Welfare Effects of International Trade in Waste*

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Abstract

I quantify the welfare effects of international trade in waste. I build a structural gravity model in which waste generation is a byproduct of manufacturing and waste is input to recycling. My estimates reveal that low-value waste is more sensitive to trade barriers than high-value waste, while richer countries import a greater share of high-value waste than low-value waste. Although existing patterns of waste trade make countries of all income levels better off, low-value waste trade, which creates large negative externalities relative to its private value, makes middle-income countries worse off. I estimate that China's 2018 ban on low-value waste imports made China and several lower-income countries better off. However, eliminating the pollution haven effect or recycling as an intermediate input to manufacturing, any waste trade makes even the lower income countries better off. Depending on the type of waste trade banned, manufacturing production across countries also faces a differentiated impact. While a high-value waste trade ban hurts manufacturing in rich countries, a low-value waste trade ban reduces the output in lower-income countries.

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International trade in waste, including that of non-recyclables, has experienced considerable growth over the past three decades. Particularly, it experienced a five-fold increase by volume from 33.9 million tons in 1988 to 156.7 million tons in 2015. Although countries have actively engaged in waste trade, it continues to be contentious as its economic and environmental ramifications on all trading partners are unclear. Although trade in waste creates benefits similar to trade in other commodities such as cheaper recycled materials, increased employment opportunities, and additional income, it also creates negative externalities locally in importing countries via the health and environmental hazards posed by its disposal (Kirby, 1994). Over the years, these 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. However, little evidence exists quantifying the effects of such waste trade regulations on welfare, waste generation, and the primary source of waste generation, manufacturing production.

I quantify the welfare effects of international trade in waste. Specifically, I estimate the *gross* gains from waste trade for comparison against its environmental costs 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 domestic or foreign recycling. As waste trade creates negative externalities, I allow both comparative advantage, due to technological differences, and *pollution haven* forces, due to differences in environmental regulations, to govern the direction of waste flows. To assess heterogeneity in welfare by type of waste, I decompose the waste flows into high- and low-value waste and allow for differences in the abilities of countries to both generate and reprocess the two types of waste. The rich countries like the US, which are technologically better, generate high-value waste while lower income countries like India, with cheaper labor, specialize in low-value waste.

My model also captures pollution haven effects in relative flows of the two types of waste observed in data. I capture the finding that richer 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. Apart from the nature of their trade flows, the two types of waste also differ in their ease of recycling with high-value waste like precious metals and yarn being easier to recycle than mixed materials and plastics part of low-value waste. Thus, my setup allows me to separately quantify not only the gains from trade but also the environmental costs from disposal in the two types. To my knowledge, mine is the first paper to formulate a structural gravity model that provides theoretical microfoundations for waste generation and waste flows as well as quantify its welfare effects.

The size of gains to trade hinges on the elasticity of the trade flows with respect to trade barriers. A well-known challenge in estimating the model parameters in a structural gravity framework is disentangling the effect of trade elasticities from that of trade costs. An additional challenge in my framework is the need for simultaneous estimation of parameters for the two waste sectors and manufactured goods. 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 instrument. 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. My estimates reveal that the heterogeneity in waste flows reflects as low-value waste 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. To quantify the externality of waste, I rely on data on disposal intensities of the two types of waste (Kaza et al., 2018; United States Environmental Protection Agency, 2020) and existing estimates of the social marginal cost of waste disposal (Bond et al., 2020; McKinsey, 2016; Eshet et al., 2005).

Another contribution of my paper is to consider a variety of counterfactual simulations to quantify the welfare consequences of waste trade. My results show that the existing patterns of waste trade make countries of all income levels better off even after accounting for its environmental costs. The global gains to waste trade comprise 0.43% of gains to all trade even though waste trade accounts for only 0.07% of overall trade by value. Thus, per unit of trade value, waste trade generates more than five times the welfare gains of regular trade. Differentiating the gains to waste trade by income level, I find that poor countries have the largest gains, at 0.021% of GDP. Further, environmental costs decline for all income levels, but for the poor, disproportionately so by 0.01% of GDP. The decline in environmental costs reflects the scale and compositional changes in the generation of the two types of waste. As countries gain access to import opportunities from opening to trade in waste, their recycling sector shifts its expenditure toward high-value waste and away from low-value waste. Thus, the scale of low-value waste, which has high disposal intensity and creates large externality costs, counterintuitively decreases even as more options for dealing with waste become available through the waste trade. Poor countries, which disproportionately both export and use low-value waste, account for 56% of the $11.3 billion *net* welfare gain globally.

I also study heterogeneity in welfare by type of waste. High-value waste trade creates welfare effects qualitatively similar to the overall waste trade, thereby making countries of all income levels better off. However, rich countries, which both specialize in and disproportionately import high-value waste, account for a share of 83% in *net* global gains of $10 billion. Conversely, allowing only low-value waste trade *increases* the scale of generation of low-value waste while its relative price falls. The two effects combined harm middle-income countries, which disproportionately both generate and use in recycling low-value waste. China's ban on low-value waste imports has qualitatively similar welfare effects to a ban on all low-value waste trade, albeit with smaller magnitudes. This policy helps China on both fronts—by increasing gross benefits and decreasing environmental costs—while also benefiting other lower-income countries such as India and the Philippines. Like an overall low-value waste trade ban, the scale of low-value waste generation declines, making lower-income countries better off.

I further contribute to the study of waste trade by assessing the effects of waste trade on manufacturing production. Depending on the type of waste trade, manufacturing production across countries also faces a differentiated impact. I find that high-value waste trade increases manufacturing output by high-income countries at the expense of lower-income countries while low-value waste trade helps the manufacturing output of poor countries at the expense of richer countries. Although the effects of waste trade bans on manufacturing production are small, they indicate that trade bans on the type of waste a country specializes in have the potential to adversely affect its manufacturing sector. The main qualitative conclusions in my paper are robust to alternative methods for quantifying the externality costs and estimates of social marginal costs of waste disposal, trade elasticities, and disposal intensities. However, eliminating the pollution haven effect or allowing recycling as an intermediate input to manufacturing, 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 the 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 thereby creating demand for waste by a country in its recycling sector for "productive" reasons rather than for final disposal.

A limited literature studies the effects of waste trade regulations. Kellenberg and Levinson (2014) estimates the effects of the Basel Convention on waste trade using a difference-in-differences approach. Further, recent work by Li and Takeuchi (2021); Unfried and Wang (2022) and Shi and Zhang (2022) study the impact of China's 2018 ban on environmental quality using data on air pollution at city or prefecture-level in China. My use of a structural framework allows me to incorporate general equilibrium forces, to consider a richer set of counterfactuals and to explicitly draw welfare conclusions that would not be possible with a reduced-form framework. Broadly, I also contribute to the debate on the effects of international trade on the environment and the validity of the *pollution haven hypothesis* (Copeland and Taylor, 1994, 2004; Antweiler et al., 2001) by considering a novel channel through which trade can affect the environment via trade in polluting waste residue itself. My findings on differences in trade elasticities across the two types of waste and manufactured goods also speak 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).

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

The paper is organized as follows: Section 2 presents the data and the patterns in waste trade. Section 3 presents stylized facts on aggregate and different types of waste flows. 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 extends the model to incorporate recycled good as an intermediate input, and Section 8 concludes.

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

2 Data

With the goal of studying the effects of waste trade on welfare and manufacturing production in a static framework, I use cross-sectional bilateral trade data for waste and manufactured goods. I use the data first to describe empirical facts and then to estimate the structural model. Section 2.1 describes the trade data, while Section 2.2 describes the other variables used to gather the stylized facts. Section 2.3 presents the patterns of waste trade in the raw data.

2.1 Trade Data

Since the focus of this paper is on waste trade, I augment the data used in prior structural trade work with data on bilateral waste trade from the UN Comtrade database for 2015. To identify the categories of waste, I use the six-digit Harmonized System (HS) categories for which the commodity description primarily uses the keywords *waste*, *scrap*, or *residual*, following Kellenberg (2012). Table A.1 lists the 62 six-digit HS categories of waste in detail. For each waste category, the database provides the value in U.S. dollars and weight in kilograms (kg) of bilateral flows among 224 countries and territories. Aggregating the trade flows by exporter-importer pairs and assuming that missing trade flows between a pair is actually zero trade flow, I obtain 49952 observations (for 224×223 country pairs).

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

2.2 Environmental Regulation, Income, and Geographic Barriers

I use several variables to gather stylized facts from the data. To capture the level of environmental regulation in a country, I use data on the Environmental Performance Index (EPI) for 2016 (Hsu et al., 2016). The EPI quantifies the environmental performance of a country's policies by combining different indicators on the protection of human health and ecosystem vitality. Although the EPI is an imperfect measure of the stringency of environmental policies of a country, it provides data on a comprehensive list of countries. Starting in 2006, the EPI Report is published every other year, so the EPIs for 2015

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

were unavailable. Thus, I use 2016 EPIs as a proxy for the stringency of environmental regulation in each country. Other variables of interest include income levels, wage rate, and output per unit of land. Thus, I obtain data on gross domestic product (GDP), GDP per capita, used as a proxy for wage rate, and land area from the World Development Indicators (WDI) database. The GDP and GDP per capita are measured in U. S. dollar terms, while land area is measured in square kilometers (sq. km).

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

2.3 Patterns in Waste Trade

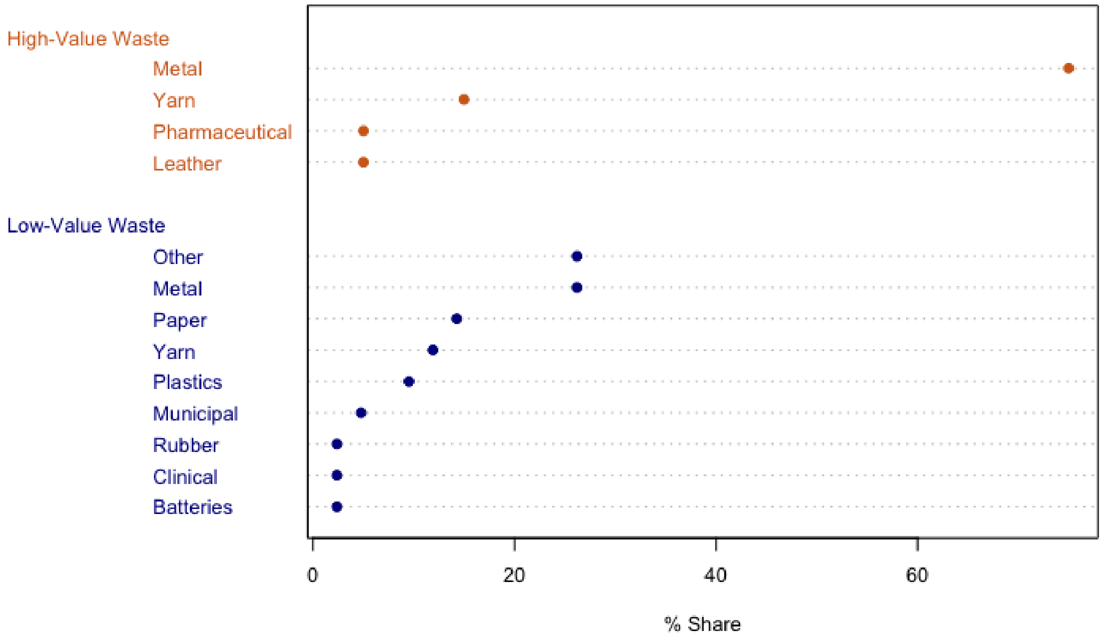
To begin, I examine patterns in total waste exports and imports across the world. Figure A.1 displays the value of total waste exports as a share of GDP, while Figure A.2 displays the value of total waste imports as a share of GDP across countries. As a share of GDP, high-income countries, mainly in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

Next, I disaggregate waste flows into two types of waste—high-value and low-value—based on value-to-weight ratios of the 62 categories of waste. To construct the value-to-weight ratios, I calculate the ratio of the average dollar value and average weight of trade in each category. Then, I divide the 62 categories into two types of waste: high-value, which corresponds to the top tercile, and low-value, which corresponds to the bottom two terciles of value-to-weight ratios (See Figure A.3). Figure 1 shows that while 75% of the materials in high-value waste are metallic in nature, low-value waste is a mix of different materials, including plastics and paper.[5]

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

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

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.

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

Table 1: Summary Statistics by Type of Waste

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

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

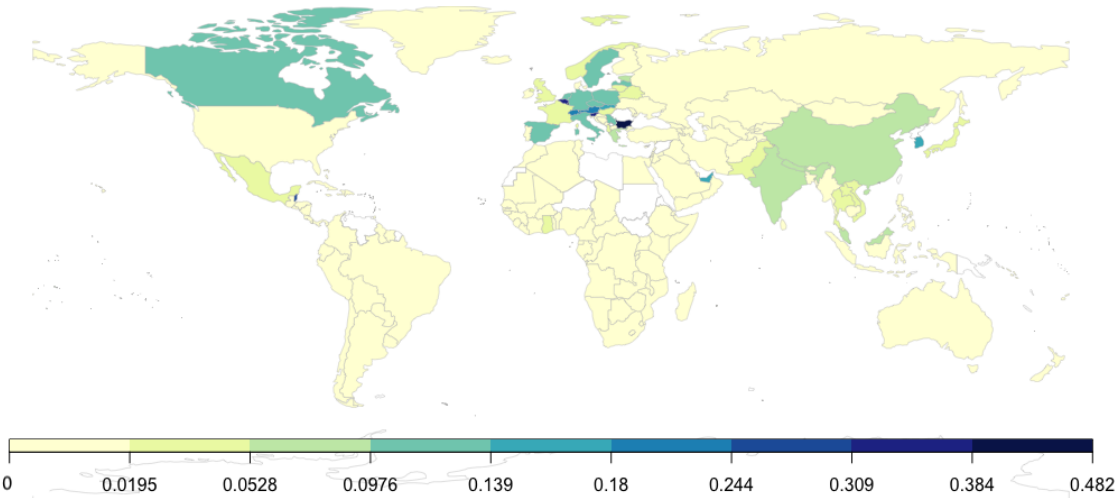
This table reports the summary statistics for the two types of waste. Panel A reports the summary statistics for the exporter- and importer-specific variables. Panel B reports the summary statistics for the bilateral variables.

3 Stylized Facts

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

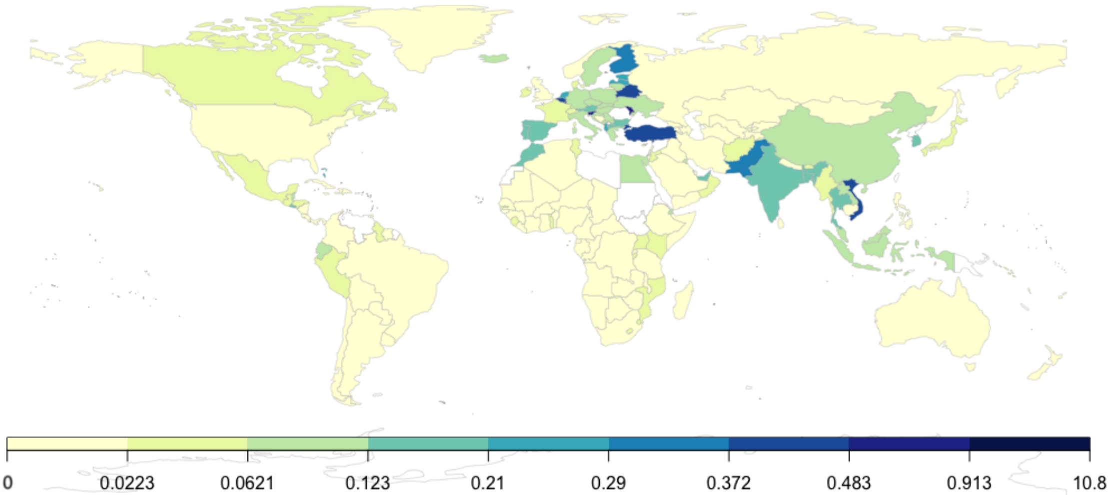
chiefly precious objects, such as gold and silk.

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



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

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



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

related to trade barriers, τ_{ij}:

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

The term τ_{ij} comprises geographic barrier variables: distance, contiguity, and common language.[6] The vector $\mathbf{Z_i}$ includes logged exporter-level controls, exporter's EPI and GDP per unit of land, while $\mathbf{Z_j}$ includes analogous importer-level controls. Finally, η_{ij} is the error term with $E[\eta_{ij}|Y_i, Y_j, \tau_{ij}, \mathbf{Z_i}, \mathbf{Z_j}] = 1$. To estimate Equation (1), I use the Poisson pseudo-maximum likelihood (PPML) method, which yields consistent and efficient estimates (Silva and Tenreyro, 2006).[7] To account for unobservable heterogeneity at the country level, I also estimate a specification with exporter and importer fixed effects, μ_i and μ_j, respectively.[8]

Further, to study the choice between high-value and low-value waste across countries, I estimate the specification by replacing the ratio of bilateral high-value to total waste trade as the dependent variable:

$$\ln Ratio_{ij} = \beta_0 + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 \ln \tau_{ij} + \boldsymbol{\beta_4 Z_i} + \boldsymbol{\beta_5 Z_j} + \boldsymbol{\varepsilon_{ij}}. \tag{2}$$

Here, Y_i and Y_j are now the exporter's and importer's per capita incomes, respectively. Since the dependent variable is a proportion, I adopt two alternative variance-stabilizing transformations—logit and inverse hyperbolic sine (IHS). The logit transformation converts this ratio to the $(-\infty, +\infty)$ scale, which prevents non-sensical results possible on the bounded scale of $[0, 1]$. However, due to the prevalence of many zeros in the dependent variable, estimating this specification in log- or logit-form would result in the loss

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

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

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

of those observations. Hence, I also estimate the specification with an inverse hyperbolic sine transformation, which closely tracks the log function but is defined at zero (Bellégo et al., 2022).[9] Due to the potential correlation between observations of the same trading partners, I cluster standard errors at the exporter-importer level in all specifications.

3.1 Aggregate Waste Flows

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

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

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

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

Table 2 shows that waste trade and distance have an inverse relationship. Specifically, I find that the magnitude of the negative elasticity of waste trade with respect to distance is 0.681-0.911 and significant at the 1% level. In contrast, the negative elasticity of manufactured goods trade is 0.457-0.653, suggesting that waste trade is more sensitive to geographic barriers than manufactured goods trade (See Table A.2). Moreover, the

[9] The formula for the inverse hyperbolic sine is $\operatorname{arcsinh}(x) = \ln(x + \sqrt{x^2+1})$. The function $\operatorname{arcsinh}(x) - \ln(2)$ 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.

coefficient on the geographic barrier variable, contiguity, is positive and significant at the 1% level. If two countries are contiguous, they trade 151-177% more in waste than noncontiguous country pairs, as opposed to manufactured goods, where they trade 68-92% more.[10] Since lower economic benefits accrue from importing waste than manufactured goods for a country, waste trade is more sensitive to trade barriers. Lastly, Table 2 shows a positive, albeit not statistically significant, correlation between waste flows and the common language dummy. These findings indicate the presence of comparative advantage forces in determining the pattern of waste trade.

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

3.2 Heterogeneity by Type of Waste

In this subsection, I discuss the stylized facts on the two types of waste. To do so, I replace the dollar value of high-value and low-value waste flows as dependent variables while estimating Equation (1). Table 2 shows that high-value and low-value waste flows qualitatively conform with the empirical facts described for aggregate waste flows in Section 3.1. Next, I discuss additional stylized facts on heterogeneity by type of waste.

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

Table 2 shows that the negative elasticity of low-value waste is larger in magnitude than the elasticity of high-value waste with respect to distance. Specifically, in columns 3 and 5, the elasticity of high-value waste with respect to distance is -0.535 as opposed to -0.781 for low-value waste, and the elasticity of low-value waste statistically significantly exceeds that for high-value waste at the 5% level. Similarly, in models with exporter- and importer-specific effects, in columns 4 and 6, the magnitude of the negative elasticity with respect to distance for high-value waste, 0.728, is statistically significantly smaller than

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

Table 2: Gravity Equation Estimates for Waste Flows

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

This table reports the results from estimation of Equation (1). Columns 1 and 2 report the results with aggregate bilateral waste flows, Columns 3 and 4 with bilateral high-value waste flows, and Columns 5 and 6 with the bilateral low-value waste flow as the dependent variables. Although I include trade flows among 224 countries or territories, the number of observations varies by specification depending on the number of missing values for independent variables, 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.

that for low-value waste, 1.055, at the 1% level. This finding indicates greater benefits to importing high-value waste than low-value waste, so trade in this type of waste is not as sensitive to trade costs as low-value waste trade. The observed trade patterns appear to arise from differences in waste-processing technology available in different countries. Processing high-value waste likely requires technology that is available in only a select set of high-income countries. As a result, technological availability swamps trade costs in determining flows of high-value waste. Conversely, trade costs swamp technological considerations while determining the direction of low-value waste trade. Thus, comparative advantage not only determines the level of high- and low-value waste trade but also relative trade in the two types of waste across countries.

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

To further understand the choice between importing the two types of waste by a country, I estimate a specification by replacing the ratio of high-value to total waste as the dependent variable. Under both logit and IHS transformations, Table 3 reveals that the importer's income per capita is positively associated with the fraction of spending on high-value waste in total waste imports. Since the IHS transformation can be interpreted the same way as the log transformation, the elasticity of the fraction spent on high-value waste imports with respect to an importer's GDP per capita is 0.03 and significant at the 1% level. Thus, richer countries allocate a greater share of their expenditure to importing high-value waste than to importing low-value waste. As richer countries have higher levels of environmental regulation, 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.

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 individual sectors, the relationships between them, and the modeling choices made to capture the comparative advantage and pollution have effect in greater detail in the rest of this section. Throughout the paper, I denote the value of a commodity by X, the sector—

Table 3: Choice between High- and Low-Value Waste

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

This table reports the results from estimation of Equation (2) with the dependent variable replaced by logit and inverse hyperbolic sine (IHS) transformations of "Ratio". Ratio is the ratio of dollar-values of bilateral high-value waste flows to total waste flows. As the high-value and total waste flows contain many zero observations, this ratio contains many 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.

manufacturing, high-value waste management, or low-value waste management—by the subscript $s \in \{m, h, l\}$, a bilateral flow using two country subscripts such as ij, and the overall value of imports using one country subscript such as j.[11]

4.1 Preferences

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

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

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:

$$W_{sj} = \chi_{sj} \xi_s \sum_i X_{sij}, \qquad s \in \{h, l\}, \tag{3}$$

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 (See specific values in Section 2.3). 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

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

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 (3) 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).[12] 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 (3) captures the externality from the portion of local waste, whether from local sources or imports, that countries end up having to dispose of.

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

$$V_j = \left(\alpha^\alpha (1-\alpha)^{1-\alpha} \frac{Y_j}{P_j}\right)^\rho - \mu\Big(\sum_s W_{sj}\Big)^\rho, \tag{4}$$

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).

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

[12] 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.

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-specific heterogeneity is absorbed by fixed effects when estimating the trade elasticities. Therefore, I do not explicitly model the level effects due to differences in environmental regulation across countries.

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.[13] Together, the parameters T_j and θ_s, which I structurally estimate, determine comparative advantage in overall and relative flows in two types of waste, thereby accounting for *Facts 1-3*.

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.[14]

[13]The expected unit cost of delivering goods from country i to country j relative to the expected unit cost of procuring it domestically is $\frac{E(p_{ij}(\nu_s))}{E(p_{jj}(\nu_s))} = \left(\frac{T_i}{T_j}\right)^{-\frac{1}{\theta_s}} \frac{\tau_{sij} w_i}{w_j}$, where 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 technology 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.

[14]One could also consider a framework where the recycled product is an intermediate input to manufacturing. Such a formulation would yield larger gross benefits to trade, as in Costinot and Rodríguez-Clare

For simplicity, I model the two types of waste as inputs to the production of manufacturing output even though they are byproducts.[15] Assuming constant returns to scale, the unit cost of production is:

$$p_j(\nu_m) = \frac{w_j^{\beta} u_{hj}^{\gamma} u_{lj}^{1-\beta-\gamma}}{z_j(\nu_m)}, \tag{5}$$

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, exogenously set by the government. 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 levels of waste generation. The revenue earned by the government via waste collection is given as a lump-sum subsidy to the domestic recycling sector.

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

$$p_j(\nu_s) = \frac{w_j}{z_j(\nu_s)}, \qquad s \in \{h, l\} \tag{6}$$

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 recycling output to allocate different fractions of their

(2014), though the main qualitative conclusions of the paper still continue to hold (See Section 7).

[15]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.

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:

$$\frac{X_{hj}}{X_{lj}} = \lambda_j^{\sigma_h - \sigma_l} \times \frac{\alpha_h P_{hj}^{1-\sigma_h}}{\alpha_l P_{lj}^{1-\sigma_l}} \tag{7}$$

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 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. Essentially, I interpret the finding summarized as *Fact 4* as the assumption $\sigma_h > \sigma_l$, and 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. Figure 4 depicts the aforementioned connections between all the sectors within a country.

4.4 Trade

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.

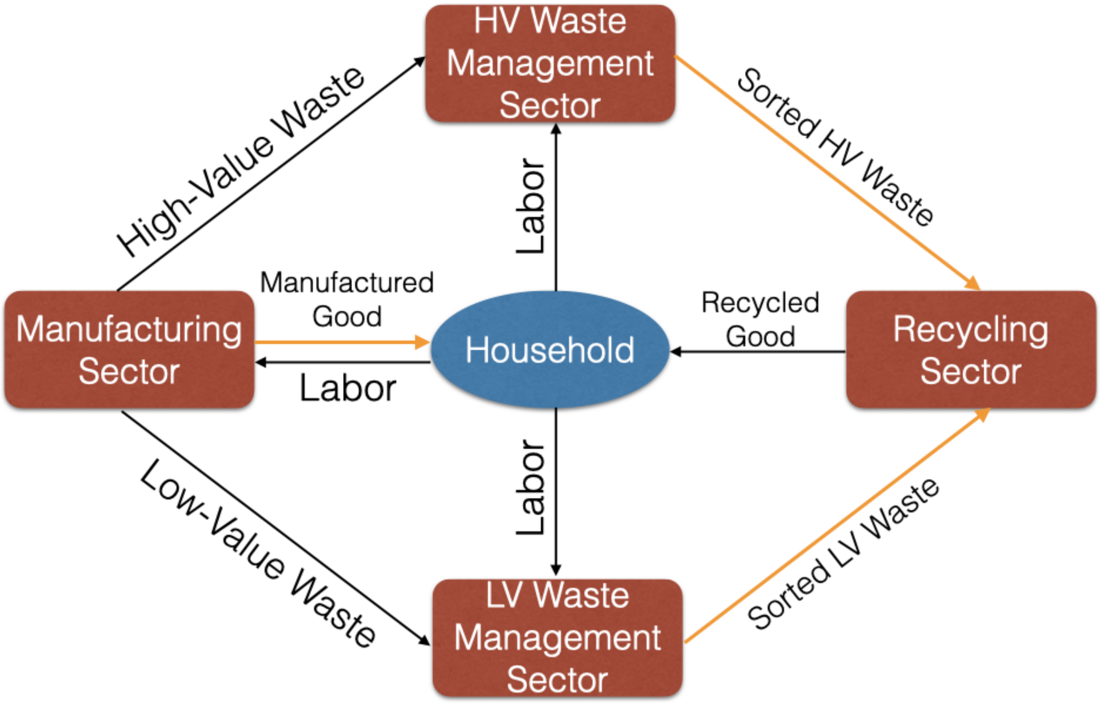
4.4.1 Price Indices

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:

$$p_{ij}(\nu_s) = \frac{w_i \tau_{sij}}{z_i(\nu_s)}. \tag{8}$$

Assuming the two types of waste to be homogeneous for collection purposes, I set $u_{si} =$

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



This figure shows the links between sectors in the general equilibrium model described in Section 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.

$w_i\ \forall s \in \{h, l\}$ in Equation (5). Hence, the term w_i in Equation (8) 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:

$$p_j(\nu_s) = \min_k \{p_{kn}(\nu_s)\}. \tag{9}$$

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:

$$P_{sj} = \left[\Gamma\left(\frac{\theta_s + 1 - \sigma_s}{\sigma_s}\right)\right]^{\frac{1}{1-\sigma_s}} \times \phi_{sj}^{-\frac{1}{\theta_s}}, \tag{10}$$

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

$$X_{mj} = \alpha w_j \bar{L}_j. \tag{11}$$

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:

$$X_{sj} = \lambda_j^{\sigma_s} \alpha_s P_{sj}^{1-\sigma_s}, \qquad s \in \{h, l\}. \tag{12}$$

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:

$$X_{sij} = \frac{T_i(w_i\tau_{sij})^{-\theta_s}}{\phi_{sj}} X_{sj}, \qquad s \in \{m, h, l\}. \tag{13}$$

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:

$$\sum_{s=\{h,l\}} X_{sj} = (1-\alpha)w_j\bar{L}_j, \qquad \forall j, \tag{14}$$

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

$$\beta\sum_i X_{mji} + \sum_i X_{hji} + \sum_i X_{lji} = w_j\bar{L}_j. \qquad \forall j \tag{15}$$

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 (10) to (13) 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 (24), and wages, $w \in \Delta(N-1)$, that solve labor market-clearing conditions (15). 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. 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) and Shapiro (2016), I reformulate the equivalent variation in terms of a proportional change in real income, $\hat{Y}_j/\hat{P}_j$, and change in the disutility term.[16] Thus, the equivalent variation for country j is:

$$EV_j = w_j \bar{L}_j \left(\left\{ \left(\frac{\hat{Y}_j}{\hat{P}_j} \right)^{\rho} - \frac{\mu(\sum_s W'_{sj})^{\rho} - \mu(\sum_s W_{sj})^{\rho}}{(\alpha^{\alpha}(1-\alpha)^{1-\alpha} Y_j/P_j)^{\rho}} \right\}^{1/\rho} - 1 \right). \tag{16}$$

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.[17] Finally, to obtain an estimate of the recycling rates for the two types of waste in the U.S., I calculate the imports-value weighted average of recycling rates for the materials in each type. Following this procedure, I calculate the average recycling rates for high-value waste and low-value waste to be 52.56% and 33.17%, respectively.[18] The higher recycling rate for high-value waste is consistent with the argument

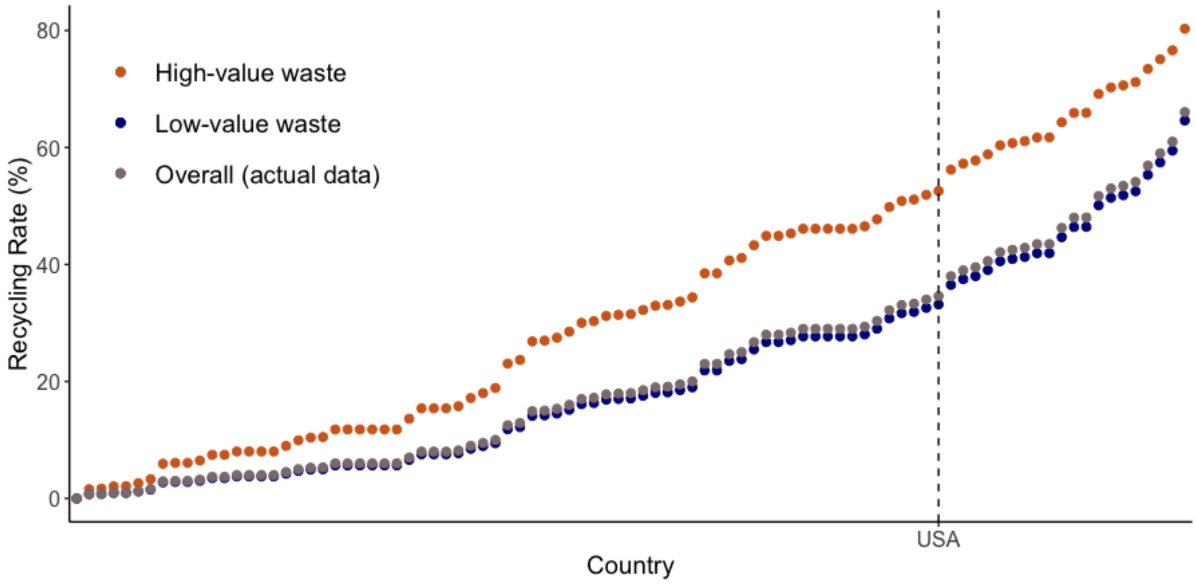
[16] To calculate the proportional change in real income, I require the proportional change in price of recycled good p_{rj}. Comparing the first-order conditions from the cost-minimization and profit-maximization problems of the recycling sector shows that $p_{rj} = \lambda_j$, which is solved implicitly using Equation (24). I use this relationship to measure the proportional change in p_{rj}.

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

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

that recycling high-value waste likely results in greater value-added to the economy than recycling low-value waste. Lastly, for other countries in my sample, I extrapolate the recycling rates by type of waste to be proportional to the overall recycling rates.[19] Figure 5 shows the distribution of recycling rates for both types of waste in my sample.

Figure 5: Recycling Rates by Type of Waste



This figure shows the extrapolated recycling rates for high- and low-value waste for the 91 countries in my sample. The "grey" dots represent the recycling rates for mixed waste from Kaza et al. (2018). The "orange" dots represent the recycling rates for high-value waste extrapolated to be proportional to overall recycling rates (grey dots) using the recycling rates for different materials under high-value waste for the USA from United States Environmental Protection Agency (2020). The "blue" dots are the analogous extrapolated recycling rates for low-value waste. See Section 4.5 for details.

4.6 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 aspects, namely, carbon dioxide emissions, air pollution, collection and sorting costs, and

robust to the extreme check of decreasing recycling rates for the lowest income group by 50%.

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

ocean clean-up costs.[20] [21] 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.[22] However, high-level of uncertainty persists in estimates of external costs of disposal due to dearth of good classification systems for waste materials and information on their heterogeneity and toxicity (Eshet et al., 2005; Liboiron, 2016). Therefore, I conduct a robustness check using estimates of social marginal costs of disposal from Eshet et al. (2005) instead and find that all main qualitative conclusions of the paper continue to hold even with estimates that are 80% smaller in magnitude than the baseline.

To formally calibrate the two utility parameters, I totally differentiate the indirect utility function in Equation (4). 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.

[20] A potential concern is that the $1000/tonne partially captures external costs at the global rather than domestic level due to the carbon dioxide emissions from waste disposal. However, of the $1000/tonne estimate, carbon dioxide emissions account for a share of only 37.5%. I find that my welfare estimates are robust to reducing the external cost for the European Union by this amount (See Section 6.6).

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

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

5 Estimation

In this section, I first present the estimation methodology and the results for trade elasticities in Section 5.1, followed by the estimation strategy for the other parameters in the model 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.

5.1 Trade Elasticities

The gravity equation (13) 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:[23]

$$\ln \frac{X_{sij}}{X_{sj}} = S_i - S_j - \theta_s \ln \tau_{sij}, \tag{17}$$

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, thereby capturing pollution haven effects in total waste flows.

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 elasticties, one must disentangle the effect of trade costs from that of trade elasticities. To do so, I use price data to construct a measure of trade barriers as in Eaton and Kortum (2002). The domestic price of any good, 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:

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

[23]Note that Eaton and Kortum (2002) estimate the equation $\frac{X_{ij}/X_j}{X_{ii}/X_i} = \left(\frac{P_i \tau_{ij}}{P_j}\right)^{-\theta}$ using a proxy for $\left(\frac{P_i \tau_{in}}{P_j}\right)$ that is constructed using price data. This version of the gravity equation, however, requires imputed gross manufacturing production data to construct the dependent variable (Simonovska and Waugh (2014)). In contrast, I estimate Equation (13) using GDP data as a proxy for X_{sj} and with country-specific effects.

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).[24] 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.3. The data from 2017 are temporally the closest to the trade data in my sample.[25] Thus, I exploit this disaggregated price data to obtain an approximate measure of trade barriers as follows:

$$\ln \hat{\tau}_{ij}^1 = \max_{\nu}\{\ln(p_j(\nu)) - \ln(p_i(\nu))\}. \tag{18}$$

where the superscript denotes the first-order statistic. However, due to lack of price data for waste, this measure of trade barriers does not vary by sector, $s \in \{m, h, l\}$. Assuming that the trade costs vary by a fixed proportion among the three sectors irrespective of the country pair, the country-specific fixed effects in Equation (17) would also absorb this unobservable heterogeneity in trade costs by sector. The trade barrier measure also suffers from measurement error due to the approximation and errors in the price data itself (Simonovska and Waugh, 2014). To address this, I estimate Equation (17) 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 (2014) show that Eaton and Kortum's measure of trade barriers, constructed using finite sample of prices, always *underestimates* the true trade costs. To address this issue, I instead use a modified trade cost measure, $2\hat{\tau}^1 - \hat{\tau}^2$, which is the 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 with less bias. Although Robson and Whitlock's approach is not based on explicit distributional assumptions like

[24] 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).

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

the 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 4 reports the trade elasticity estimates in the three sectors: manufactured goods, high-value waste, and low-value waste. I find that the OLS estimates with origin- and destination-level effects have the expected negative sign and increase in magnitude when moving from manufacturing to low-value waste sector, consistent with the pattern in Tables 2 and A.2. However, the measurement error in the trade barrier variable can lead to attenuation bias in the OLS estimates. In support of this interpretation, I find that the negative 2SLS estimates are larger in magnitude, in the range of 7.260 to 9.831. As before, the size of the estimates increases from manufactured goods to low-value waste. This finding implies that a 1% decrease in trade costs causes a 7.26% increase in manufacturing, a 7.29% increase in high-value waste, and a 9.83% increase in low-value waste flows. Since most countries accrue lesser benefits from importing low-value waste than from importing high-value waste or manufactured goods, the low-value waste flows are the most sensitive to trade costs.

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

	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 (17). 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.

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. In other words, ad-valorem costs are larger for commodities with larger weight-to-value ratios, i.e., low-value waste. Additionally, I show that among the two waste types, trade flows in high-value waste behave similar to manufactured goods while trade flows in low-value waste are more sensitive to trade costs. As a result, we observe large imports of low-value waste by lower income countries.

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

5.2 Price of Recycled Good, Technology, and Trade Costs

Equations (10) to (13) specify the value of trade flows from country i to country n in sector s:

$$
\begin{aligned}
X_{sij} = \frac{T_i(w_i\tau_{sij})^{-\theta_s}}{\phi_{sj}} X_{sj}, \qquad s \in \{m,h,l\}, \\
X_{mj} = \alpha w_j \bar{L}_j, \\
X_{sj} = \lambda_j^{\sigma_s} \alpha_s P_{sj}^{1-\sigma_s}, \qquad s \in \{h,l\}, \\
P_{sj} = \left[\Gamma\left(\frac{\theta_s + 1 - \sigma_s}{\sigma_s}\right)\right]^{\frac{1}{1-\sigma_s}} \times \phi_{sj}^{-\frac{1}{\theta_s}}, \\
\phi_{sj} = \sum_i T_i(w_j\tau_{sij})^{-\theta_s},
\end{aligned} \tag{19}
$$

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 (24), and the technology parameters, T_j, are solved using Equation (15). 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.

My sample comprises data on 91 countries. Trade among countries within my sample accounts for 91% of world trade in manufactured goods, 95% of world trade in high-value waste, and 96% of world trade in low-value waste. To perform the estimation, I set $\alpha = 0.993$ 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 (24) 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 (15) 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.[26]

Stage III: Trade Costs. Substituting implicit solutions of $\{T_i\}_{i=1}^N$ and $\{\lambda_j\}_{j=1}^N$ into Equation (19), which describes trade flows in the three sectors, I obtain the stochastic

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

form of trade flow equations as:

$$X_{sij} = h(w, L; \alpha, \beta, \alpha_h, \theta_m, \theta_h, \theta_l, \sigma_h, \sigma_l, \{\tau_{mij}\}_{i,n=1}^N, \{\tau_{hij}\}_{i,n=1}^N, \{\tau_{lij}\}_{i,n=1}^N) + \epsilon_s \quad (20)$$

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.[27]

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 also avoids solving an NLLS optimization problem using the polytope method, which runs into the issue of convergence to a local rather than global minima in multivariate cases (Judd, 1998).

A drawback of my approach, however, is that I cannot separately identify bilateral trade costs from heterogeneity at the country level (Costinot and Rodríguez-Clare, 2014), such as country-specific preferences towards different commodities. To verify that the trade cost estimates capture actual trade barriers, 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.

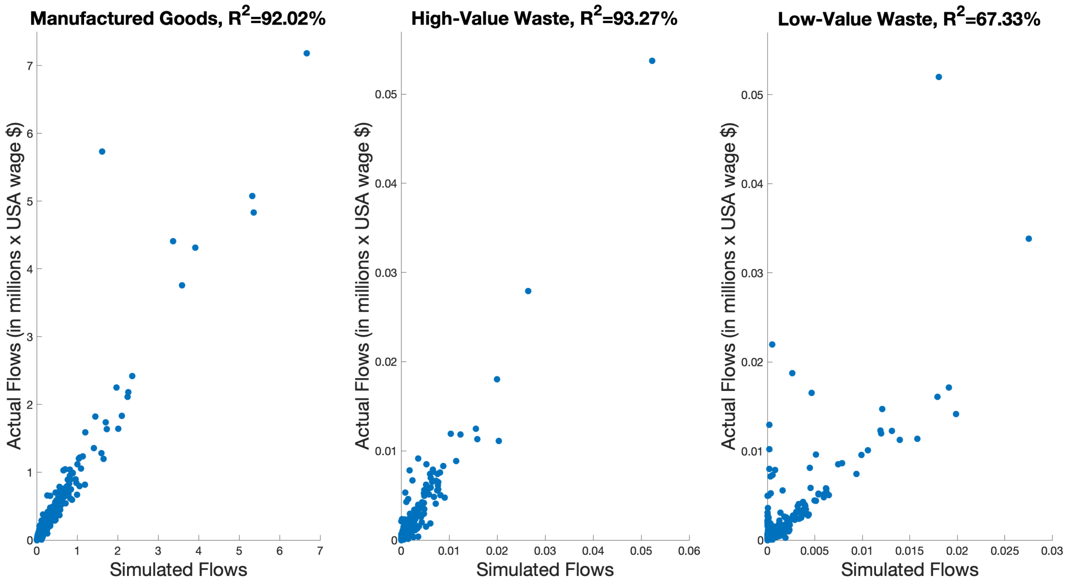
5.3 Goodness of Fit

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

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

align with facts in the data. Figure 6 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.[28]

Figure 6: 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:

$$\log(\hat{\tau}_{sij}) = \gamma_1 + \gamma_2 Distance_{ij} + \gamma_3 Distance_{ij}^2 + \boldsymbol{\delta}\mathbf{D_{ij}} + \varepsilon_{sij}, \qquad s \in \{m, h, l\} \qquad (21)$$

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,

[28] 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 5 shows that the $\bar{R}^2$ for the three sectors is in the range of 4.3-9.4%. Even though the R^2 are relatively low because I exclude country- and sector-specific trade barriers for this sanity check, they suggest that the estimated trade costs capture variation due to geographic barriers. In addition, since the coefficient on $Distance$ is positive and significant while the coefficient on $Distance^2$ is negative and significant, the estimated trade costs are a concave function of distance. Thus, the positive marginal effect of distance on trade costs is decreasing with distance. The signs on the rest of the dummies—contiguity, common language, and free trade agreement—are consistent with the stylized facts obtained from the raw data.

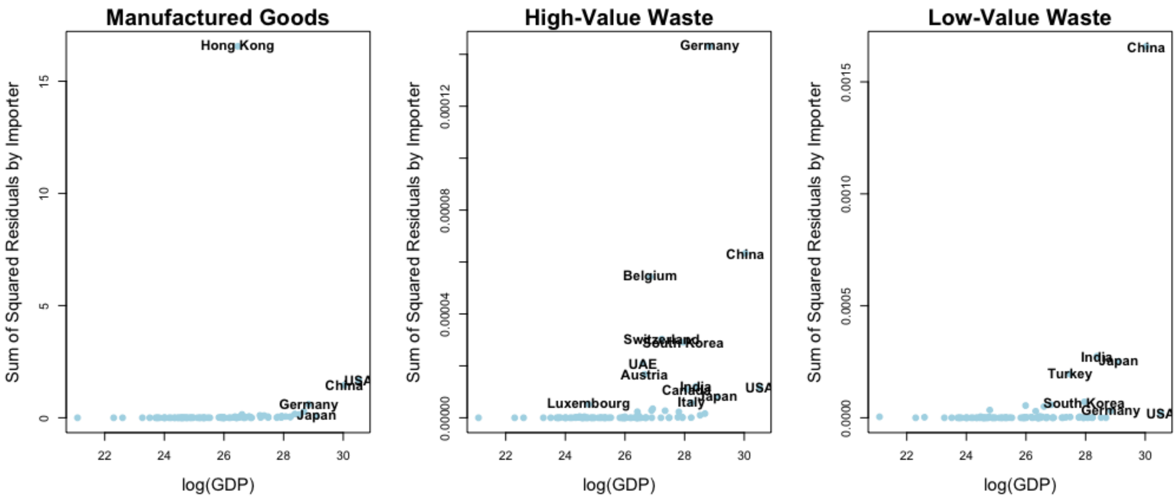
Table 5: Goodness of Fit-Estimated Trade Costs and Geographic Barriers

	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 (21). 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 7 shows that the residuals are larger for higher-income countries. Table 6 shows that–as a percentage of GDP, trade among the 30 richest countries in the sample is 12.558% for the manufacturing sector, 0.048% for high-value waste, and 0.047% for low-value waste. The model closely predicts these shares to be 12.396%, 0.050%, and 0.040%, respectively. Unlike the Eaton and Kortum (2002) model, which underestimates trade flows in general, the model captures trade among rich countries well. Consistent with Fieler (2011), this finding is robust to the choice of weights, as the dependent variable X_{ij} in Stage III places higher weights on larger countries.[29] Thus, even though the residuals are higher for larger countries, the model adequately captures trade among them. Further, the fact that the model underpredicts low-value waste trade for the rich, who trade relatively less in this sector explains the finding that the R^2 for this sector in Figure 6 is lower than that for the other two.

Figure 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.

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.

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

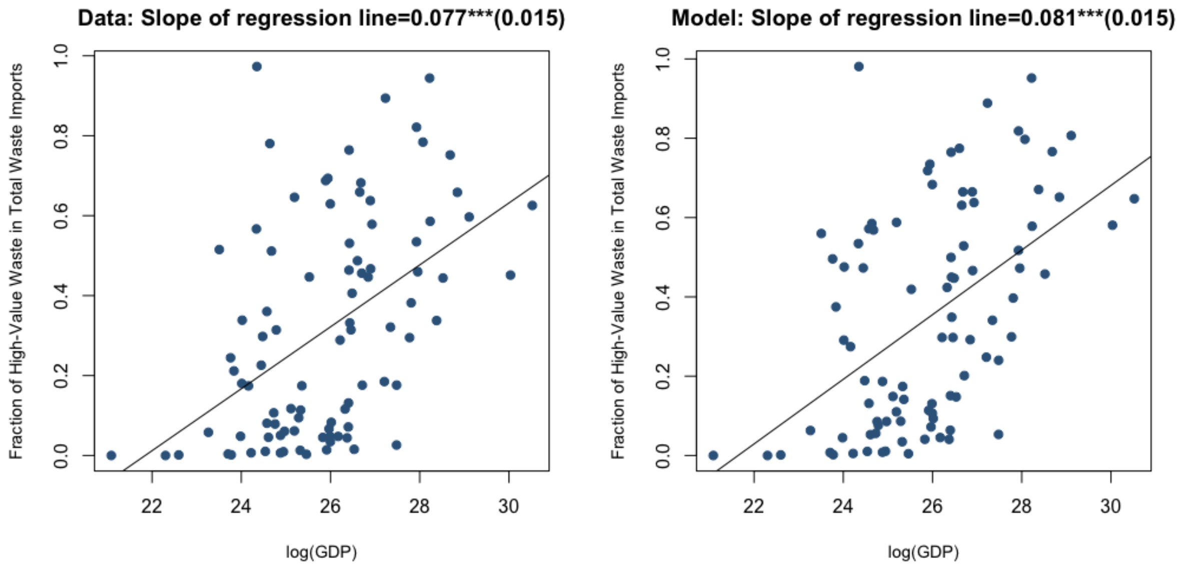
Table 6: Goodness of Fit-Trade as a % of GDP

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.

Figure 8 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 7 shows that the model also captures the increasing relationship between the sector-specific share of total trade in GDP, which I henceforth refer to as "openness" for that sector, and income per capita. While the data show a positive and statistically significant relationship between openness and income per capita for the manufacturing and high-value waste sectors, the model captures the positive relationship across all three sectors, which is not statistically significant in any sector.

Figure 8: 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 $log(GDP)$.

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

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

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	$-0.004^{***}(0.001)$	$-0.003^{***}(0.001)$

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.

6 Counterfactuals

In this section, I analyze a set of policy counterfactuals to study the effects of waste trade. Since the counterfactuals related to waste trade policies are novel exercises, I first present the results from the standard autarky counterfactual as a benchmark in Section 6.1. Then, I present the results from the waste-autarky counterfactual in which all waste trade is shut down in Section 6.2, the results from China's ban on certain categories of waste imports in Section 6.3, and the welfare implications of the Basel Ban amendment, which bans exports of all hazardous waste from developed to developing countries, in Section 6.4.

For each policy change, I change the relevant set of trade costs and solve the market-clearing conditions (24) and (15) 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 (16) to calculate the effect of the policy change. When calculating the externality costs at the new equilibrium using Equation (3), only the pattern of trade, captured by $\sum_i X_{sij}$, changes while the disposal intensity, χ_{sj}, remains constant.[30] Thus, while the *technique* of disposal remains unchanged, the *composition* of waste changes as the buyers alter their demand for the volumes and varieties of the two waste types from different countries.

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

6.1 Autarky

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

Panel A in Table 8 presents the gross benefits and environmental costs of shutting down all trade. The rich countries have the largest gains to trade of 3.25% of GDP. Further, countries, such as Belgium and Singapore, that are relatively open to trade have among the highest benefits, while countries that are relatively closed to trade, such as the United States, have among the lowest benefits to trade (See Table A.6). A host of modeling assumptions on the supply-side—market structure, firm-level heterogeneity, one sector, multiple sectors, intermediate goods, and multiple factors of production—and the demand side—CES utility—play a role in explaining the modest size of these benefits (Costinot and Rodríguez-Clare, 2014). However, both the the size and the pattern of the gains across countries are consistent with the findings in the standard gravity literature (Eaton and Kortum, 2002).

On the environmental costs side, middle-income countries disproportionately bear the externality costs due to trade of 0.85% of GDP. This finding reflects that middle-income countries spend a higher fraction of their GDP on importing disposal-intensive low-value waste. Although poor countries also allocate large fractions of their GDP on low-value waste imports, middle-income countries have higher social marginal costs of waste disposal than those countries. At the country level, I find that although most countries incur larger environmental costs from opening to trade, some small-sized countries, such as the Seychelles and Moldova, incur smaller costs too. Such smaller economies have limited domestic capacity to recycle and thus rely primarily on exports to deal with waste. Since waste trade accounts for only 0.07% of overall international trade in commodities, the small environmental costs due to waste, approximately 0.23% of gross benefits, are unsurprising.

Table 8: Counterfactual Results

Income Group	Δ Gross Benefits (%GDP)	Δ Gross Benefits (billions $)	Δ Environmental Costs (%GDP)	Δ Environmental Costs (billions $)
	Panel A: Autarky			
Global	-3.05	-2168	-0.70	-494
Rich	-3.25	-1480	-0.65	-294
Middle	-2.63	-589	-0.85	-189
Poor	-3.21	-99	-0.35	-11
	Panel B: Waste-Autarky			
Global	-0.013	-9	0.003	2.3
Rich	-0.014	-6	0.003	1
Middle	-0.009	-2	0.003	0.7
Poor	-0.021	-0.6	0.009	0.3
	Panel C: High-Value Waste-Autarky			
Global	-0.01	-7	0.004	3
Rich	-0.012	-6	0.005	2.3
Middle	-0.007	-2	0.003	0.8
Poor	-0.001	-0.04	0.001	0.02
	Panel D: Low-Value Waste-Autarky			
Global	-0.004	-3	-0.001	-0.5
Rich	-0.006	-3	-0.0002	-0.08
Middle	0.001	0.2	-0.002	-0.4
Poor	-0.004	-0.1	0.00001	0.0003
	Panel E: China Ban			
Global	-0.002	-1	0.0003	0.2
Rich	-0.002	-1	0.001	0.3
Middle	-0.0001	-0.03	-0.0002	-0.05
Poor	0.002	0.06	-0.002	-0.05
	Panel F: Ban Amendment			
Global	-0.003	-2	0.001	0.7
Rich	-0.003	-2	0.0004	0.2
Middle	-0.002	-0.4	0.002	0.4
Poor	-0.010	-0.3	0.005	0.1

Each panel in this table reports the results from a counterfactual exercise. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The Δ Gross Benefits are calculated in terms of proportional changes in real income, $w_j \bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$, and Δ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. See Sections 4.5 and 6 for further details.

6.2 Waste-Autarky

In the waste-autarky counterfactual, trade in both 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. Panel B in Table 8 reports the gross benefits and environmental costs of prohibiting trade in waste. Globally, the gains due to trade in waste are 0.013% of GDP. Thus, even though waste trade accounts for only 0.07% of overall trade by value, the gains from waste trade are 0.43% of the gains from overall trade.[31] This finding suggests that, per unit of trade value, waste trade creates more than five-times the gains from regular trade. As opposed to trade in manufactured goods, waste trade poses negative externalities on the local environments. Thus, countries have sufficient incentive to trade in waste only when the gross benefits from it exceed those from trade in manufactured goods.

Differentiating the gains by income group, I find that poor countries disproportionately benefit from trade in waste, at 0.021% of GDP. Similarly, allowing waste trade counterintuitively decreases the environmental costs for countries of all income levels but for the poor disproportionately so at 0.009% of GDP. Two main forces govern the differentiated effects on countries. First, the commodity a country specializes in, which is governed by the trade elasticities. Second, 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, which has high disposal intensity and creates large externality costs, even though more options for dealing with waste become available through the waste trade. As a result, the environmental costs counterintuitively decline for all income levels with waste trade. Moreover, as poor countries disproportionately import low-value waste, their environmental costs decline disproportionately.

Globally, I find that the volume of high-value waste rises by 12.25%, while the volume of low-value waste declines by 0.73%. Equation (12) shows that the changes in the prices of the two inputs to recycling, i.e., high- and low-value waste, relative to the price of recycled output are sufficient to explain the changes in overall volumes of waste generation. Thus, a rise in the price of low-value waste and a fall in the price of high-value waste relative to the price of recycling output explain the volume changes. Since low-income countries specialize in low-value waste, the relative price increase for this input also benefits them the most. In summary, all country groups are better off with

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

waste trade even after accounting for its environmental costs—restricting waste trade is inefficient due to incomplete specialization.

I find that high-value waste trade creates welfare effects that are qualitatively similar to the overall waste trade. However, rich countries, which specialize in high-value waste exports and disproportionately use it as an input in their recycling, gain the most—0.012% of GDP—and incur the largest decline in environmental costs—0.005% of GDP—governed by substitution away from generation of low-value waste on allowing high-value waste trade (Panel C in Table 8). In contrast, with low-value waste trade, the direction of changes in the volume of generation of the two types of waste flips; high-value waste generation decreases while low-value waste generation increases while its price falls. As a result, the middle-income countries are worse off as these countries disproportionately import and dispose of low-value waste as a residual of their recycling. (Panel D in Table 8).

I also report country-level estimates of the gross benefits and costs of imposing waste-autarky in Table A.7. On the benefits side, countries more open to trade in waste, such as Belgium and Vietnam, experience the largest gains to waste trade, while countries relatively closed to waste trade, such as the United States and Brazil, experience the lowest benefits. Some small countries, such as the Seychelles and Zambia, experience negative gains and positive externality costs due to waste trade. Such countries that are reliant on exports to deal with waste increase the volume of generation of both waste types as more options for dealing with waste become available with allowing waste trade. In addition, the price of recycled good increases relative to wages, leading to a decrease in their real incomes.

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

6.3 China Ban

In 2018, China imposed an import ban on 24 categories of waste that included types of plastics, paper, and yarn. Over the next two years, it expanded the banned categories to include scrap metal, old ships, slag, stainless steel, and timber (You, 2018). Since the banned categories have substantial overlap with low-value waste in my sample, I shut down imports of low-value waste by China, a major importer of this type of waste, to study the effects of the ban. Table A.8 shows that the policy helps China on both fronts, with an increase in gross benefits and a decrease in environmental costs, while also helping other low-income countries, such as India and the Philippines, in the same manner.

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

Finally, the Chinese ban also reorganizes the production of manufactured goods globally in accordance with the commodity each country specializes in. Similar to a complete ban on low-value waste trade, the China ban hurts the manufacturing production in poor countries, with volume decrease of 0.001%, while helping the production in middle-income countries, with a volume increase of 0.002%.

6.4 Ban Amendment

The Ban amendment to the Basel Convention, which came into force in 2019, is an agreement among parties to the Convention to prohibit exports of all hazardous waste from the Organization of Economic Cooperation and Development (OECD), the EU, and Liechtenstein to other countries that primarily include developing countries (Basel Action Network and International Pollutants Elimination Network, 2019). According to the amendment, Annex VII countries that have ratified the amendment are prohibited from exporting hazardous waste to any Non-Annex VII country, regardless of whether they ratified the amendment or not. Similarly, the Non-Annex VII countries that have ratified the amendment are prohibited from accepting imports of hazardous waste from any Annex VII country. The amendment also bans trade in non-hazardous waste that is contaminated with hazardous substances and defers to country definitions of hazardous waste in several cases. Since all waste can, arguably, have some degree of hazardous content (Kellenberg and Levinson, 2014), I impose the Ban amendment by shutting all waste exports from Annex VII countries that ratified the amendment to all Non-Annex VII countries and all waste imports of Non-Annex VII countries that ratified the amendment from all Annex VII countries. Table A.9 lists the 36 Annex VII countries, of which 29 ratified the amendment, and the 52 Non-Annex VII countries, of which 29 ratified the amendment within the sample.

Panel F in Table 8 reports the gross benefits and environmental costs of the Ban amendment. I find that the results are qualitatively similar to the waste-autarky counterfactual, albeit the magnitudes are lower. The welfare effects of imposing the Ban amendment are 23-33% of the effects of imposing an overall waste trade ban. Surprisingly, my estimates reveal that this policy that is meant to favor the developing countries that ratified the amendment is most harmful to them, similar to an overall waste trade ban, which is also most harmful to poor and developing countries. The lower income countries care more about bolstering their manufacturing production via secondary inputs than the environmental externalities created by their disposal while the rich countries are more sophisticated entities that at least partially account for the externality costs while making trading decisions. Thus, even a partial restriction of exports of waste from the rich to the poor hurts the poor the most.

6.5 Importance of Pollution Haven Effects

To study the role of pollution haven effect in altering trade patterns and welfare, I impose a counterfactual scenario where ratio of expenditure on high- to low-value waste is independent of the income level of a country, i.e., $\sigma_h - \sigma_l = 0$. Panel A in Table 9 shows that removing the PHE lowers the environmental costs of the middle-income and low-income countries while raising them for the high-income countries. 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 the 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 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 benefits for the poor increase. Overall, not allowing pollution havens makes the lower-income countries better off at the expense of the rich.

As pollution havens are created on liberalization of trade, I study the welfare effects of trade policies in a framework where there are no pollution haven effects. Comparing

Panels B-E in Table 9 with Table 8 shows that the lower income countries now no longer bear the disproportionately high environmental costs of waste disposal from liberalization of all types of trade. Further, unlike the model with PHE, 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 effects impose welfare losses on lower-income countries due to waste trade.

6.6 Robustness Checks

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

First, I test the robustness of my environmental cost estimates to a 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:[32]

$$V_j = \alpha^{\alpha}(1-\alpha)^{1-\alpha} \times \frac{Y_j}{P_j} \times \frac{1}{1+\sum_s W_{sj}^2}, \tag{22}$$

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}, the volume of waste that is 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.[33]

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, $e_j(v, P, \{W_s\}_{s=h,l}) = V_n P_n(1 + \sum_s W_{sj}^2)$.

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

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

Table 9: Importance of Pollution Haven Effect

Income Group	Δ Gross Benefits (%GDP)	Δ Gross Benefits (billions $)	Δ Environmental Costs (%GDP)	Δ Environmental Costs (billions $)
	Panel A: Removing Pollution Haven Effect			
Global	-0.003	-2	0.001	0.4
Rich	-0.009	-4	0.003	2
Middle	0.009	2	-0.004	-1
Poor	0.012	0.4	-0.007	-0.2
	Panel B: Autarky			
Global	-3.04	-2158	-0.53	-376
Rich	-3.22	-1467	-0.45	-207
Middle	-2.64	-591	-0.71	-160
Poor	-3.23	-100	-0.33	-10
	Panel C: Waste-Autarky			
Global	-0.013	-9	0.003	2.3
Rich	-0.015	-7	0.003	1
Middle	-0.007	-1	0.002	0.4
Poor	-0.028	-0.9	0.014	0.4
	Panel D: High-Value Waste-Autarky			
Global	-0.01	-7	0.004	3
Rich	-0.011	-5	0.004	2
Middle	-0.006	-1	0.003	0.6
Poor	-0.022	-0.7	0.013	0.4
	Panel E: Low-Value Waste-Autarky			
Global	-0.004	-2.5	-0.001	-0.4
Rich	-0.003	-1	-0.001	-0.6
Middle	-0.003	-0.8	0.001	0.1
Poor	-0.012	-0.4	0.004	0.1

Each panel in this table reports the results from a counterfactual exercise. Panels B-E are the welfare effects from changes in trade policy in a model without the pollution haven effect, i.e., $\sigma_h = \sigma_l$. 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, $w_j \bar{L}_j(\hat{Y}_j/\hat{P}_j - 1)$, and Δ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. See Section 6.5 for further details.

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.[34] 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 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. I also present the corresponding calibrated externality parameters for high- and low-value waste in Figures A.4 and A.5, respectively. Panel A in Table A.11 shows the externality cost estimates by income group under each counterfactual. Since the substitution across goods and the externality is less sensitive to price changes in the Cobb-Douglas formulation than in the baseline CES formulation, the environmental cost estimates are larger. The robustness of the results suggests that rather than the functional form of the externality, the social marginal cost of disposed waste and the general equilibrium changes from a policy drive the results.

Another potential concern in the calculation of externality costs is the choice of estimates for the social marginal cost of disposed waste. In particular, the costs from carbon dioxide emissions from waste disposal are borne by the world as a whole. Therefore, the estimate of \$1000/tonne from Bond et al. (2020) partially accounts for external effects at the global rather than the domestic level. Of the \$1000/tonne estimate, carbon dioxide emissions account for a share of only 37.5%. I check the robustness of my welfare estimates to reducing the social marginal cost for the European Union to \$625. These social marginal costs translate to $\mu = 0.0065$ and $\rho = 0.5174$, i.e., $\sigma = 2.07$. Panel B shows that the external costs for all income groups decrease across counterfactuals. The decrease in the external costs are explained by an increase in ease of substitution across

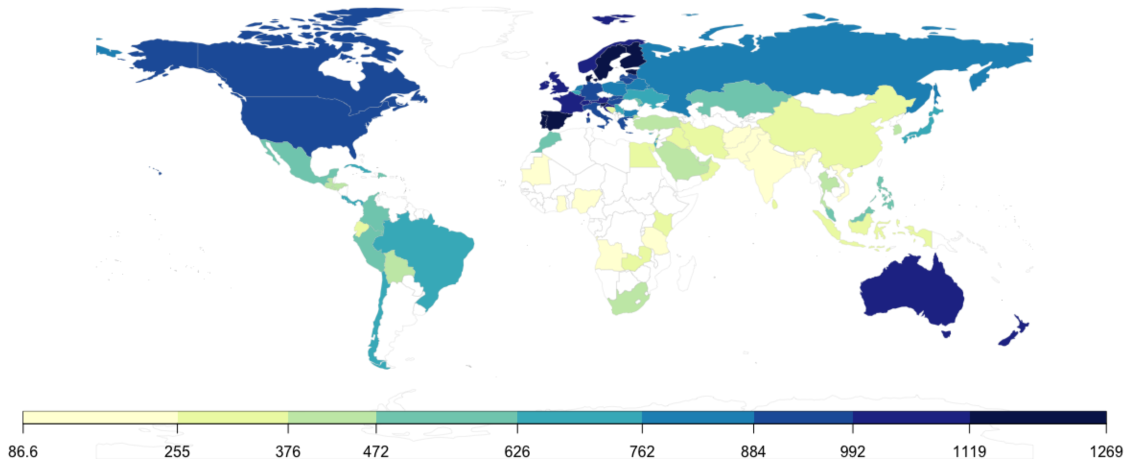
[34] I solve the following two equations in two unknowns:

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

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

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 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. Section 4.6 describes the extrapolation methodology in detail.

goods and bads. Despite the decrease in the external costs, however, the main qualitative conclusions continue to hold.

However, high-level of uncertainty persists in estimates of external costs of disposal due to 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 disameneties from landfilling and incineration. I sum the mid-points from these three range 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. Panel C shows that even with such low external cost estimates, all qualitative conclusions go through.

I also assess the robustness of my results to alternative trade elasticity estimates. Specifically, Simonovska and Waugh (2014) show that the true trade elasticity for manufactured goods is roughly 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.5. Table A.12 shows the welfare estimates across counterfactuals. As the variability in labor efficiencies increases, i.e., the size of the trade elasticity estimates decreases, the size of welfare gains increases across all counterfactuals (Simonovska and Waugh, 2014; Shapiro, 2016). However, the qualitative conclusions of the paper are robust to these changes.

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

7 Extension: Recycled Good as an Intermediate Input

A more realistic framework is one where the recycled good serves an an intermediate input to manufacturing production instead of as a final consumption good. Therefore, 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:

$$p_j(\nu_m) = \frac{w_j^{\beta'} p_{rj}^{1-\beta'}}{z_j(\nu_m)}, \tag{23}$$

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:

$$\sum_{s=\{h,l\}} X_{sj} = (1-\beta') \sum_i X_{mji}, \qquad \forall j. \tag{24}$$

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

$$U_j = Q_j^{\rho} - \mu\Big(\textstyle\sum_{s=\{h,l\}} W_{sj}\Big)^{\rho},$$

where

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

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

$$X_{mj} = w_j \bar{L}_j. \tag{25}$$

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, $\beta' = 0.993$.

Upon re-estimating the parameters under this modified framework, I conduct the counterfactual exercises as before to study the welfare effects with recycled good as an intermediate input. Table Table A.13 shows that all qualitative conclusions of the paper hold except that any type of waste trade now hurts the lowest income countries. Allowing any waste trade decreases the price of recycled product relative to manufactured goods. Thus, gross benefits for the lowest income countries decline as they specialize in waste reprocessing. Further, as volume of recycling increases, the environmental costs also increase for the poorest countries.

8 Conclusion

I quantify the welfare implications of international trade in waste. To this end, I build a structural gravity model with the generation of waste micro-founded as a by-product of manufacturing where waste itself is an input to recycling. I further decompose the waste flows into low-value waste and high-value waste and allow for heterogeneity in the abilities of countries to both generate and recycle the two types of 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 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 other key empirical facts in waste trade data. I find that richer countries import a greater share of high-value than low-value waste. I capture this finding by formulating non-homothetic production in a country's recycling sector that uses both types of waste to produce a recycled good. Apart from the nature of their trade flows, the two types of waste also differ in their ease of recycling. So, my setup allows me to determine separately not only the gains from trade in the two types but also the environmental costs from their disposal.

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 to tackle this issue. I first estimate the trade elasticities by using model predictions to construct an economic measure of trade barriers and using the geographic barrier distance as an instrument for it. 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, a 7.3% increase in high-value waste, 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. Further, these countries have much higher open dumping rates that contribute to the environmental costs from 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 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 different assumptions on social marginal costs of disposal and trade elasticities. The only exception to this occurs on allowing trade in recycled goods indirectly through manufacturing trade in which case the lowest income countries are hurt by any form of waste trade.

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

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A Social Marginal Cost of Waste Disposal

I use the form in Equation (22) to calibrate social marginal cost of waste disposal for use in the counterfactual calculations. To do so, I calibrate a lower bound of the social marginal cost of low-value waste disposal for countries that implemented the Ban amendment. I use the Ban amendment implementation as a revealed preference to solve for estimates of the social marginal cost of low-value waste such that the net benefits from the policy change are zero. Since I aim to capture lower bounds on the economic valuation of only low-value waste, I set the externality parameter for high-value waste, $\mu_{hn} = 0$, and focus on countries whose gross benefits and environmental costs both decrease with the policy change.[35] Consequently, I infer the externality parameter and the corresponding social marginal cost of low-value waste for four countries: Belgium, Finland, UK, and Zambia. Then, I extrapolate social marginal cost and the corresponding externality parameters to the rest of the countries in my sample based on log incomes. In this way, I use the model to get a lower bound of the social marginal cost of disposed low-value waste for each country to use for the calculation of environmental costs in the counterfactuals.

Panel D in Table A.11 shows the results with these alternative estimates of social marginal costs of disposed waste. I find that the results are *qualitatively* similar, i.e., the direction of change in the environmental costs holds, but *quantitatively* larger than with the baseline social marginal cost estimates. These results suggest that the changes in scale and composition of waste disposal are the same, but the willingness-to-pay to avoid waste disposal is larger than in the literature.

One caveat of this approach to estimating social marginal costs of waste disposal is that ratifying countries likely only considered the waste re-location effects of the policy while the social marginal costs that I infer from the model are accounting for its general equilibrium effects. Thus, the values I infer from the model are higher than the true valuation placed by countries on the externality due to disposed waste. Even in this case,

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

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

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

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

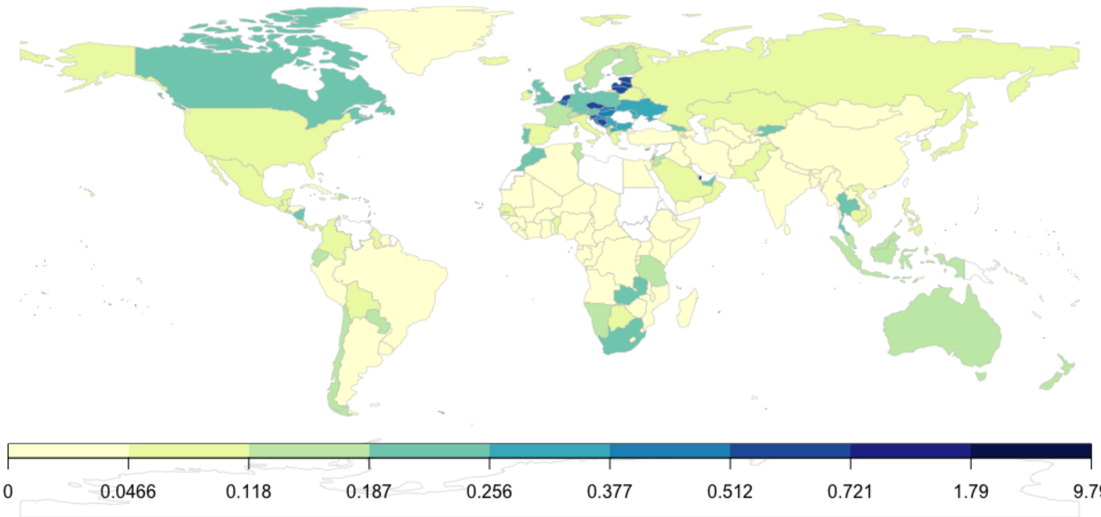

Figure A.2: Aggregate Waste Imports (as % of GDP)

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

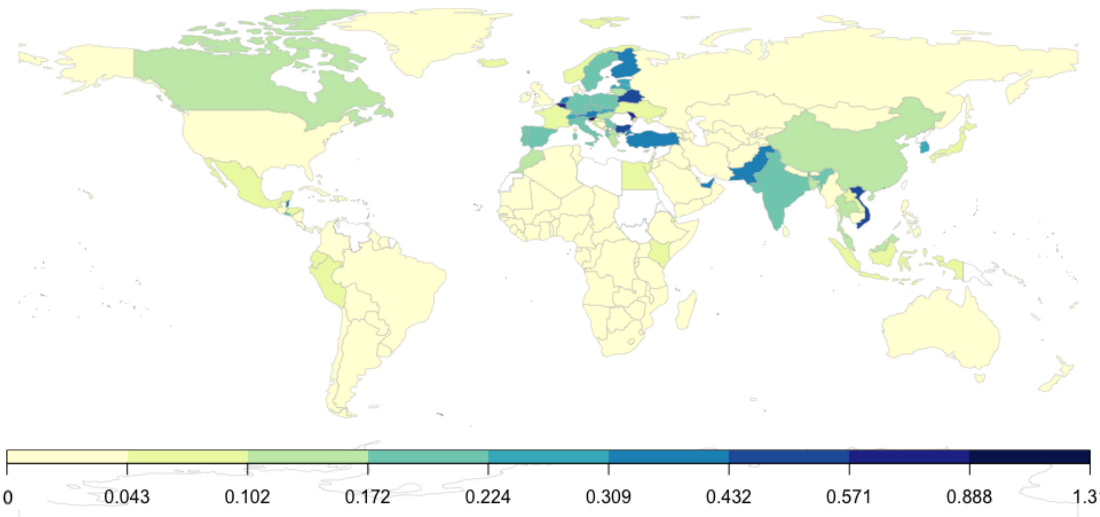

Figure A.3: Value-to-weight Ratios for Waste Categories

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

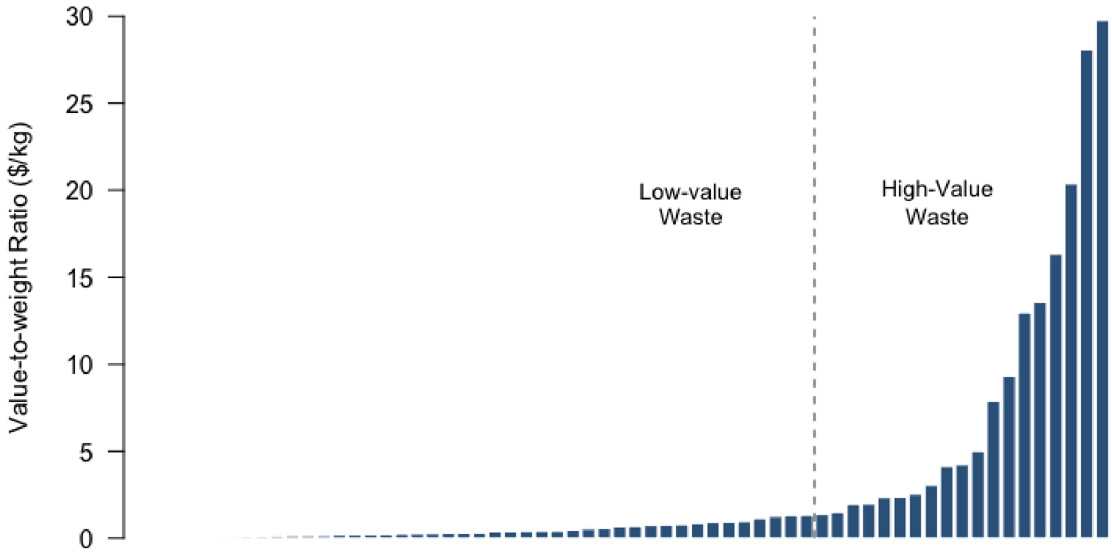

Figure A.4: Externality Parameter for High-Value Waste, μ_h

This figure shows the calibrated externality parameters for high-value waste for each country in my sample. See Section 4.6 for details on the calibration methodology.

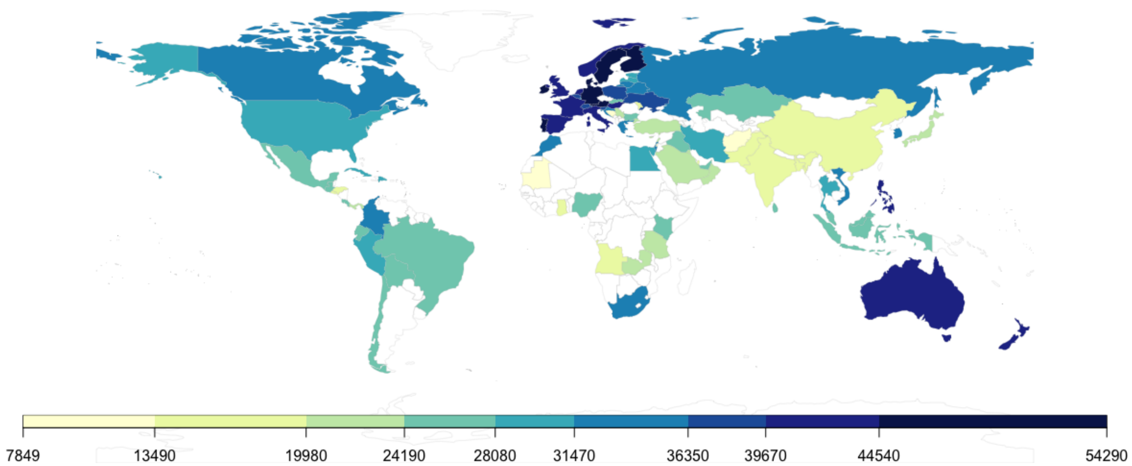

Figure A.5: Externality Parameter for Low-Value Waste, μ_l

This figure shows the calibrated externality parameters for low-value waste for each country in my sample. See Section 4.6 for details on the calibration methodology.

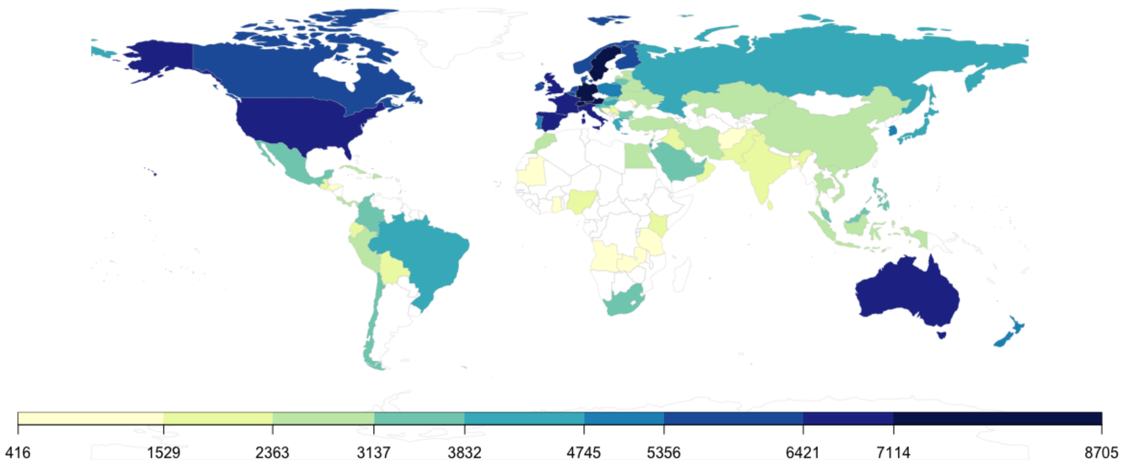

Table A.1: Harmonized System (HS) Categories of Waste

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

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

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

This table reports the results from estimation of Equation (1). The dependent variable is bilateral manufactured good flows. Although I include trade flows among 233 countries or territories, the number of observations varies by specification depending on the number of missing values for independent variables, 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.

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

Table A.3: 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.4: Estimating Trade Elasticities with Trade Barrier= $\hat{\tau}^2_{in}$

This table reports the results from estimation of Equation (17). 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.5: Estimating Trade Elasticities with Trade Barrier= $\hat{\tau}^1_{in}$

This table reports the results from estimation of Equation (17). 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.6: Country-by-Country Impacts in Autarky Counterfactual

This table reports the country-level results of the Autarky counterfactual (See Section 6.1). All figures are in % of 2015 GDP.

Country	ΔGross Benefits	ΔEnvironmental Costs	Country	ΔGross Benefits	ΔEnvironmental Costs
China, Hong Kong SAR	-45.500	-0.108	El Salvador	-3.46	0.00823
Viet Nam	-19.200	-0.124	Chile	-3.27	-0.199
Singapore	-18.700	-0.148	Angola	-3.25	-0.0947
Belgium	-14.700	-0.204	Israel	-3.19	-0.217
Hungary	-12.700	-0.099	Spain	-3.18	-1.34
Estonia	-12.100	0.011	Norway	-3.17	-0.234
Slovakia	-11.500	-0.068	Italy	-3.13	-1.3
Slovenia	-11.300	-0.009	South Africa	-2.97	-0.205
Latvia	-11.200	0.007	France	-2.93	-1.32
Netherlands	-10.700	-1.200	Kazakhstan	-2.78	-0.168
Malaysia	-10.500	-0.195	Bolivia	-2.71	-0.0129
Lithuania	-8.710	-0.020	Bangladesh	-2.66	-0.166
Honduras	-7.690	0.010	United Kingdom	-2.51	-1.29
Mauritania	-7.250	0.031	Turkey	-2.43	-0.345
Bulgaria	-7.090	-0.028	Russian Federation	-2.4	-0.401
Bahrain	-6.920	-0.003	Indonesia	-2.38	-0.347
Oman	-6.510	-0.061	Sri Lanka	-2.36	-0.0917
Panama	-6.400	-0.041	Costa Rica	-2.32	-0.0478
Thailand	-6.360	-0.247	Kenya	-2.3	-0.0554
United Arab Emirates	-6.270	-0.205	China, Macao SAR	-2.26	-0.03
Poland	-5.830	-0.246	Guatemala	-2.23	-0.0594
Belarus	-5.540	-0.059	Peru	-2.17	-0.168
Bosnia Herzegovina	-5.530	0.030	Lebanon	-2.15	-0.0284
Austria	-5.380	-0.193	Greece	-2.14	-0.156
Seychelles	-5.300	0.368	Occ. Palestinian Terr.	-2.14	0.0363
Serbia	-5.160	-0.009	Dominican Rep.	-2.05	-0.0488
Mexico	-4.940	-0.377	Ecuador	-2.05	-0.0881
Ukraine	-4.850	-0.086	China	-2.04	-1.4
Ghana	-4.790	-0.029	Iran	-1.98	-0.248
Rep. of Korea	-4.740	-1.250	Saudi Arabia	-1.91	-0.3
Ireland	-4.680	-0.193	Colombia	-1.9	-0.221
Germany	-4.620	-1.190	India	-1.9	-0.449
Switzerland	-4.600	-1.270	New Zealand	-1.83	-0.145
Croatia	-4.560	-0.039	Japan	-1.79	-1.39
Luxembourg	-4.280	-0.044	Cyprus	-1.78	0.00109
Qatar	-4.280	-0.154	Afghanistan	-1.75	0.0137
Philippines	-4.230	-0.218	Australia	-1.74	-1.31
Rep. of Moldova	-4.210	0.052	Kuwait	-1.68	-0.1
Zambia	-4.180	0.007	Pakistan	-1.66	-0.196
Portugal	-4.160	-0.170	United States of America	-1.66	0.000815
Iraq	-4.150	-0.162	United Rep. of Tanzania	-1.64	-0.0363
Sweden	-3.890	-0.249	Egypt	-1.48	-0.216
Finland	-3.690	-0.179	Nigeria	-1.47	-0.274
Canada	-3.670	-1.340	Brazil	-1.3	-0.447
Denmark	-3.670	-0.208	Cuba	-0.661	-0.103
Morocco	-3.630	-0.089			

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

This table reports the country-level results of the Waste-Autarky counterfactual (See Section 6.2). All figures are in % of 2015 GDP.

Country	ΔGross Benefits	ΔEnvironmental Costs	Country	ΔGross Benefits	ΔEnvironmental Costs
Luxembourg	-0.187	-0.002	France	-0.016	0.00134
Lebanon	-0.107	0.012	India	-0.0149	0.00823
Belgium	-0.094	0.012	Israel	-0.0147	0.00512
Viet Nam	-0.080	0.022	Russian Federation	-0.0142	0.0048
Austria	-0.077	0.031	Italy	-0.0141	0.00627
Latvia	-0.076	0.003	Ireland	-0.0132	0.00756
Cyprus	-0.068	0.009	United Kingdom	-0.012	-0.00169
Panama	-0.067	0.009	China, Hong Kong SAR	-0.011	0.0184
United Rep. of Tanzania	-0.060	0.013	Indonesia	-0.00804	-0.00138
Bosnia Herzegovina	-0.059	0.001	China	-0.00769	0.00508
El Salvador	-0.057	0.005	Mexico	-0.00736	-0.000984
United Arab Emirates	-0.053	0.015	United States of America	-0.00718	0.000885
Netherlands	-0.050	-0.005	Norway	-0.00707	0.00016
Hungary	-0.049	0.011	Bulgaria	-0.00702	0.00434
Occ. Palestinian Terr.	-0.047	0.006	Turkey	-0.00679	0.00137
South Africa	-0.046	0.015	Kuwait	-0.00648	-0.000805
Poland	-0.042	0.012	Chile	-0.00552	-0.00411
Guatemala	-0.040	0.015	New Zealand	-0.00513	-0.00221
Ukraine	-0.037	0.006	Japan	-0.00494	0.000416
Switzerland	-0.037	0.019	China, Macao SAR	-0.00475	-0.0043
Ecuador	-0.036	0.013	Rep. of Korea	-0.0047	0.00475
Sweden	-0.035	0.016	Philippines	-0.00409	-0.00109
Bolivia	-0.035	0.015	Spain	-0.00309	-0.00229
Singapore	-0.033	0.016	Brazil	-0.00247	0.00102
Slovakia	-0.033	0.015	Mauritania	-0.00221	0.000806
Kenya	-0.031	0.011	Afghanistan	0.00279	-0.0216
Serbia	-0.031	0.008	Costa Rica	0.00299	-0.0128
Greece	-0.030	0.016	Cuba	0.00329	-0.00645
Ghana	-0.030	0.015	Qatar	0.00363	-0.00587
Germany	-0.028	0.010	Finland	0.0053	-0.0092
Dominican Rep.	-0.028	0.006	Denmark	0.00769	-0.012
Estonia	-0.028	0.012	Bahrain	0.00778	-0.00238
Lithuania	-0.027	0.001	Colombia	0.0136	-0.0123
Honduras	-0.025	-0.008	Angola	0.0149	-0.00744
Croatia	-0.025	-0.012	Peru	0.0162	-0.0108
Egypt	-0.024	0.011	Iraq	0.018	-0.00801
Saudi Arabia	-0.024	0.005	Sri Lanka	0.018	-0.0134
Bangladesh	-0.024	0.011	Portugal	0.0183	-0.0155
Nigeria	-0.022	0.011	Iran	0.0203	-0.00994
Morocco	-0.022	0.003	Thailand	0.0232	-0.0186
Kazakhstan	-0.020	0.009	Oman	0.0242	-0.000404
Canada	-0.019	0.005	Zambia	0.0431	-0.0186
Pakistan	-0.018	0.008	Belarus	0.045	-0.0111
Malaysia	-0.018	0.003	Rep. of Moldova	0.247	0.0046
Slovenia	-0.017	0.008	Seychelles	0.479	-0.0186
Australia	-0.016	0.004			

Table A.8: Country-by-Country Impacts in China Ban Counterfactual

This table reports the country-level results of the China Ban counterfactual (See Section 6.3). All figures are in % of 2015 GDP.

Country	ΔGross Benefits	ΔEnvironmental Costs	Country	ΔGross Benefits	ΔEnvironmental Costs
Dominican Rep.	-0.036	0.020	Poland	-0.000517	-0.000217
Viet Nam	-0.034	0.011	United States of America	-0.000442	-5.98e-05
Indonesia	-0.030	0.016	Israel	-0.000287	-9.16e-05
Nigeria	-0.029	0.015	China	0.000239	-0.000466
Bangladesh	-0.027	0.015	Bulgaria	0.000251	-7.72e-05
Lebanon	-0.024	0.014	Iraq	0.000517	-0.00124
Italy	-0.024	0.011	Russian Federation	0.0017	-0.00111
United Arab Emirates	-0.022	0.011	Rep. of Moldova	0.00183	-0.00141
Angola	-0.022	0.014	Saudi Arabia	0.00201	-0.00141
Serbia	-0.021	0.014	Slovakia	0.00224	-0.00158
Austria	-0.021	0.010	Kazakhstan	0.00236	-0.00161
Canada	-0.020	0.009	Qatar	0.00287	-0.00202
Latvia	-0.019	0.011	Turkey	0.00298	-0.00181
Cyprus	-0.019	0.011	Chile	0.00351	-0.00178
Ireland	-0.018	0.009	Bolivia	0.0046	-0.00263
Iran	-0.017	0.009	Oman	0.00502	0.00089
Morocco	-0.017	0.009	Denmark	0.00515	-0.00238
Belgium	-0.015	0.007	Belarus	0.00517	-0.00412
Singapore	-0.014	0.006	United Rep. of Tanzania	0.00554	-0.00392
Pakistan	-0.013	0.006	China, Macao SAR	0.00574	-0.0049
Finland	-0.012	0.006	Ukraine	0.00587	-0.00293
Hungary	-0.011	0.006	Ghana	0.0063	-0.00574
Estonia	-0.011	0.006	Sweden	0.00664	-0.00375
South Africa	-0.009	0.005	Mauritania	0.00685	-0.00805
Guatemala	-0.009	0.005	Thailand	0.00735	-0.0057
Lithuania	-0.009	0.006	Zambia	0.00826	-0.00663
Slovenia	-0.008	0.001	India	0.00934	-0.00509
Kuwait	-0.008	0.005	Norway	0.00997	-0.00528
Bahrain	-0.008	0.004	Rep. of Korea	0.01	-0.00492
Honduras	-0.007	-0.0003	Luxembourg	0.01	-0.0059
Panama	-0.006	0.003	Occ. Palestinian Terr.	0.0104	-0.00631
Germany	-0.006	0.002	Peru	0.0109	-0.00606
Ecuador	-0.005	0.004	Greece	0.0111	-0.00684
Spain	-0.005	0.001	China, Hong Kong SAR	0.0122	-0.00158
New Zealand	-0.004	0.001	Croatia	0.0124	-0.00708
Bosnia Herzegovina	-0.004	0.001	El Salvador	0.0151	-0.0104
Costa Rica	-0.002	0.0001	Colombia	0.0155	-0.00806
Egypt	-0.002	0.001	Malaysia	0.0159	-0.0107
Seychelles	-0.002	-0.00003	Philippines	0.0166	-0.00984
Japan	-0.002	-0.0002	Portugal	0.0173	-0.00964
Kenya	-0.002	0.001	Switzerland	0.0194	-0.00925
Netherlands	-0.002	-0.002	Cuba	0.0215	-0.0122
United Kingdom	-0.001	-0.0004	Sri Lanka	0.0226	-0.0137
France	-0.001	0.001	Mexico	0.0248	-0.0137
Brazil	-0.001	0.001	Afghanistan	0.0258	-0.0176
Australia	-0.001	-0.0003			

Table A.9: Ban Amendment Ratification Status of Within-Sample Countries

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

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

Table A.10: Country-by-Country Impacts in Ban Amendment Counterfactual

This table reports the country-level results of the Ban Amendment counterfactual (See Section 6.4). All figures are in % of 2015 GDP.

Country	ΔGross Benefits	ΔEnvironmental Costs	Country	ΔGross Benefits	ΔEnvironmental Costs
Egypt	-0.034	0.017	Finland	-0.00162	-0.000637
Latvia	-0.028	0.008	Singapore	-0.00116	0.00368
Pakistan	-0.026	0.014	Morocco	-0.00114	0.00487
Indonesia	-0.025	0.014	Zambia	-0.000513	-0.00275
Guatemala	-0.024	0.016	Rep. of Korea	0.000751	-0.000506
Angola	-0.022	0.014	Bahrain	0.000786	-0.00122
United Rep. of Tanzania	-0.022	0.014	United Arab Emirates	0.00114	0.00217
Cyprus	-0.021	0.007	Rep. of Moldova	0.00121	0.00237
New Zealand	-0.021	0.009	Serbia	0.00123	0.008
South Africa	-0.021	0.012	Luxembourg	0.0013	-0.000952
Dominican Rep.	-0.020	0.014	Seychelles	0.00276	7.02e-05
Austria	-0.020	0.010	Occ. Palestinian Terr.	0.00357	-0.0029
Hungary	-0.019	0.008	Qatar	0.00367	-0.00118
Netherlands	-0.019	0.001	China, Macao SAR	0.00369	-0.00134
Russian Federation	-0.019	0.010	Lithuania	0.0042	-0.0055
Greece	-0.018	0.007	Mauritania	0.00446	0.00106
Slovenia	-0.017	0.004	Sweden	0.00491	-0.00334
Estonia	-0.016	0.006	France	0.00502	-0.00272
Turkey	-0.015	0.007	Iran	0.00623	-0.00289
Bangladesh	-0.015	0.007	Slovakia	0.00633	-0.00552
Lebanon	-0.015	0.011	Kazakhstan	0.0085	-0.00595
Viet Nam	-0.014	-0.001	Kenya	0.00885	-0.00539
Ukraine	-0.014	0.009	Peru	0.009	-0.00324
Iraq	-0.014	0.008	Honduras	0.00903	-0.00795
Italy	-0.012	0.005	El Salvador	0.0104	-0.00145
Spain	-0.012	0.004	Bulgaria	0.0105	-0.00821
Saudi Arabia	-0.012	0.008	Brazil	0.0107	-0.00494
Ecuador	-0.012	0.015	Israel	0.0111	-0.00601
Kuwait	-0.012	0.009	Malaysia	0.012	-0.00268
Philippines	-0.010	0.005	China, Hong Kong SAR	0.0128	0.00235
Norway	-0.009	0.005	Ghana	0.014	-0.00939
Ireland	-0.009	0.005	Switzerland	0.0144	-0.00682
India	-0.009	0.004	Mexico	0.0144	-0.00928
Bolivia	-0.007	0.006	Oman	0.0145	-0.00112
Nigeria	-0.006	0.003	Portugal	0.0153	-0.00911
Belgium	-0.006	-0.0003	Afghanistan	0.0165	-0.00958
Croatia	-0.006	0.001	Poland	0.0177	-0.0101
Germany	-0.005	0.002	Cuba	0.0178	-0.00929
United Kingdom	-0.005	-0.0004	Chile	0.0181	-0.0155
Panama	-0.005	0.005	Thailand	0.0185	-0.0101
Japan	-0.004	0.0003	Costa Rica	0.0189	-0.0106
Canada	-0.004	0.0001	Denmark	0.0227	-0.0121
Australia	-0.004	0.0004	Sri Lanka	0.0237	-0.0144
United States of America	-0.003	0.00003	Colombia	0.0343	-0.0166
China	-0.003	0.002	Belarus	0.0389	-0.0242
Bosnia Herzegovina	-0.003	0.007			

Table A.11: Robustness Checks

Each panel in this table reports the change in environmental costs from a robustness check exercise for each counterfactual. Panel B presents estimates from excluding the CO_2 component from social marginal cost of waste disposal while Panel C presents estimates using alternative measures of social marginal cost of waste disposal that I back out from the model. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The Δ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. All figures are % of 2015 GDP. See Section 6.6 for details on the methodology.

	Δ Environmental Costs (% of GDP)			
	Autarky	Waste-Autarky	China Ban	Ban Amendment
	Panel A: Externality Functional Form			
Rich	-0.35	0.019	0.006	0.003
Middle	-0.49	0.016	-0.003	0.007
Poor	-0.19	0.024	-0.006	0.013
	Panel B: Social Marginal Cost of Disposed Waste			
Rich	-0.002	0.00003	0.00001	0.000005
Middle	-0.004	0.00004	-0.000001	0.00002
Poor	-0.003	0.0001	-0.00002	0.00007
	Panel C: Social Marginal Cost from Eshet et al. (2005)			
Rich	-0.005	0.0001	0.00002	0.00001
Middle	-0.008	0.0001	-0.000003	0.00003
Poor	-0.006	0.0002	-0.00004	0.0001
	Panel D: Social Marginal Costs from the Model			
Rich	-0.76	0.048	0.013	0.009
Middle	-1.61	0.049	0.009	0.033
Poor	-1.55	0.16	-0.065	0.093

Table A.12: Robustness Checks–Alternative Estimates for Trade Elasticities

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

	Δ Gross Benefits		Δ Environmental Costs	
Income Group	(%GDP)	(billions \$)	(%GDP)	(billions \$)
	Panel A: Autarky			
Global	-4.39	-3118	-0.56	-398
Rich	-4.70	-2140	-0.51	-234
Middle	-3.74	-838	-0.69	-155
Poor	-4.51	-139	-0.30	-9
	Panel B: Waste-Autarky			
Global	-0.029	-21	0.006	4
Rich	-0.037	-17	0.008	3
Middle	-0.014	-3	0.003	0.7
Poor	-0.019	-0.59	0.005	0.2
	Panel C: High-Value Waste-Autarky			
Global	-0.018	-13	0.007	5
Rich	-0.021	-10	0.008	4
Middle	-0.013	-3	0.006	1
Poor	-0.006	-0.2	0.002	0.1
	Panel D: Low-Value Waste-Autarky			
Global	-0.008	-6	-0.002	-1
Rich	-0.012	-6	-0.002	-0.7
Middle	-0.003	-0.6	-0.001	-0.3
Poor	0.009	0.3	-0.007	-0.2
	Panel E: China Ban			
Global	-0.001	-0.8	-0.0003	-0.2
Rich	-0.002	-1	0.0003	0.1
Middle	0.001	0.1	-0.001	-0.2
Poor	0.008	0.2	-0.005	-0.1
	Panel F: Ban Amendment			
Global	-0.007	-5	0.002	1
Rich	-0.007	-3	0.001	0.5
Middle	-0.007	-2	0.004	0.8
Poor	-0.007	-0.2	0.003	0.08

Table A.13: Counterfactual Results with Recycled Good as an Intermediate Input

Each panel in this table reports the results from a counterfactual exercise. The income groups, in Column 1, are based on 2015 GDP per capita. The poor comprise 13 countries with GDP per capita < \$2400. The middle and the rich each comprise 39 countries with GDP per capita >= \$2400 and < \$14000 and GDP per capita >= 14000, respectively. The Δ Gross Benefits are calculated in terms of proportional changes in real income, $w_j \bar{L}_j (\hat{Y}_j / \hat{P}_j - 1)$, and Δ Environmental Costs are simply the differences between gross and net benefits, i.e., equivalent variation. Baseline GDP is 2015 GDP. See Section 7 for further details.

Income Group	Δ Gross Benefits (%GDP)	Δ Gross Benefits (billions \$)	Δ Environmental Costs (%GDP)	Δ Environmental Costs (billions \$)
	Panel A: Autarky			
Global	-3.11	-2209	-0.50	-352
Rich	-3.33	-1517	-0.37	-169
Middle	-2.65	-592	-0.75	- 167
Poor	-3.25	-100	-0.52	-16
	Panel B: Waste-Autarky			
Global	-0.014	-10	0.006	4
Rich	-0.016	-7	0.006	3
Middle	-0.013	-3	0.007	2
Poor	0.002	0.05	-0.008	-0.3
	Panel C: High-Value Waste-Autarky			
Global	-0.009	-6	0.005	4
Rich	-0.012	-5	0.007	3
Middle	-0.006	-1	0.003	0.6
Poor	0.005	0.1	-0.009	-0.3
	Panel D: Low-Value Waste-Autarky			
Global	-0.002	-1	-0.002	-1
Rich	-0.002	-1	-0.002	-0.9
Middle	-0.001	-0.1	-0.002	-0.4
Poor	0.001	0.04	-0.005	-0.1
	Panel E: China Ban			
Global	-0.001	-0.5	-0.0003	-0.2
Rich	-0.001	-0.7	0.0004	0.2
Middle	-0.0002	-0.04	-0.0006	-0.1
Poor	0.008	0.3	-0.008	-0.3
	Panel F: Ban Amendment			
Global	-0.003	-2	0.001	0.5
Rich	-0.002	-1	-0.001	-0.4
Middle	-0.005	-1	0.005	1
Poor	0.005	0.1	-0.006	-0.2