Section 5.1, followed by the estimation strategy for the rest of the parameters in Section 5.2 and the fit between simulated flows at the estimated parameter values and actual trade flows in the data in Section 5.3. 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.

5.1 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:

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

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 while $S_j \equiv \ln \phi_{sj}$ is a measure of importing country j's prices. The heterogeneity due to environmental regulations is also absorbed by these country-specific effects. The estimation of Equation (16) requires data on expenditure on the three sectors in each country, X_{sj}. I use Equations (10) and (13) to measure this domestic expenditure as $\alpha w_j \bar{L}_j$ for manufacturing and $(1-\alpha) w_j \bar{L}_j$ for waste, using α calibrated in Section 5.2.[13]

One challenge in estimating the trade elasticities is that if we observe data on only the trade flows, changes in these trade flows can be rationalized by changes in either the trade elasticity parameter or the trade cost parameter. Hence, to identify the trade elastictiies, one must disentangle the effect of trade costs from that of trade elasticities. To

[13] 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 $\left(\frac{P_i \tau_{ij}}{P_j}\right)$ that is constructed using price data. This version of the gravity equation, likewise, requires imputed gross manufacturing production data to construct the dependent variable (Simonovska and Waugh (2014)).

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, ν, must be bounded above by the price at which a consumer can buy the good from another country i. Thus, for the producer of ν in country j to stay competitive, the following no-arbitrage condition must hold:

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

Further, 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).[14] Of the 155 basic-headings in the ICP data, I keep price data on 66 tradable commodities (Simonovska and Waugh, 2014), listed in Table A.2. The data from 2017 are temporally the closest to the trade data in my sample.[15] Thus, I exploit this 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. Due to lack of price data for waste, this measure of trade barriers does not vary by sector, $s \in \{m, h, l\}$. However, estimating Equation (16) separately for each sector, the intercept would absorb this unobservable heterogeneity in trade costs assuming that the trade costs vary by a fixed proportion among the three sectors, whether due to sector-specific trade agreements or nontariff measures, irrespective of the country-pair. The trade barrier measure also suffers from measurement error due to the approximation and errors in the price data itself (Simonovska and Waugh, 2014). Therefore, I estimate Equation (16) via two-stage least squares 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. However, Simonovska and Waugh

[14] 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).

[15] 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.

(2014) show that Eaton and Kortum's measure of trade barriers, constructed using a finite sample of prices, always *underestimates* the true trade costs. To address this issue, I instead use a modified trade cost measure, $2\hat{\tau}^1 - \hat{\tau}^2$, a sum of first-order statistic and the difference between first- and second-order statistics. Robson and Whitlock (1964) show that this modified measure is as efficient as $\hat{\tau}^1$ but less biased. Although Robson and Whitlock's 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.

5.1.1 Results

Table 3 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 the low-value waste sector, consistent with *Fact 1* in Section 3 and the pattern in reduced-form results in Table 1. 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, 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 lower 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.

My finding that low-value waste is more sensitive to trade barriers than high-value waste and manufactured goods speaks to the findings in Hummels and Skiba (2004). They show that smaller unit costs of transportation deteriorate the quality-mix of exports as a result of an increase in the relative price of high-quality goods leading to countries exporting heavier goods. Further, Lee et al. (2020b) show that such decreases in unit trade costs are generated by a trade surplus in the importing country. To rule out trade imbalance or unit shipping costs as an explanation of comparative advantage across sectors, I find that even after controlling for the trade surplus, $ln(trade\_volume_{ji}/trade\_volume_{ij})$, the magnitude of the trade elasticity estimates and the differences across sectors persist.

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.3, 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).

Table 3: Estimating Trade Elasticities with Trade Barrier= $2\hat{\tau}_{in}^1 - \hat{\tau}_{in}^2$

	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

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 5.1 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., 2020a). Standard errors clustered by exporter-importer pairs are in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1.

However, consistent with the argument in Simonovska and Waugh (2014), the difference in estimates between Tables A.3 and A.4 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 3. Additionally, the 2SLS estimate for manufactured goods in Table 3 is close to the median estimate of 8.28 in Eaton and Kortum (2002).

5.2 Price of Recycled Good, Technology, and Trade Costs

Equation (9) to 12 specify the value of trade flows from country i to country j in sector s:

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

where $\sum_{s\in\{h,l\}} \alpha_s^{1/\sigma_s} = 1$, the shadow prices of recycled good λ_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 input in recycling, α_h.

To perform the estimation, I set $\alpha = 0.993$ to match the share of manufacturing trade in total trade and $\alpha_h^{1/\sigma_h} = 0.456$ to match 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 β 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 matches one minus the share of expenditure on waste-management in overall income from manufacturing for the U.S. (Simmons, 2016).

Stage I: Price of Recycled Good. To estimate the shadow price of the recycled good, λ_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 λ_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 these market-clearing conditions. Solving for the technology parameters in this way further reduces the number of parameters to be estimated by 91.[16]

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

[16] 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.

form of trade flow equations as:

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

where ϵ_s is the error term. Under the restriction that the trade costs $\tau_{sij} \geq 1$ and $\tau_{sjj} = 1 \ \forall s$, I 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.[17]

Similar to Fieler (2011), I simulate the whole economy to account for endogenous variables, including wages, and zero trade flows. However, Fieler assumes trade costs to be 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). In contrast, as I'm dealing with the larger problem of solving for the parameters of three sectors simultaneously, I choose to infer trade costs in an analytically straightforward way as opposed to Fieler's NLLS and Simonovska and Waugh's SMM approach. My approach 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, 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.

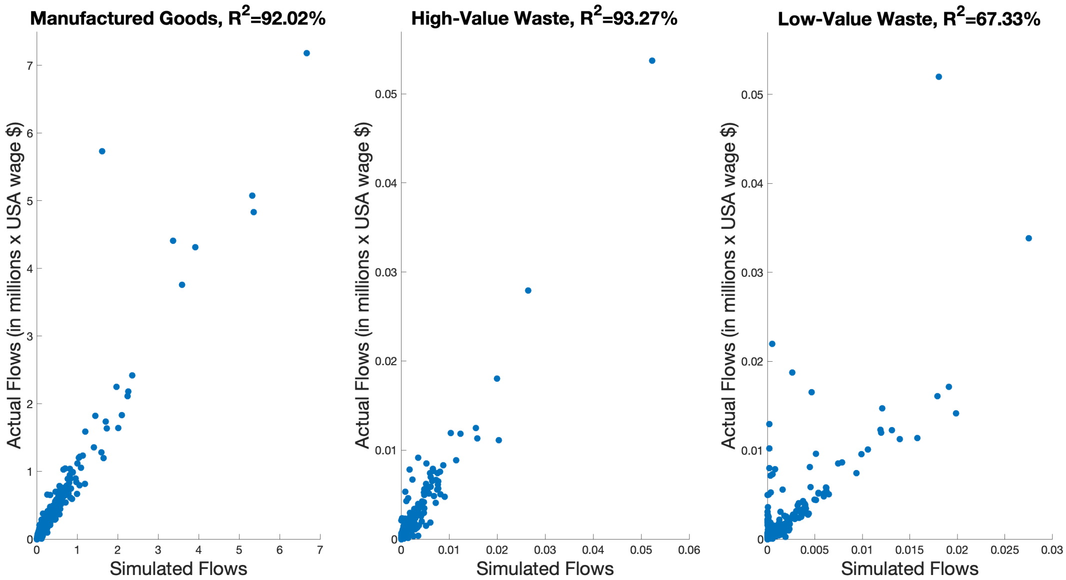
5.3 Goodness of Fit

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

[17] 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, $\tau_{sij} \geq 1$.

align with facts in the data. Figure 2 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. Thus, at first glance, the model fits the data well. Further, the model fit worsens when the ratio of expenditure on high- to low-value waste is independent of the income level of a country, i.e., $\sigma_h - \sigma_l = 0$. Specifically, the R^2 is lower by at least 8%, indicating the presence of a pollution haven effect in data.[18]

Figure 2: Goodness of Fit-Trade Flows



This figure shows the simulated flows at the estimated parameter values from Sections 5.1 and 5.2 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^2s from the OLS regression of actual flows on simulated flows.

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

[18] I experiment with different values of σ_h and σ_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%.

common language, and free trade agreement. For high- and low-value waste, I only include the dummies for contiguity and common language. Table 4 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 facts obtained in Section 3.

Table 4: Goodness of Fit-Estimated Trade Costs and Geographic Barriers

	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

This table presents the results from estimation of Equation (20). The dependent variables are the log of estimated trade costs from Section 5.2 for the three sectors in my model. See Section 5.3 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.

Figure A.7 shows that the residuals are larger for higher-income countries. Table 5 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.[19] 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 2 is lower than that for the other two.

Table 5: Goodness of Fit-Trade as a % of GDP

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%

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.

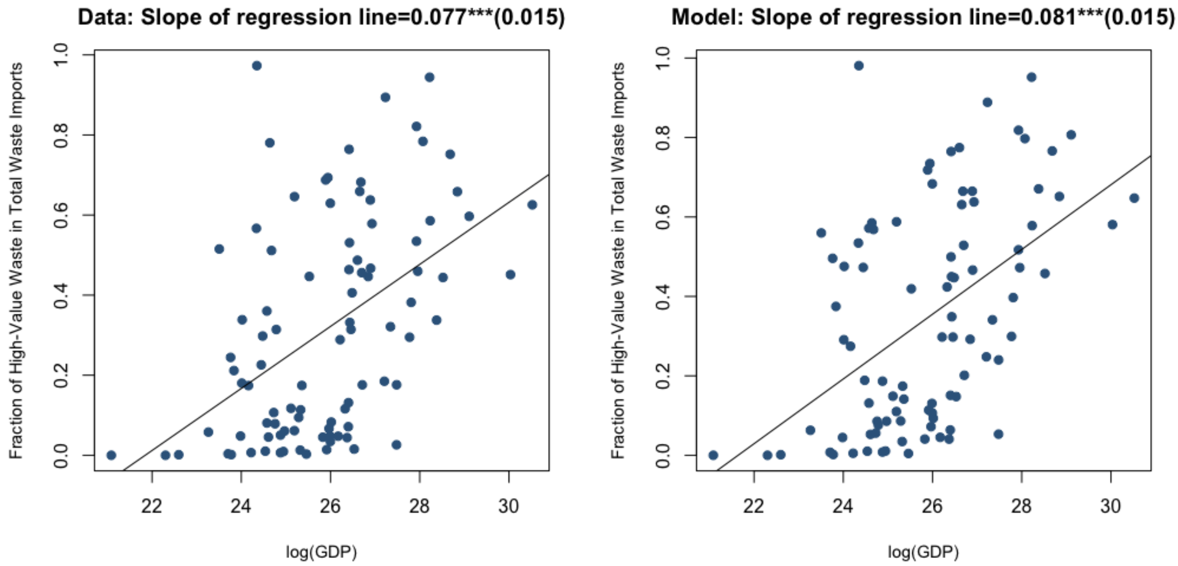
The model's prediction for trade among the rest of the countries is also close—5.513%, 0.011%, and 0.023% against 6.137%, 0.011%, and 0.022% in the data. Thus, the model captures the empirical fact that rich countries trade more in all three sectors than lower-income countries. Additionally, it accounts 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 3 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 total waste and income, and the model correctly predicts this relationship. Panel A in Table A.5 shows that the model also captures the increasing relationship between the sector-specific share of total trade in GDP, which I refer to as "openness" for that sector, and income per capita. Panel B in Table A.5 replaces income per capita

[19] 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.

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.

Figure 3: 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 $log(GDP)$.

6 Counterfactuals

In this section, I study a set of policy counterfactuals to study the effects of waste trade. 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 (26) to calculate the effect of the policy change.

6.1 Importance of Pollution Haven Effect

To study the role of pollution haven effect in altering trade patterns and economic gains, I impose a counterfactual where the ratio of expenditure on high- to low-value waste is independent of the income level of a country, i.e., $\sigma_h - \sigma_l = 0$. Table 6 shows that the rich countries lose \$4 billion while the lower-income countries gain \$2.4 billion on eliminating the pollution haven effect.

In the absence of PHE in relative flows of the two types of waste, the recycling sector in lower (high) income group now allocates a lower (higher) fraction of its expenditure to importing and reprocessing low-value waste. This change disrupts the demand for low-value waste by lower-income countries and high-value waste by high-income countries. Therefore, as poor (rich) countries specialize in exports of low-value (high-value) waste, their manufacturing production is adversely affected. However, recycling production in lower (high) income countries is made better (worse) off as they now reprocess a larger fraction of high-value (low-value) waste. Combining the effects on manufacturing and recycling production, I find that the benefits for the rich decrease and the benefits for the poor increase. Overall, not allowing pollution havens makes the lower-income countries better off at the expense of the rich. In addition to a global gain of \$2 billion that can be attributed to the PHE, the data support the presence of this effect (See Section 5.3). Therefore, I conduct the policy counterfactuals below while allowing for the pollution haven effect.

Table 6: Importance of Pollution Haven Effect

Income Group	Δ Gross Benefits (%GDP)	(billions \$)
Global	-0.003	-2
Rich	-0.009	-4
Middle	0.009	2
Poor	0.012	0.4

This table reports the benefits from removing the pollution haven effect, i.e. setting $\sigma_h = \sigma_l$. 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, $w_j \bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$. Baseline GDP is 2015 GDP. See Section 6.1 for further details.

6.2 Waste-Autarky

In the waste-autarky counterfactual, trade in only high-value waste and low-value waste is shut down, i.e., $\tau_{sin} \to \infty \ \forall i \neq n \ \forall s \in \{h, l\}$. This counterfactual shows the effect of not only changes in waste trade patterns but also of the changes in scale of production in all three sectors of the economy that ensue from this policy change. Column 1 in Panel A in Table 7 reports the gross benefits of prohibiting trade in waste. Globally, the gains due to trade in waste are 0.013% of GDP. While waste trade accounts for 0.7% of overall trade by value, the gains from waste trade are only 0.43% of the gains from overall trade.[20] This finding suggests that, per unit of trade value, waste trade creates about 60% the gains from regular trade.

Differentiating the gains by income group, I find that poor countries disproportionately benefit from trade in waste, at 0.021% of GDP. Two main forces govern the differentiated effects on countries. First, the non-homotheticity in the demand for the two types of waste makes richer countries spend a greater fraction on high-value waste than low-value waste. Thus, as countries gain access to import opportunities from opening to trade in waste, their recycling sector shifts its expenditure toward high-value waste and away from low-value waste. This substitution leads to a decline in the scale of generation of low-value waste even though more options for dealing with waste become available through the waste trade. Globally, 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 such volume changes. The second force is the commodity a country specializes in, governed by trade elasticities. Since low-income countries specialize in low-value waste, the relative price increase for this input benefits them the most. In summary, all country groups are better off with waste trade, i.e., restricting waste trade is inefficient due to incomplete specialization.

I find that high-value waste trade creates effects that are qualitatively similar to the overall waste trade. However, rich countries, which specialize in high-value waste export and disproportionately use it as an input in their recycling, gain the most—0.012% of GDP (omitted in the table for space). 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 by 1.5% while low-value waste generation increases by 1.8% as its relative price falls. As a result, middle-income countries, which specialize in low-value waste are worse off (Panel B in Table 7).

I assess the robustness of my estimates to a variety of alternatives: First, Simonovska and Waugh (2014) show that the true trade elasticity for manufactured goods is roughly

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

Table 7: Gross Benefits

Income Group	Baseline (%GDP)	Baseline (billions $)	Trade Elasticities (%GDP)	Trade Elasticities (billions $)	PHE (%GDP)	PHE (billions $)	Intermediate Input (%GDP)	Intermediate Input (billions $)
				Panel A: Waste-Autarky				
Global	-0.013	-9	-0.029	-21	-0.013	-9	-0.014	-10
Rich	-0.014	-6	-0.037	-17	-0.015	-7	-0.016	-7
Middle	-0.009	-2	-0.014	-3	-0.007	-1	-0.013	-3
Poor	-0.021	-0.6	-0.019	-0.6	-0.028	-0.9	0.002	0.05
				Panel B: Low-Value Waste-Autarky				
Global	-0.004	-3	-0.008	-6	-0.004	-2.5	-0.002	-1
Rich	-0.006	-3	-0.012	-6	-0.003	-1	-0.002	-1
Middle	0.001	0.2	-0.003	-0.6	-0.003	-0.8	-0.001	-0.1
Poor	-0.004	-0.1	0.009	0.3	-0.012	-0.4	0.001	0.04
				Panel C: China Ban				
Global	-0.002	-1	-0.001	-0.8	0.0003	0.2	-0.001	-0.5
Rich	-0.002	-1	-0.002	-1	0.001	0.3	-0.001	-0.7
Middle	-0.0001	-0.03	0.001	0.1	-0.001	-0.3	-0.0002	-0.04
Poor	0.002	0.06	0.008	0.2	0.009	0.3	0.008	0.3

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, $w_j \bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$. Baseline GDP is 2015 GDP. See Sections 4.5 and 6 for further details.

half of the estimate found 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.4. Column 2 in Table 7 shows the estimates across counterfactuals. As the variability in labor efficiency increases, i.e., the size of the trade elasticity estimates decreases, the size of gains increases across all counterfactuals (Simonovska and Waugh, 2014; Shapiro, 2016). However, the qualitative conclusions—that waste trade makes countries of all income levels better while low-value waste trade makes lower-income countries worse off—are robust to these changes (See Column 2 in Table 7).

Next, as pollution havens are created on liberalization of trade, I test whether low-value waste trade still makes lower-income countries worse off in the absence of the PHE. Column 3 in Table 7 shows that allowing trade in low-value waste now makes both middle- and low-income countries better off. Thus, by removing the pollution haven effect as a source of waste flows, all countries are better off with trade in even low-value waste. In summary, the pollution haven effect plays a crucial role in creating economic losses due to waste trade in lower-income countries.

Finally, a more realistic framework is one where the recycled good serves as an intermediate input to manufacturing production instead of as a final consumption good. This modified framework is in Appendix A. Upon re-estimating the parameters under this modified framework, I conduct the counterfactual exercises. Column 4 in Table 7 shows that all qualitative conclusions of the paper hold except that any type of waste trade now hurts the lower income countries. Allowing any waste trade decreases the price of recycled product relative to manufactured goods. Thus, gross benefits for the lower income countries decline as they specialize in waste reprocessing.

6.3 China Ban

In 2018, China imposed an import ban on 24 categories of waste that included 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, a major importer of this type of waste, to study the effects of the ban. The policy increased China's gross benefits while helping other low-income countries, such as India and the Philippines, in the same manner.

Panel C in Table 7 presents the impacts on gross benefits aggregated by income level. Column 1 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 specialize in low-value waste, they experience positive benefits from this policy change, explained by the increase in the relative price of low-value waste. Similar to a ban on low-value waste trade, I find that the overall volume of high-value waste increases by 0.46%, while that of low-value waste decreases by 0.11%. Thus, the rich are worse off, while the lower-income countries are better off. Even with a less radical regulation on low-value waste trade, the lower-income countries are better off at the expense of the rich who now reprocess more of the low-value waste. Columns 2-4 show that these results are robust to alternative estimates of trade elasticities and recycled good as an intermediate input, but not to eliminating the PHE.

6.4 Environmental Costs

In this section, I present estimates of the environmental costs of waste trade for comparison against the gains from waste trade shown above. Imported recyclable waste that is mixed with non-recyclable waste inevitably generates a negative externality via disposal (Gutierrez, 2016). Further, recycling firms don't always internalize such externalities while making the decision to trade in waste (Vidal, 2014). The methodology for calculation of the externality costs is in Appendix B. Comparing Column 1 in Table 8 with that in Table 7 reveals that countries of all income levels are better off with waste trade while lower-income countries are worse off with low-value waste trade even after accounting for the environmental costs.

A concern in the calculation of externality costs is the choice of estimates for the social marginal cost of disposed waste. In particular, the costs of 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), which I use for the baseline, partially accounts for external effects at the global rather than the domestic level. Carbon dioxide emissions account for a share of 37.5% of this number. Thus, I check the robustness of my welfare estimates to lowering the social marginal cost for the European Union to \$625 instead. The results in Column 2 of Table 8 show that the results are robust to this change.

However, a high level of uncertainty persists in estimates of external costs of disposal due to the dearth of good classification systems for waste materials and information on their heterogeneity and toxicity (Eshet et al., 2005; Liboiron, 2016). Eshet et al. (2005) provide estimates of economic valuation of emissions and leachate from landfilling and incineration of waste. In addition, the authors provide a range for economic valuation of disamenities from landfilling and incineration. I sum the mid-points from these three ranges of estimates to come up with a figure of \$193.85/tonne, which is 80% smaller in magnitude than the baseline, to use as a robustness check. Column 3 of Table 8 shows that qualitative conclusions are robust to even the lower environmental costs.

I also test the robustness of my environmental cost estimates to a Cobb-Douglas formulation of the utility across the composite of manufactured goods, recycled products, and the externality, based on Shapiro (2016) (See Appendix B.3 for methodology). Since the substitution across goods and the externality is less sensitive to price changes in the Cobb-Douglas formulation than in the baseline nested CES formulation, the environmental cost estimates are larger in magnitude (See Column 4 in Table 8). However, even after accounting for the environmental costs under different scenarios, the main qualitative conclusions of the paper 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.

7 Conclusion

I quantify the economic implications of international trade in waste and the associated regulations. To this end, I build a structural gravity model with the generation of waste

Table 8: Environmental Costs

	Baseline		SMC excluding CO_2		SMC from Eshet et al. (2005)		Functional Form	
Income Group	(%GDP)	(billions $)	(%GDP)	(billions $)	(%GDP)	(billions $)	(%GDP)	(billions $)
				Panel A: Waste-Autarky				
Global	0.001	0.4	0.00001	0.004	0.00001	0.007	0.002	1
Rich	0.0001	0.05	-0.000001	-0.0007	-0.000001	-0.0003	0.0004	0.2
Middle	0.001	0.1	0.00001	0.0014	0.00001	0.003	0.003	0.7
Poor	0.007	0.2	0.0001	0.0033	0.0001	0.005	0.016	0.5
				Panel B: Low-Value Waste-Autarky				
Global	-0.003	-2	-0.00004	-0.03	-0.0001	-0.04	-0.019	-13
Rich	-0.003	-1	-0.00003	-0.01	-0.0001	-0.02	-0.017	-8
Middle	-0.004	-1	-0.0001	-0.01	-0.0001	-0.02	-0.022	-5
Poor	-0.002	-0.05	-0.00002	-0.001	-0.00003	-0.001	-0.005	-0.1
				Panel C: China Ban				
Global	-0.00004	-0.03	-0.000001	-0.0008	-0.000001	-0.001	0.001	1
Rich	0.001	0.4	0.00001	0.004	0.00001	0.007	0.006	3
Middle	-0.001	-0.3	-0.00002	-0.004	-0.00003	-0.007	-0.008	-2
Poor	-0.002	-0.05	-0.00002	-0.001	-0.00004	-0.001	-0.006	-0.2

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 Environmental Costs are the differences between gross and net benefits, i.e. equivalent variation. Baseline GDP is 2015 GDP. See Section 6.4 for further details.

micro-founded as a by-product of manufacturing where waste itself is an input to recycling and waste flows are governed by both comparative advantage and the pollution haven effect. I further allow for heterogeneity in the abilities of countries to both generate and recycle two types of waste, high- and low-value waste. The rich countries like the US which are technologically better generate high-value waste like metals while the lower-income countries with cheaper labor specialize in low-value waste like plastics. In trade data, this heterogeneity reflects as low-value waste being more sensitive to trade barriers than high-value waste and is crucial in determining the size of gains from trade in the two types. My model also captures the PHE in relative flows of two types of waste by formulating a non-homothetic production in a country's recycling sector that uses both types of waste to produce a recycled good.

One challenge in estimating the model parameters in a structural gravity framework is to disentangle the effect of trade elasticities from that of trade costs due essentially to the curse of dimensionality. I propose a sequential estimation approach whereby I first estimate the trade elasticities by using model predictions to construct an economic measure of trade barriers, for which the geographic barrier variables serve as instruments. Then, I estimate the rest of the key parameters of the model, including the trade costs, by simulating the world economy. I find that a 1% decrease in trade costs causes a 7.3% increase in manufactured goods and high-value waste flows and a 9.8% increase in low-value waste flows.

My counterfactual simulations show that the existing patterns of waste trade make countries of all income levels better off even after accounting for the costs of negative externalities from waste disposal. Conversely, allowing trade in only low-value waste makes lower-income countries worse off. Kaza et al. (2018) asserts that global waste generation will grow by 69% by 2050, with most of this increase coming from lower-income countries whose incomes are rising. These countries also have much higher open dumping rates that contribute to the environmental costs of waste. My paper shows that targeted waste trade policy has the potential to tackle the issue of waste through the creation of scale and compositional changes in waste generation. Thus, in the absence of a first-best policy, such as a domestic tax on waste disposal on manufacturers, waste trade policy can serve as a second-best instrument. I also show that a low-value waste trade ban helps lower-income countries, which suggests that a policy regulating the flow of low-value waste would facilitate an equitable distribution of the burden of waste across countries. Even a less radical regulation on low-value waste trade such as China's 2018 ban on low-value waste imports makes lower income countries better off at the expense of the rich that then have to process more of the polluting low-value waste.

The main qualitative findings of the paper continue to hold under alternative trade elasticity estimates, recycled good as an intermediate input, and a range of environmental cost estimates. The only exception to this occurs when the PHE is eliminated, where liberalization in any waste trade makes even the lower-income countries better off. Thus, the economic loss in lower-income countries due to trade in low-value waste is attributed to the pollution haven effect.

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Online Appendix to
"The Economic Consequences of Waste Trade: Evidence from the Gravity Model"

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Figure A.1: Waste Exports (% 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.

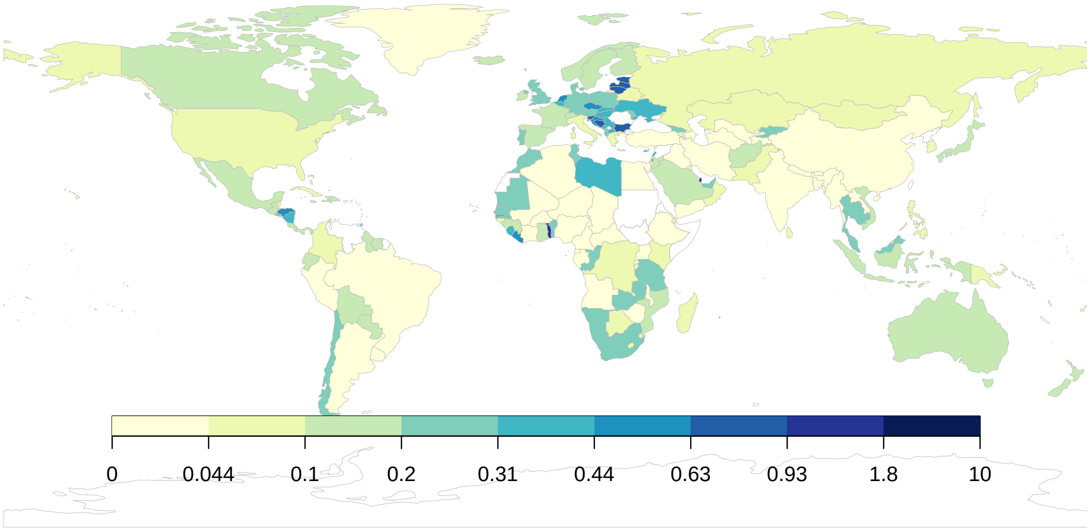


Figure A.2: Waste Imports (% of GDP)

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 are 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.

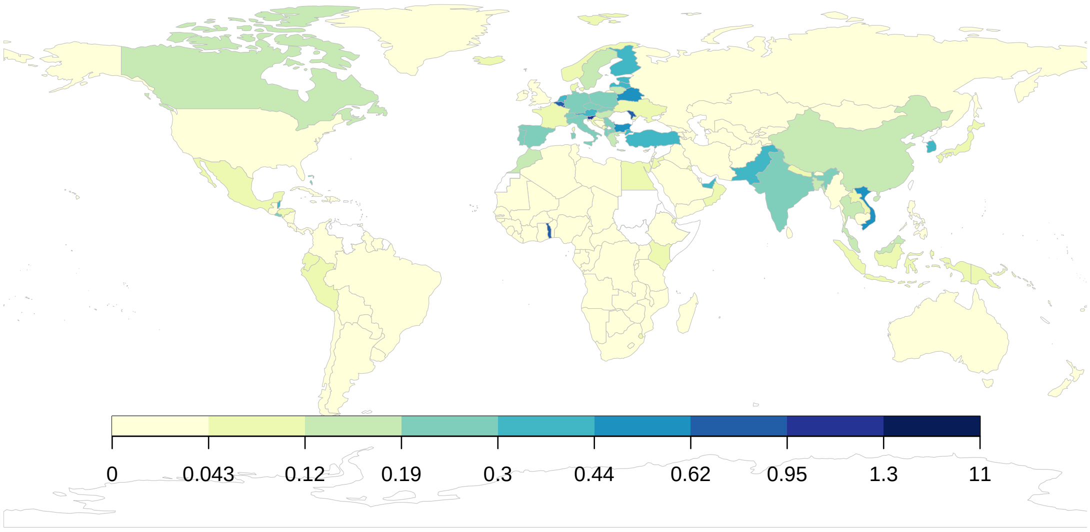


Figure A.3: High-Value Waste Imports (% of GDP)

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 are the country's waste imports as a share of its income. White represents missing data.

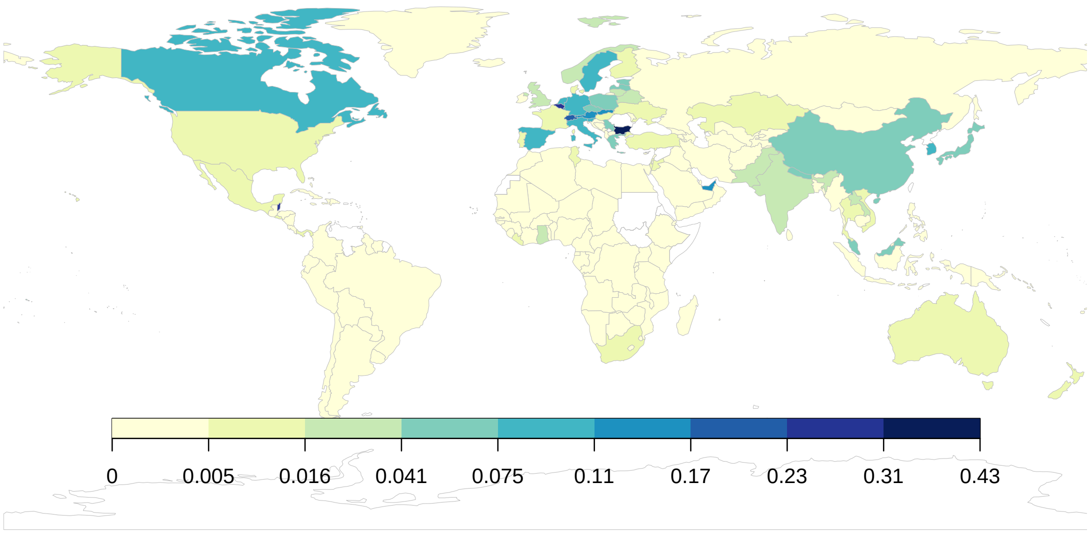


Figure A.4: Low-Value Waste Imports (% of GDP)

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 are the country's waste imports as a share of its income. White represents missing data.

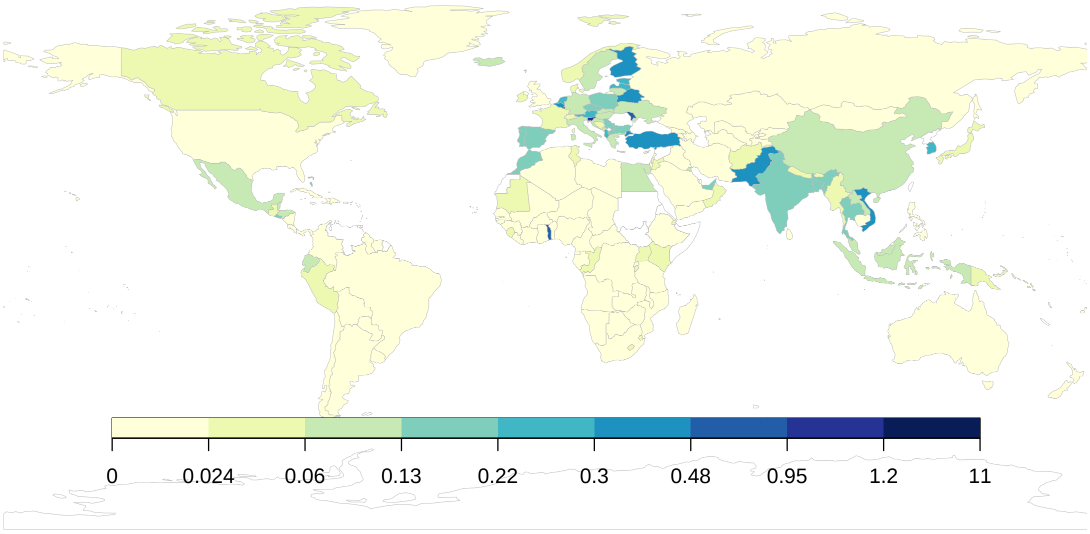


Figure A.5: Flow of Goods and Services between Sectors in a Country

This figure shows the links between sectors in the general equilibrium model described in Section 4. 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 domestic flows while the orange arrows represent both domestic and international flows. See Section 4 for further details.

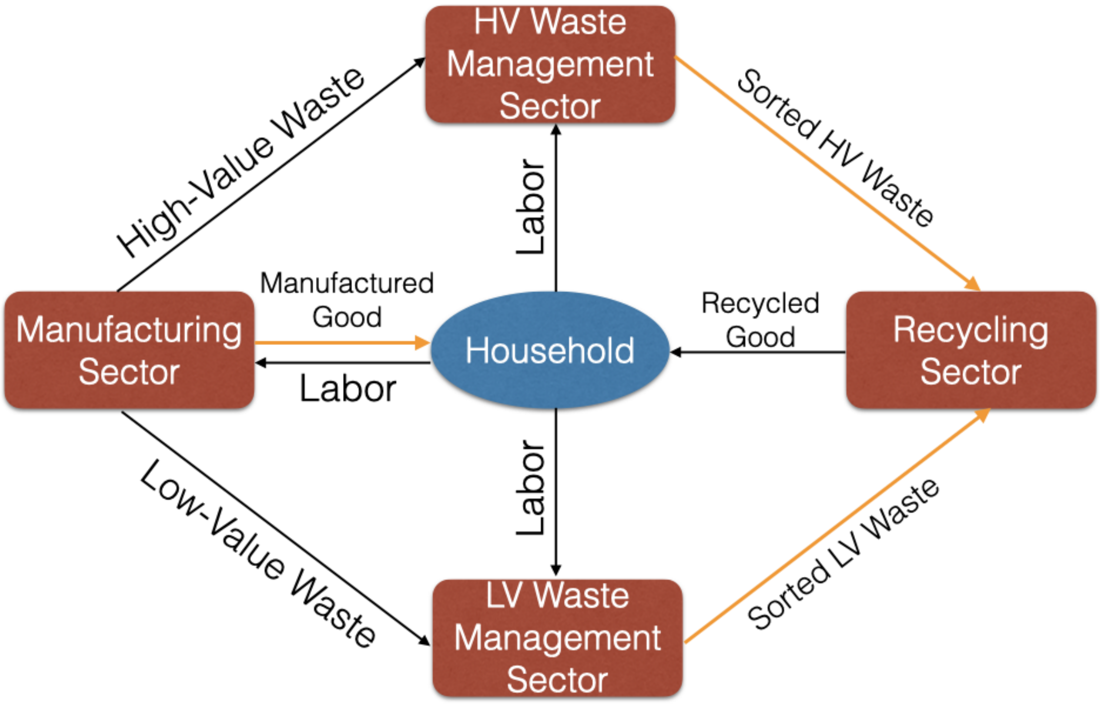


Figure A.6: Value-to-weight Ratios for Waste Categories

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.

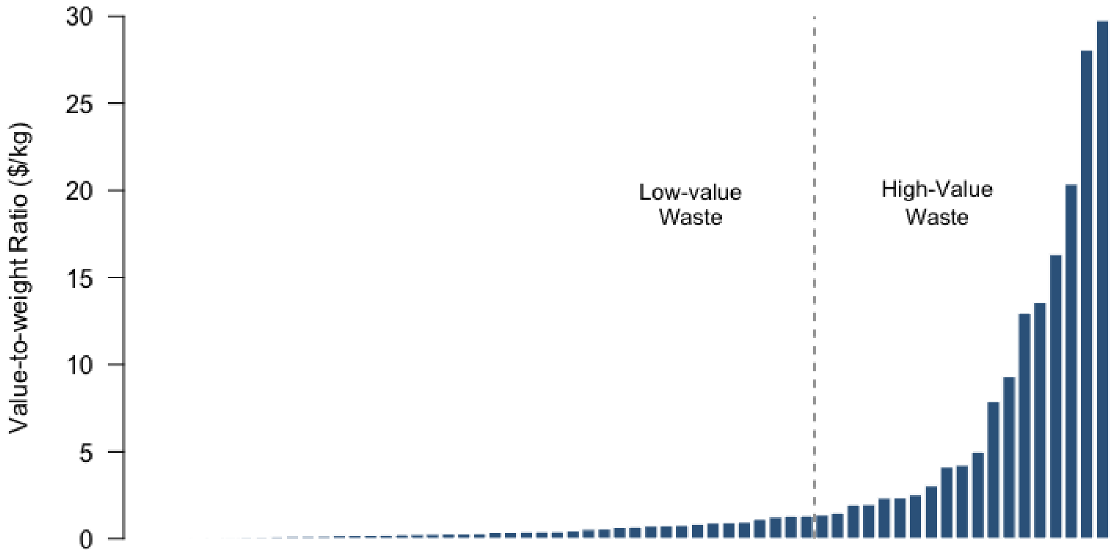


Figure A.7: Goodness of Fit-Sum of Square Residuals by Importer

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 5.1 and 5.2.

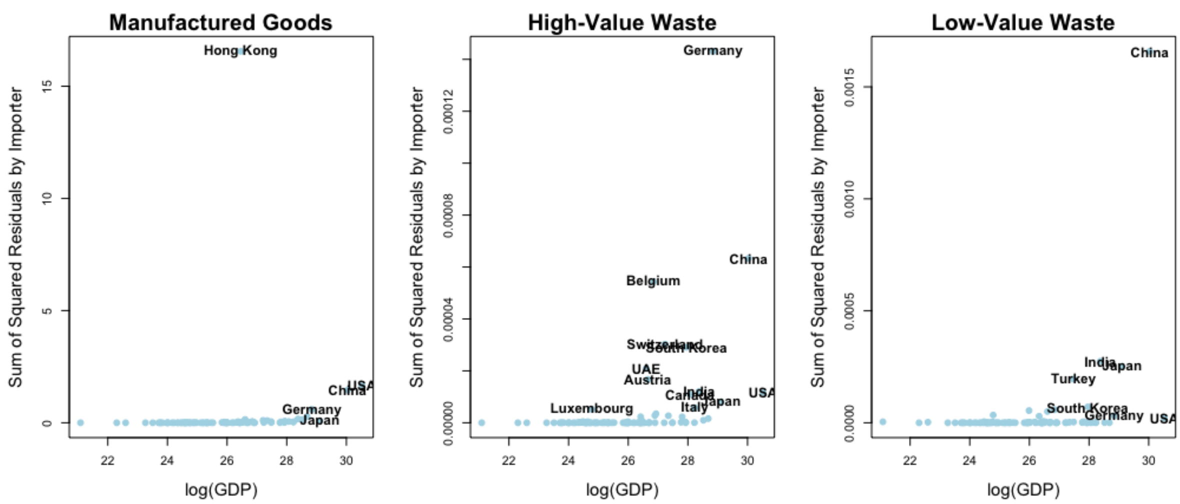


Table A.1: Harmonized System (HS) Categories of Waste

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: 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 5.1 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.3: 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 5.1 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., 2020a). 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.4: 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 5.1 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., 2020a). 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.5: 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	$-0.004^{***}(0.001)$	$-0.003^{***}(0.001)$

A Recycled Good as an Intermediate Input

I consider Cobb-Douglas form across labor, two types of waste, and the recycled good as inputs to manufacturing production. Here, the unit cost of production is:

$$p_j(\nu_m) = \frac{w_j^{\beta'} {p_{rj}^{1-\beta'}}}{z_j(\nu_m)}, \tag{21}$$

where β' is the combined share of labor and two types of waste in the production of the manufactured good. As the recycled product now serves as an input to manufacturing, the market clearing condition of the recycled good is given by:

$$\sum_{s=\{h,l\}} X_{sj} = (1-\beta') \sum_i X_{mji}, \qquad \forall j. \tag{22}$$

Finally, as the households consume only manufactured goods, their preferences assume the following CES form:

$$U_j = Q_j,$$

where

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

and the fraction of income allocated to manufactured goods in country j is:

$$X_{mj} = w_j \bar{L}_j. \tag{23}$$

As in Section 5.2, I calibrate share of labor to be 0.973 assuming the share of expenditure on recycled product to be 0.007 and the share of expenditure on waste-management to be 0.02. Therefore, I set the share of labor and waste-management, $\beta' = 0.993$.

B Externality of Waste Trade

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 the country j takes the following nested CES form:

$$U_j = \left(Q_j^{\alpha} C_j^{1-\alpha}\right)^{\rho} - \mu\left(\sum_{s=\{h,l\}} W_{sj}\right)^{\rho},$$

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 ν_m, and C_j denotes the consumption of the recycled good. The substitution parameter $\rho = (\sigma - 1)/\sigma$ represents ease of substitution across goods and the externality, and μ is the weight on externality in the utility.

The term $-\mu(\sum_s W_{sj})^\rho$ denotes the disutility from high-value and low-value waste that is disposed domestically. Each externality term:

$$W_{sj} = \chi_{sj} \xi_s \sum_i X_{sij}, \qquad s \in \{h, l\}, \tag{24}$$

is the product of the fraction of waste disposed, χ_{sj}, and the total volume of waste accumulated via domestic production or imports, $\xi_s \sum_{i=1}^N X_{sij}$. Here, X_{sij} is the dollar value of imports of waste type s from country i. The term ξ_s is a conversion factor that converts the dollar value of waste to tonnes (calculated using trade data for 2015). I model the externality as a pure externality, which households take as given while making consumption decisions. The externality also does not influence the decisions of private firms about how much waste to trade. I rely on the existing literature to quantify the substitutability across goods and bads and the weight on the externality, summarized by the parameters ρ and μ, respectively. Thus, I calibrate the parameters ρ and μ so that households are willing to pay the economic valuation of the externality provided by the literature to avoid one additional tonne of waste disposal.

Next, I discuss the implication behind Equation (24) 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).[21] 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 (24) captures the externality from the portion of local waste, whether from local sources or imports, that countries end up having to

[21] 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.

dispose of. Now, the social welfare of a country is given by its indirect utility:

$$V_j = \left(\alpha^\alpha(1-\alpha)^{1-\alpha}\frac{Y_j}{P_j}\right)^\rho - \mu\Big(\sum_s W_{sj}\Big)^\rho, \tag{25}$$

B.1 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 for country j is:

$$EV_j = w_j\bar{L}_j\left(\left\{\left(\frac{\hat{Y}_j}{\hat{P}_j}\right)^\rho - \frac{\mu(\sum_s W'_{sj})^\rho - \mu(\sum_s W_{sj})^\rho}{(\alpha^\alpha(1-\alpha)^{1-\alpha}Y_j/P_j)^\rho}\right\}^{1/\rho} - 1\right). \tag{26}$$

To ensure that the externality costs are driven by changes in volume of traded waste and not its value, I keep the prices of high-value and low-value waste in the counterfactual constant. To do this, I convert the waste disposed domestically under the counterfactual, $W'_{sj} = \chi_{sj}\xi_s\sum_i X'_{sij}$, back to its value in current prices by multiplying it with the price ratio P_{sj}/P'_{sj}.

To measure the disposal intensity, χ_{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.

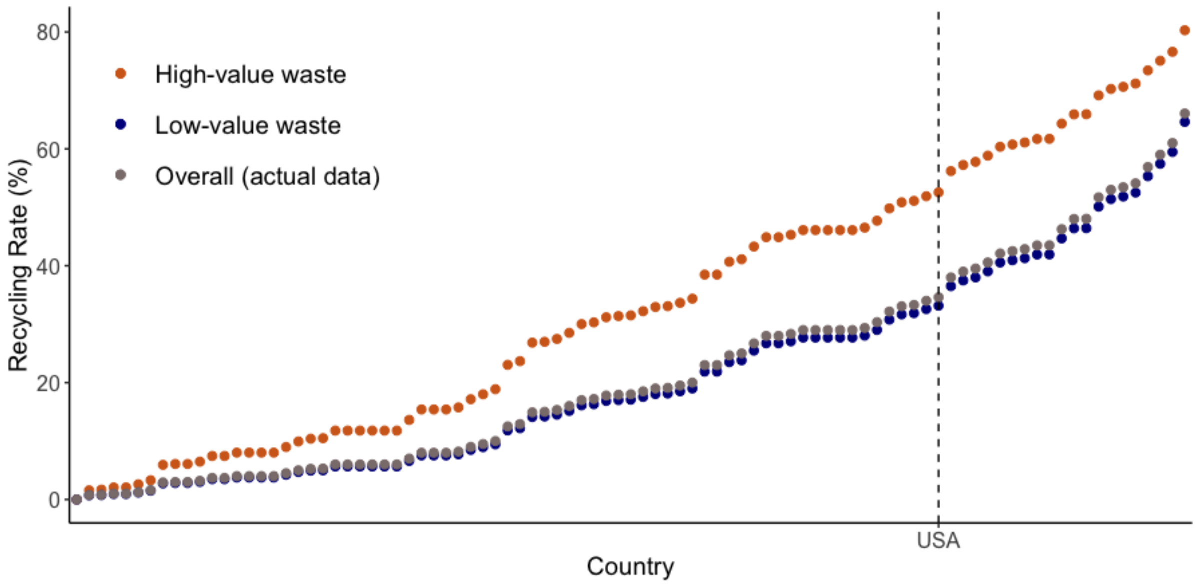
To infer the recycling rates by type of waste, I supplement the overall recycling rate data with recycling rates for different materials in the U.S. for 2015 from United States Environmental Protection Agency (2020). Specifically, I use data on recycling rates for "Paper and Paperboard", "Ferrous Metals", "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.[22] 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%,

[22] 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.

respectively.[23] 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.[24] Figure A.8 shows the distribution of recycling rates for both types of waste in my sample.

Figure A.8: 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 Appendix B.1 for details.



B.2 Calibration of the Externality Parameters

To quantify the externality costs from waste disposal, I calibrate the parameters ρ and μ, which represent the substitutability across goods and bads and the weight on the externality in the utility, respectively. I rely on the existing estimates of external costs of waste from Bond et al. (2020) and McKinsey (2016) to measure ρ and μ. Bond et al. (2020) quantify the external costs from plastic waste to be \$1000/tonne from four

[23] 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. My counterfactual results are also robust to the extreme check of decreasing recycling rates for the lowest income group by 50%.

[24] 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.

aspects, namely, carbon dioxide emissions, air pollution, collection and sorting costs, and ocean clean-up costs.[25] The fact that the European Union tax on non-recycled plastic waste levied on member countries starting on January 1, 2021 is equal to \$1000/tonne provides support in favor of using this figure in my calculations. 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.[26]

To formally calibrate the two utility parameters, I totally differentiate the indirect utility function in Equation (3). Setting $dV_j = 0$, I obtain:

$$\frac{dY_j/Y_j}{d\sum_s W_{sj}/\sum_s W_{sj}} = \frac{\mu(\sum_s W_{sj})^\rho}{(\alpha^\alpha(1-\alpha)^{1-\alpha}Y_j/P_j)^\rho}$$

Using current data on income and waste disposal and the social marginal cost estimates in the aforementioned studies, I solve for two equations in two unknowns, ρ and μ. Specifically, I solve for μ and ρ 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. I find $\mu = 0.0067$ while my estimate of $\rho = 0.1225$ translates to an elasticity of substitution, $\sigma > 1$, which is larger than what the elasticity of substitution would have been in a Cobb-Douglas formulation across goods and bads. The greater ease of substitution means that for each additional tonne of waste disposal, the marginal increase in real income required to keep the households at the same level of utility is decreasing with the volume of disposal.

B.3 Alternative Functional Form

First, I test the robustness of my environmental cost estimates to a Cobb-Douglas formulation of the utility across the composite of manufactured goods, recycled product, and the externality, based on Shapiro (2016). The indirect utility for the alternative formulation is as follows:[27]

$$V_j = \alpha^\alpha(1-\alpha)^{1-\alpha} \times \frac{Y_j}{P_j} \times \frac{1}{1+\sum_s W_{sj}^2}, \tag{27}$$

[25] 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.

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

[27] To measure the effect of a policy change, I calculate the empirical analogues of the equivalent variation: $EV_j = w_j \bar{L}_j(\hat{V}_j - 1)$.

The term $\frac{1}{1+\sum_s W_{sj}^2}$ denotes the disutility from waste that is disposed domestically. Each waste-type-specific externality term, $W_{sj} = \mu_{sj}\chi_{sj}\xi_s \sum_i \frac{X_{sij}}{w_j \bar{L}_j}$, is the product of an externality parameter, μ_{sj}, and the volume of waste disposed domestically, $\chi_{sj}\xi_s \sum_i \frac{X_{sij}}{w_j \bar{L}_j}$. Here, X_{sij} is the dollar value of imports of waste type s from country i, which is weighted by total income, $w_j \bar{L}_j$. The externality parameter μ_{sj} captures the social marginal cost of waste disposal and is allowed to vary by type of waste, s, and country, j. 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.[28]

To quantify the externality costs from waste disposal, I calibrate the parameter μ_{sj}, to represent the social marginal cost of disposal of waste type s. Formally, I write the indirect utility function in money-metric terms, $e_j(v, P, \{W_s\}_{s=h,l}) = V_n P_n (1 + \sum_s W_{sj}^2)$. Then, I differentiate the money-metric utility function with respect to the volume of waste disposed, $\chi_s \xi_s \sum_i X_{sij}$, and choose the value of μ_{sj} so that the marginal cost of disposed waste equals the economic valuation of the externality provided in the literature. Specifically, I choose μ_{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.[29] As a result, the parameter μ_{sj} is isomorphic to the social marginal cost of disposed waste type s in country j. While the disposal intensity is decreasing in the income level of a country, the externality cost per unit of waste is increasing in income level. Figure A.9 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.

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

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

$$log(1000) = \beta_0 + \beta_1 EPI_{EU},$$

$$log(375) = \beta_0 + \beta_1 EPI_{SEA},$$

where EPI_{EU} and EPI_{SEA} are the average environmental performance indices for the EU and the relevant Southeast Asian (SEA) countries. I use the values of β_0 and β_1 to extrapolate economic valuation for the countries in my sample.

Figure A.9: 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 Environmental Performance Indices. Appendix B.3 describes the extrapolation methodology in detail.