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Will you take my (s)crap? Waste havens in the global plastic waste trade

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April, 2023

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Keywords: Plastic waste, gravity model, pollution haven, waste haven, developing countries
JEL classification: F14, F18, F64, O19

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Abstract

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1 Introduction

The idea that the wealth of a nation is correlated both with willingness to pay for environmental amenities and with the quality of environmental regulation is widely accepted. For both reasons, less wealthy countries likely have a higher tolerance for waste disposal methods and direct disposal costs that are low in relation to those in wealthy countries, but which may present or augment significant environmental threats. It is also possible that waste may be traded or smuggled among developing countries.[4] In either case, if a larger portion of waste is being disposed of in a weak environmental regulation regime, the probability that such waste ends up as pollution in the global ecosystem is higher. This problem is especially salient for the case of long-lived materials, notably plastics (Kershaw and Rochman, 2015).

The direct motivation for this study came from a major policy shock affecting international trade in plastic waste. Between 1992 and 2016, China imported over half of the world's traded waste products (Brooks et al., 2018). After 2008, according to UN Comtrade data, China's imports exceeded 70% of the global total. But in July 2017, China notified the World Trade Organization (WTO) of its intention to ban imports of 24 categories of post-consumer recyclable waste by year's end, including post-consumer plastic waste (Igini, 2022). Despite some doubts prior to implementation, the ban proved to be effective, and the quantity of plastic waste imported annually by China fell by 99% in 2018 (Staub 2017b, Staub 2019).

China's abrupt exit threw the global recycling industry into turmoil.[5] Countries whose recycling systems depended on China's willingness to import their scraps[6] began to struggle with ever-growing piles of recyclable waste that had nowhere to go.[7] For lack of alternative outlets, more recyclable waste entered landfills and incineration facilities; recyclable prices dropped as the cost of recycling rose; the recycling industry—especially material recovery facilities (MRFs), companies that sort and sell scrap collected in municipal recycling bins—struggled with reduced profits. In the United States, cities and counties began to scale back the range of items accepted for recycling (Paben, 2019).

Although they shipped very little of their own plastic waste to China, developing countries were also affected as waste exporters sought alternative destinations. Malaysia, Vietnam, Thailand, and Turkey, among others, experienced a sharp spike in waste imports immediately after the ban was announced. Thailand, for example, saw plastic waste imports from the United States increase by almost 2,000% towards the end of 2017, relative to imports in the first half of the same year

[4]See, Retamal et al. (2020).

[5]The Institute of Scrap Recycling Industries, a US industry association, condemned the ban, saying that such action "would be catastrophic to the recycling industry" (Staub, 2017a).

[6]In this study, we use the term *scraps* and recyclable waste interchangeably. Depending on the context, we may address recyclable waste as *waste* for conciseness.

[7]For a complete timeline of events related to the waste ban, please visit Resource Recycling's web page.

(Parker, 2018).

This additional trade volume undoubtedly exceeded domestic recycling capacity, so the surge in trade generates both economic and environmental puzzles. It implies that after the ban, not all "recyclable" waste was being traded for the purpose of recycling. Just as the US increased dumping of its own recyclable wastes in the wake of the ban, the new destination countries have almost undoubtedly increased their own disposal of recyclable waste due to recycling capacity constraints and lags in the creation of new capacity, despite adopting increasingly restrictive policies (Kojima, 2020). International efforts to reduce and regulate trade in plastic waste were formalized in 2019 as a set of amendments to the Basel Convention;[8] however, it is still early to know whether these efforts will be effective (Benson and Mortensen, 2021).

Against this background, our study has two empirical goals. The first is to investigate if global plastic waste trade follows a *waste haven* pattern (Kellenberg 2012) in which trade shifts the environmental costs of plastic waste from richer to poorer countries. The second is to evaluate whether China's import ban caused significant change in the country composition of trade in the plastic waste market. The market's adjustment to this shock likely has significant implications for global social welfare and the environment.

Using a gravity model, we find that post-ban trade diversion in the global market for plastic waste is dominated by increased flows from high-income to upper-middle-income countries, and from countries with stronger environmental regulations to those where such regulations are weaker. We find further that this trade pattern deepened after the ban, and that bilateral differences in environmental policy regimes were prominent drivers.

Specifically, our estimates show that prior to the China import ban, for every 1% that an importer's GDP per capita falls below that of an exporting partner, the importer will experience a 0.018% increase in waste imports from the exporter. As for regulatory quality, we find that disparity in the Environmental Performance Index (EPI) scores of exporting and importing countries has no statistically significant relationship in the pre-ban period. In the post-ban period, however, our preferred estimates indicate that for every 1% that an importer's EPI score is lower than that of an exporting partner, the importer will experience a 0.431% increase in waste imports from the exporter.

To our knowledge, this is the first empirical analysis to ask whether international waste trade follows a waste haven pattern, and the first to address the effect of the China's 2018 ban on trade in plastic waste. We base these empirical tests upon a micro-theoretic foundation that rationalizes the actions of entities at both the origin and the end point of global plastic waste trade. The remainder of this paper develops as follows: the second section is a literature review, the third

[8]Formally, the Basel Convention on the Control of Transboundary Movement of Hazardous Wastes and their Disposal. The amendments to cover plastic waste were to be implemented from 2021.

section develops the theoretical framework, the fourth section describes the data, the fifth section reports estimation and results, and the last section concludes.

2 Literature Review

Empirically, this paper is closely related to two recent studies. Balkevicius et al. (2020) use trade data from 2010-15 to estimate the effect of China's 2013 "Operation Green Fence" policy on global trade in non-hazardous waste. A working paper by Thakur (2022) presents a structural gravity model which evaluates the relationship between country income and the import of high-value versus low-value waste and explores how trade in these responds to trade barriers. To evaluate the welfare impact of the China's 2018 waste ban, Thakur presents counterfactual outcomes using estimates from a gravity model which using cross-sectional data from 2015, among other datasets.

Conceptually, the idea that dirty industries and activities may be moved among countries to minimize cost is widely accepted. But whereas the familiar *pollution haven hypothesis* refers to the movement of industries to locations where process-related pollution is less costly, the *waste haven hypothesis* (Kellenberg, 2012) posits that international trade allows for waste to be redistributed from its country of origin to foreign destinations, thereby transferring the costs and negative externalities of waste disposal across international borders. Empirical analyses of trade data consistently find that developing countries serve as waste havens for developed countries. Kellenberg (2015), for example, uses UN Comtrade data to show that, between 1992 and 2011, the volume of global trade in waste commodities increased by roughly 500%, from 45.6 million to 222.6 million tons. Over the same period, the share of waste imported by developing countries grew by more than 40%, while the share imported by developed countries declined.

A growing literature confirms the existence of waste havens (Matsuda et al. 2021, Balkevicius et al. 2020, Kumamaru and Takeuchi 2021). Work on identifying the mechanisms that dictate international waste flows remains inconclusive because waste commodities have some special characteristics that set them apart from general traded goods. In the following review we discuss three aspects of the international trade in plastic scraps which have been explored in the literature. The first addresses variables that determine the international trade of commodities in general. These are country and bilateral characteristics that are the default variables in a parsimonious gravity analysis, including economic size (GDP) and trade cost (distance and non-distance) variables. The second includes variables that are suggested by the pollution haven hypothesis as determinants of international trade and investment flows that enable cross-border movements of goods associated with negative environmental externalities. These are, notably, income (GDP per capita) and environmental regulation quality. The third includes variables that are specific to the trade of plastic scrap, such as recycling capacity.

1. Gravity Variables

Scrap products are traded at a price just like general market goods. For this reason, factors that determine the trade of general commodities are relevant to the trade of scrap products. The gravity model, the tool of empirical trade studies, has been applied to trade in waste products (Baggs 2009, Kellenberg 2012, Kellenberg and Levinson 2014, Higashida and Managi 2014, Okubo et al. 2016). While these studies display many variants, they collectively predict that the two major factors that influence the volume of bilateral trade are the economic size of each country and cost of trade between them.

Larger economic size encourages trade due to a greater capacity to consume and produce, while higher costs discourage trade. These relationships have been observed for trade in both hazardous and non-hazardous waste products (Anderson and Van Wincoop 2003, Baggs 2009. As with conventional gravity model studies, non-distance determinants of trade costs, such as common language, common colonial ties, and joint membership of international trade agreements are also found to be important. Kellenberg and Levinson (2014), for example find that factors that indicate similarity between trading partners are also associated with higher waste trade volume.

2. Waste Haven Variables

As its name suggests, "waste haven" can be interpreted as a type of pollution haven. The pollution haven hypothesis (PHH) predicts pollution-intensive industries will relocate from countries with higher income and stricter environmental regulations to countries with lower income and laxer environmental regulation (Taylor, 2004). Instead of dirty industry relocation, studies of the waste haven phenomenon test the hypothesis that differences in income and quality of domestic environmental regulation drive the transboundary movement of goods associated with negative externalities, operating through international waste trade. In general, empirical findings support the hypothesis that waste trade tends to flow from wealthier countries with stricter environmental regulations to poorer countries with weaker environmental regulations (Balkevicius et al. 2020, Kellenberg and Levinson 2014).

The two waste haven determinants – wealth of a country and environmental regulation quality – are closely related.

First, institutions and regulatory quality can play a large role in bringing about economic growth (North 2016, Kaidi et al. 2019). Second, the environmental Kuznets curve (Grossman and Krueger 1991) suggests that the relationship between GDP per capita and environmental degradation follows an inverse U-shape. A poor country is willing to accept environmental degradation in exchange for economic growth up to a threshold beyond which willingness to degrade the environment starts to fall. Baggs (2009) uses GDP per capita as a proxy for the stringency of environmental regulation and finds that countries with higher GDP per capita ship more waste abroad, but the effect is statistically insignificant after controlling for capital intensity and population density.

Fikru (2012) explores the relationship between regulation and hazardous waste trade within the EU. Using facility-level data, she finds that countries with a greater number of hazardous waste regulations and higher hazardous waste tax rates have a higher propensity to export waste to countries with fewer regulations and lower tax rates.

For global trade of non-hazardous waste, Kellenberg (2012) uses the Global Competitiveness Report (GCR) of 2003-2004 to compute an environmental regulation "gradient" index which measures the difference in the stringency of environmental regulation for each exporter-importer pair. A positive value indicates that the importing country has a relatively weaker environmental regulation. According to the PHH, this should encourage waste flow into the importing country. Results from a cross-section analysis suggest that all else equal, for every 1% that an importer's environmental regulation quality falls below that of an exporter, the importer will experience 0.22% higher waste imports from that exporter.

A study by Okubo et al. (2016) also uses GCR data to measure the impact of the gap in environmental regulation stringency on the volume of recyclable waste exports from Japan. This study distinguishes three types of GCR scores based on overall regulation, toxic waste regulation, and air pollution regulation. It finds that the bilateral export volume from Japan increases with the gap in all types of GCR scores between Japan and its trade partner.

3. Plastic Scrap Trade Variables

As discussed above, trade costs and sizes of trading countries are considered to be the key determinants of bilateral trade volume in general. Environmental regulation stringency is a determinant that is theoretically relevant to any transboundary activities that enable the redistribution of negative environmental externalities, such as the relocation of firms that produce dirty goods or the shipment of waste products.

In addition to these two key determinants, some empirical studies acknowledge factors that are more specific to the waste trade context. Researchers often incorporate these factors, although often without formally establishing a theoretical relationship. In his study of hazardous waste, Baggs (2009) incorporates the capital/labor ratio of exporters and importers into the gravity model as a proxy for technological capabilities in the hazardous waste disposal sector. He finds that countries with higher capital/labor ratios tend to import a higher volume of hazardous waste. This effect, however, goes away when GDP per capita is included in the estimation. Kellenberg (2012) includes recycling industry wage rates to reflect the marginal productivity of workers in the recycling sector, assuming that higher wage rates reflect higher productivity. He computes the recycling wage gradient which measures the difference in recycling productivity between the exporting and importing countries. He finds that, as expected, the more productive the exporting country is at recycling relative to the importing country (positive gradient), the smaller the volume of waste flow between the country pair.

Our study focuses on trade in recyclable plastic. We know of two studies presenting models designed specifically to explain international trade in recyclable waste. Sugeta and Shinkuma (2012) develop a two-country theoretical model that addresses the role that cross-country heterogeneity in recycling technology plays in determining the pattern of international recyclable waste flow and the corresponding environmental harm. Both countries produce, consume and trade consumption goods and recycled materials but have different recycling technologies, resulting in different recovery rates. The model demonstrates that whether a country gains net benefit or suffers net environmental harm from trade in recyclable waste depends on the recovery rates of the two countries as well as efficiency in the production of consumption goods. The model implies, however, that the incentive to import and export recyclable waste should depend on the production characteristics of the recycling industry as well as the production sector that uses recycled materials as input.

Higashida and Managi (2014) develop a gravity model for recyclable waste trade. They specify the demand and supply equations of recyclable wastes and use them to derive the commodity-specific gravity equation. The model suggests that the trade volume is determined by transportation cost, the scale of the recycling sector, and the ratio of imported waste that enters landfills to total waste imports. It predicts that if final consumption goods that use recyclable waste as production inputs are not freely traded in the global market, then domestic demand for those goods will encourage imports of recyclable waste.

3 Theoretical Framework

3.1 The Gravity Model

In this section we explore *ex ante* drivers of waste trade patterns and the effects of shocks (specifically, a large negative demand shock) on that trade. However, the models we develop are intended to inform an empirical exercise using a gravity model of trade, so we begin with a very brief outline of that model.

The basic gravity model embodies two ideas: larger countries trade more, and higher trade costs reduce trade flows. Let X_{ij} be bilateral trade flow from country i to country j. Let G_i and G_j be the economic sizes of the two countries, and let τ_{ij} represent the bilateral trade cost. In its "intuitive" form, country size is represented by GDP and trade costs by bilateral distance, yielding an estimating equation (in log-log form) as:

$$logX_{ij} = \alpha_0 + \beta_1 logG_i + \beta_2 logG_j + \beta_3 \tau_{ij} + \epsilon_{ij}$$

where ϵ_{ij} is an i.i.d. error term. Empirical applications of this model have deployed a wide range of additional determinants of trade costs, including wealth (per capita income), bilateral tariffs, common languages, shared borders, colonial ties, joint membership in trade agreements, and more (Shepherd et al., 2019). Another substantive modification that is now widely used strives to deal with omitted variable bias that arises when bilateral trade flows between two countries also depend on trade costs across all other trading country pairs in the market—that is, when $\partial X_{ij}/\partial \tau_{ij}^k \neq 0$ for $k \neq i, j$. As the originators of this approach demonstrate, these "multilateral resistance terms" appear in estimation as importing and exporting country fixed effects (Anderson and Van Wincoop, 2003). This so-called "gravity with gravitas" model can be used to describe trade flows of goods from multiple sectors of an economy. It can also be conveniently scaled down for applications involving the trade flows of a single sector.

3.2 The Dynamics of Plastic Scrap Trade

The fundamental determinants of trade flows for general commodities as suggested by the gravity model are also relevant to trade in plastic scrap. Plastic scrap, however, has an additional characteristic not shared by most commodities. It has a double identity in that it can be a raw material if it gets recycled, or a piece of trash if gets dumped. In fact, since all scrap contains at least some non-recyclable contaminants, it is guaranteed that some additional costs will be incurred – either to remove and dispose of contaminants, or to dispose of the entire shipment if processing is uneconomic. This feature also means that the value of scrap depends not only on the price of virgin plastic, for which it is a substitute, but also on the costs of processing to remove contaminants and disposal of non-recyclable material. Importantly for the trade story, processing and disposal can occur at either (or both) ends of the trade flow; therefore, trade depends on relative processing and disposal costs across trade partners.

This intrinsic feature (the double identity) implies that export of scrap from country i to country j may also function as the purchase of disposal services by country i from country j, where the service fee is embedded in the price of the scrap commodity. In other words, scrap importers may be paying a low price for raw materials (the recyclable portion) in exchange for bearing the cost of disposing of unusable waste (the non-recyclable portion). Thus, trade flow in plastic scrap is likely driven by two forces: importers' demand for plastic scrap, and exporters' demand for disposal services. In the exporting country, decisions over processing, disposal and/or export originate with *recyclers*, formally known as *material recovery facilities* (MRFs). In the importing country, entities that purchase, process and/or dispose of scrap are known as *reclaimers*.

Our model has two actors, recyclers and reclaimers. Both are modeled as representative agents in a population of many identical firms with unrestricted entry and exit. We assume these firms to be profit-maximizing, price-taking entities. Trade in plastic waste, when it occurs, originates with recyclers and flows to reclaimers. Our model considers their responses to price changes induced by China's plastic waste import ban. The following provides a skeletal description of the model and its predictions; both the recycler and reclaimer models are fully and formally set out in the appendix.

3.2.1 Supply: Recyclers

A recycler with a municipal recycling collection contract takes in an exogenous quantity of domestic recycling with an exogenous initial contamination rate. It processes this waste to produce a mix of recyclable plastics and waste for disposal. The mix produced depends on the initial contamination rate and the effort expended by the recycler to separate contaminants from usable plastic scrap. Additional effort is costly, and so is additional waste disposal. The price at which the recycler can sell recyclable plastic is a diminishing function of the post-processing contamination rate. The higher is the contamination rate of scrap offered for sale by the recycler, the greater is the effort required to be expended by buyers (the reclaimers) in order to generate feedstock for the manufacture of post-consumer resin (PCR) pellets. There is an upper threshold on this contamination rate, based on the reclaimer's processing costs and the price of PCR pellets; above that threshold the price offered to recyclers is zero. If producing output with a contamination rate below this the threshold is not economically feasible, a recycler may choose to exert no effort and instead dispose of all its collected recyclable waste. A recycler may be willing produce and sell recyclable plastics at a loss, however, as long as that loss is smaller than the cost of sending what it collects to a landfill.

International trade occurs when recyclers and reclaimers are in different countries. Suppose that the cost of effort is a function of prevailing wage that may vary across labor markets. Similarly, suppose that waste disposal costs also vary across jurisdictions, according to the stringency of environmental regulations. Then the price and the threshold contamination rate of scrap offered by sale by a recycler may vary among countries with different labor costs and environmental management regimes. This provides the basis for changes in trade volumes and destinations. In addition, the supply of disposal services may be more or less elastic in different markets, so disposal costs may also vary differentially in response to increases in demand.[9]

The withdrawal of China from the plastic waste market affects production and trade decisions world-wide. The China import ban reduces demand for plastic scrap sold by recyclers. This will

[9] One limiting case would be if disposal were completely unregulated, meaning that the supply of disposal services is completely elastic.

lower the world price of scrap. In addition, when exports of scrap to Chinese reclaimers cease, then the supply of PCR from Chinese reclaimers also falls, leading to a rise in PCR pellet prices. These predictions conform with reported trends for HDPE plastic scrap prices (IRSI 2018) and PCR supply and price (Yoshida 2022).

What are the likely effects on the industry, and on trade? For recyclers, a lower plastic scrap price means reduced profits at all contamination rates. Returns to effort decrease. The model predicts that recyclers that face high disposal costs, such as those in wealthier countries, are more likely to continue producing and selling recyclable plastics, whereas those with lower disposal costs are more likely to reduce effort and increase disposal. Recyclers that continue to sell may increase or decrease effort to remove contamination, depending on how the ban changes the additional value of a lower contamination rate relative to the costs of disposal and contaminant removal. Overall, the model predicts that the global scrap exports will decrease, and total disposal quantity will increase. Sales to markets where disposal services are elastic and/or where the cost of effort to remove contaminants is lower will increase. This corresponds to real-world observations of shipments from wealthy to developing countries that were labeled as recyclable scrap, but which in reality were simply trash, or had contamination rates above the acceptable threshold (Law et al. 2020). In all countries, the activities of recyclers will cause demand for landfill and other disposal services to increase.

3.2.2 Demand: Reclaimers

A reclaimer produces post-consumer resin (PCR) pellets using three types of input: plastic scraps, labor, and capital. Pellets are sold into a market in which prices depend on demand and the price of virgin plastic; these prices are exogenous to the reclaimer. The reclaimer's willingness to pay for plastic scrap depends on its contamination rate as well as unit costs of labor and capital and PCR prices. Production of PCR is a vertically integrated process with two steps. First, plastic waste is sorted to remove contamination. Second, the granulation process turns sorted plastic scraps into PCR pellets.

In the sorting step, a reclaimer employs labor to separate contaminants from clean feedstock. The removed contaminants are disposed of at a non-negative cost. The unit cost of sorting increases with the wage and the contamination rate. Since sorting removes all contaminants, the granulating function (the second step) does not depend on the contamination rate. A reclaimer earns revenue by selling PCR pellets. Taking prices and technology as given, profits are maximized by choosing the contamination rate, the amount of scrap input, labor, and capital to employ in the production process.

The China import ban affects reclaimers in two ways. First, it at least weakly decreases the price of plastic scrap as China exits the market. Second, it at least weakly increases the price of

PCR. This is because the ban cuts off Chinese reclaimers' access to foreign plastic scrap, thereby reducing supply in the PCR market (Yoshida, 2022). The model predicts that these price changes at least weakly encourage reclaimers outside China to increase production. Their demand for capital and labor inputs increases, but changes in the scrap input quantity and contamination rate are ambiguous depending on the sorting function (the rate of change of the sorting output with respect to contamination rate relative to the rate of change with respect to the scrap input volume). This is because an increase in the clean feedstock of plastic scraps can be achieved either by adjusting the input quantity, or the contamination rate of purchased scrap, or both.[10] In addition, heterogeneity in labor costs contributes to variation in the magnitude of input adjustment across reclaimers in different labor markets.

3.2.3 Determinants of Plastic Scrap Trade

For simplicity, assume that technologies are identical across countries. These include the contamination removal function, scrap sorting function, and granulating function. For ease of interpretation, let us categorize determinants of plastic scrap trade into three groups: (1) general bilateral trade factors, (2) plastic waste supply factors, and (3) plastic waste demand factors.

Two types of bilateral trade factors enter the gravity model. The first is the economic mass of traders. The larger the mass of trading partners, the larger the trade volume. The second is bilateral trade costs such as distance and non-distance trade frictions. The higher the trade costs, the smaller the trade volume. Factors that determine plastic waste supply in the international market are identified by the recycler model. These include waste generation, initial contamination rate, disposal cost, effort cost, and the price of plastic scraps. Factors that determine international demand for plastic waste are identified by the reclaimer model. These include disposal cost, price of plastic scraps, and the price of PCR.

Notice that some factors, such as disposal cost and trade/transaction costs belong in more than one of the three groups. Moreover the quantity of waste generated in the recycler model likely coincides with economic mass in the gravity model.

In addition to these three types of determinants, factors that determine the supply of disposal services may also play a role in shaping the international trade of plastic waste. We have not modeled these, but intuitively, the main factor determining the supply of disposal services is their cost. The higher is this cost, the lower the willingness of any reclaimer to import scrap.

[10]For details, see the appendix.

3.3 Predicted Response to Trade Diversion

The recycler model indicates that countries with higher disposal costs are more likely to continue to export plastic scrap after the ban, and countries with lower disposal costs are more likely to switch from selling to disposal. The reclaimer model suggests that countries with higher disposal costs are less likely to expand PCR production as PCR prices rise. Thus, we expect that other things equal, export of waste from countries with higher disposal costs to those where such costs are lower will increase after the ban.

The recycler model shows that, when faced with sufficiently high disposal costs, a recycler may continue to export even at a loss. Wealthier nations tend to have better and more formalized waste management systems, which likely translates to higher domestic disposal costs. In global plastic waste trade, this implies that a recycler may seek to export waste even at a loss if that option, after accounting for additional transaction costs, is cheaper than domestic disposal. This is where waste trade intersects with the pollution haven hypothesis: lower disposal costs reduce the unit costs of processing plastic scrap — whether through recycling or disposal. However, the distinction between these two choices has environmental implications. The larger the portion of imported scrap that enters the PCR production process, the greater are the environmental benefits (other things equal), whereas environmental costs are larger, the greater is the portion that is discarded. In cases where disposal costs are low due to greater tolerance for open dumping and other improper waste management methods, the environmental impacts of disposal will likely be higher.

4 Data

We obtain annual trade data of plastic scraps between 2008 and 2019 from UN Comtrade. The 4-digit HS commodity code that corresponds to plastic scraps is 3915. There are four 6-digit subcategories under HS-3915: (1) 391510 includes ethylene polymers waste, parings, and scrap, (2) 391520 includes styrene polymers waste, parings, and scrap, (3) 391530 includes vinyl chloride polymers waste, parings, and scrap, and (4) 391590 includes other plastics.

The desirability of plastic scraps as raw materials in the production of recycled plastic pellets varies according to the type of plastic. In general, ethylene polymer (391510) is the most desirable type of plastic waste for recycling. The commonly known types for this category of plastics are PET, HDPE, and LDPE. They correspond to recycling numbers 1, 2, and 4 respectively. In this analysis, we use data of the 4-digit code.[11]

We limit the sample to 74 countries that traded more than 20 metric tons of plastic scraps every year between 2008 and 2016 or in 2018 or 2019. For each exporting country in each year, we define its destination choice set as countries that (1) imported at least some plastic scraps in that

[11] Accounting for different plastic types is a potentially meaningful extension of this research.

year from and (2) imported plastic scraps from the exporting country at least once between 2008 and 2019. This makes 2,888 country pairs and 33,969 exporter-importer-year observations.

We obtain data on bilateral characteristics that are commonly used in the gravity model from CEPII database. In addition to distance, we use the following bilateral indicators: contiguous border, common official language, common currency, common regional trade agreement, origin is/was a colonizer of destination, and destination is/was a colonizer of origin.

Bilateral tariffs on plastic scrap commodities (HS-3915) are computed using most-favored-nation (MFN) tariff rates and preferential tariff rates from WTO. Data on total GDP and GDP per capita data are from the World Bank. Lastly, the Environmental Performance Index (EPI) data are from NASA's Socioeconomic Data and Application Center (SEDAC).

The EPI score is published every even-numbered year from 2006. It is designed to reflect the environmental quality of a country. The score ranges between 0 and 100, with higher scores reflecting better environmental quality. The overall EPI score is computed from a set of scores assigned to an arbitrary set of environmental indicators. The set of indicators varies from year to year. The purpose of including the EPI score in this study is to use it as a proxy for disposal cost. This means we assume that countries with higher environmental quality have a higher disposal cost. The EPI score of 2020 is the one that includes waste management in the set of indicators of environmental quality. More specifically, the computation of the 2020 EPI score includes the share of solid waste properly managed (WMG),[12] among other indicators.

Figure 1 shows a scatter plot that visualizes the correlation between the overall 2020 EPI score and the share of solid waste properly managed[13]. There is a strong positive correlation between the two variables. For this reason, we believe that while using the EPI score as a proxy for disposal cost is not perfect, it may be a reasonable option given limited data availability.

Figure 2 shows the correlation between GDP per capita and EPI score by income group. There is considerable variation in EPI score among countries with similar income levels. Table 1 shows the five countries with the highest and lowest average EPI scores within each income group. It shows that there are lower-middle income countries with higher EPI score than high income countries. For example El Salvador, a lower-middle income country, has an average EPI score of 60.7 which is higher than the average score of UAE (59.5), a high-income country.

[12]According to 2020 EPI technical document: "Controlled solid waste refers to the proportion of household and commercial waste generated in a country that is collected and treated in a manner that controls environmental risks. This metric counts waste as "controlled" if it is treated through recycling, composting, anaerobic digestion, incineration, or disposed of in a sanitary landfill."

[13]These shares are computed from World Bank's What a Waste database. We have obtained this dataset. We do not use it in analysis because the data is only cross-sectional.

4.1 Summary Statistics

Table 2 compares the pre-ban and post-ban averages of bilateral characteristics. The pre-ban period is defined as 2008 to 2016 and the post-ban period includes 2017 through 2019. We include 2017 as part of the post-ban period because even though the ban became officially effective in January of 2018, adjustments to the ban occurred before its official implementation date. The monthly time trend of plastic scraps imported by China shows a sharp drop after July 2017 when the ban was announced (see figure 3).

As seen in Table 2, bilateral export quantities increased and import quantities decreased after the ban. Trade values decreased for both exports and imports, however, indicating that the unit value of plastic scrap decreased after the ban. Origin-minus-destination differences in GDP per capita are positive in all three cases (all-period, pre-ban, and post-ban). This confirms that plastic scraps are traded from richer countries to poorer countries, on average. Origin-minus-destination differences in EPI score are also positive in all three cases, confirming that on average, plastic scrap is traded from countries with stronger environmental regulation to those where it is weaker. The gap is larger in the post-period, but the pre-post ban difference is not statistically significant.

Table 3 compares averages of characteristics of net importers and net exporters. Panel (A) uses data from the whole period of study (2008-19), while panels (B) and (C) use pre-ban and post-ban data respectively. Overall, these statistics show that while net importers have significantly more import partners (i.e., they import from more countries) than net exporters, they have a similar number of export partners (i.e., number of countries they export to). Net importers have lower GDP per capita than net exporters on average in all three cases. The gap increased by a factor of almost two in the post-period. Net importers have a lower EPI score than net exporters on average in all three cases. The gap increased in the post-period, more than doubling in magnitude. These statistics suggest that poorer countries likely take in more plastic scraps than richer countries and that this pattern became more pronounced after the ban.

Simple mean comparisons of bilateral and country-specific characteristics suggest that the international trade of plastic scraps follow a waste-haven type pattern where plastic scraps, a high environmental-cost commodity, flow from richer to poorer nations. These of simple statistics, however, give contrasting impressions of how the waste haven pattern changed after the ban. In the next section, we present a gravity analysis that examines this question further.

4.2 Evidence of Trade Diversion

Figure 3 showed monthly variation in the quantity of plastic scraps imported by the world (black) and by China (blue) between 2015 and 2019. Each vertical line corresponds to an event that is relevant to China's ban on plastic scraps import. The first line, in July 2017, marks China's announcement of intent to ban imports of post-consumer plastic scrap. The second line, in January 2018, is when the ban went into effect. The third line, April 2018, is when China announced its intention to expand the list of banned items; this expansion went into effect in January 2019, which is the rightmost line. Our study concerns the first two of these events. There is a sharp decrease in the Chinese imports from announcement date, perhaps because exporters were unable or unwilling to initiate new shipments after that date. For this reason, in our annual data series we treat 2017 as a post-ban period. As the figure makes clear, world imports of plastic scrap declined along with Chinese imports — but by less than the decline in the latter. This is evidence of trade diversion.

Figure 4 shows the change in net export of plastic scraps by income group, excluding China.[14] Light blue columns correspond to pre-ban quantities: the sum of net export in 2015 and 2016. Dark blue columns correspond to post-ban quantities: the sum of net export in 2018 and 2019. The two left-most columns shows that high-income countries decreased their net export quantity by more than half, from 11.6 to 4.4 million tons, but remained net exporters as a group. The middle two columns show that upper-middle-income countries were collectively net exports before the ban but became net importers afterward. Strikingly, post-ban net import quantity (2 million tons) is more than double of the pre-ban net export quantity (0.94 million tons). The two right-most columns show that lower-middle-income countries also changed from net exporters to net importers as a group, with the post-ban net import quantity (0.91 million tons) being about thee times the size of the pre-ban net export quantity (0.32 million tons).

Figure 5 shows yearly variation in import quantity by income group, and figure 6 shows variation in export quantity (again, China is excluded from these data). While upper-middle and lower-middle-income countries experienced an increase in import quantity between 2016 and 2018, high-income countries saw a decrease. Export quantities from all country groups declined around the time of the ban.

For middle-income countries, the increase in net imports is due to reduced exports and increased imports. For high-income countries, the decrease in exports is large enough to more than offset a simultaneous fall in imports. The distinction is important for analysis of trade diversion and welfare impacts. Middle-income countries adjust to the ban by exporting less *and* becoming destinations for trade diversion, whereas high-income countries trade less, and absorbing more waste domestically. Given that middle-income countries were net exporters prior to the ban, it is unlikely that they had sufficient capacity to properly process the net import increase.

Figure 7 shows a scatter plot of the net-import quantity in 2016 (x-axis) and 2018 (y-axis). Countries in the lower left quadrant such as Japan and the US, were net exporters in 2016 and remain net exporters in 2018. Countries in the upper left quadrant, such as Thailand and Indonesia, were also net exporters in 2016 but became net importers in 2018. Out of 74 countries in this study,

[14]Income group assignment is based on the country classification of UNCTAD.

14 changed from net exporter in 2016 to net importer in 2018.

Table 4 lists net import quantities in 2016 and 2018 of these countries, ranked by 2018 net import quantity (large to small). The table also shows 2018 net import quantity as a share of 2016 net export quantity (column 4), the change in net import quantities (column 5), and the change in net import quantity as a share of 2016 net export quantity (column 6). For eight countries,net import quantity more than doubled. For six of these , 2018 net import quantity was more than double its 2016 value. If we assume that the net-import quantity in 2016 reflects the capacity to process plastic waste, it is very unlikely that these countries would have been able to ramp up recycling capacity within less than a year to accommodate the increase in waste inflow from the diversion.

Some countries that were net importers in 2016 and 2018 may also have struggled with capacity constraints. Malaysia, for example, had net imports of 124 million tons in 2016 but by 2018, this increased to 825 million tons, more than a 6-fold increase. Similarly the Czech Republic increased its net import quantity from 5.8 million tons to 45.5 million tons, an increase of more than 600%. This suggests that some countries must have struggled with capacity constraints after the ban. This pattern of change suggests that a large share of plastic scrap imports may have entered the disposal system as trash instead of entering the recycling system as raw materials. In this case, countries that started receiving overwhelming amount of plastic waste in the post-ban period likely face negative environmental consequences such as plastic waste pollution.

5 Empirical Analysis

5.1 Estimation Models

We augment the standard gravity model with two variables relevant to the waste haven hypothesis (WHH): GDP per capita, and EPI score[15] We use the gravity model to evaluate bilateral trade in plastic scrap (commodity code HS-3915) from origin country o to destination country d in year t, with t between 2008 and 2019. We specify two models: one with country-level WHH variables, and another with variables for each bilateral pair.

Model with Country-level WHH Variables

Let Q_{odt} be the IHS transformation of the quantity of HS-3915 exported from country o to country d in year t. Let $\boldsymbol{G'\xi}$ be a set of additional control variables commonly used in gravity

[15] Because the EPI scores are only available for even years between 2006 and 2020, for each odd year t, we assign an EPI score by taking the average between the scores of $t-1$ and $t+1$. Let $GDPC_{it} = IHS(\text{GDP per Capita}_{it})$, where $i \in \{d, t\}$. Let EPI_{it} denote the EPI score of country i in year t.

model estimation.[16]

The WHH variables in model 1 are country characteristics: origin's and destination's GDP per capita (w_{ot}, w_{dt}) and EPI score (e_{ot}, e_{dt}). Model 1 also includes interactions of the post-ban indicator ($post_t$) with each of these WHH variables which allows for a comparison of the pre-ban and post-ban relationships between the augmented variables and the trade flow volume.

We estimate the model with fixed effects (FE) for year (ϕ_t), exporter (ϕ_o), importer (ϕ_d), and country pairs (ϕ_{od}). Standard errors are clustered at the country pair level. The first model uses country-specific characteristics.

Model 1:

$$\begin{aligned} Q_{odt} = \; & \eta_1 w_{ot} + \eta_2 w_{ot} \times post_t + \eta_3 w_{dt} + \eta_4 w_{dt} \times post_t + \eta_5 e_{ot} + \eta_6 e_{ot} \times post_t + \\ & \eta_7 e_{dt} + \eta_8 e_{dt} \times post_t + \boldsymbol{G'\xi} + \phi_o + \phi_d + \phi_t + \phi_{od} + \epsilon_{odt} \end{aligned} \tag{1}$$

Model 1 decomposes the impact of GDP per capita and EPI scores into pre-ban and post-ban parts. There are eight coefficients of interest. η_1 and η_3 measure the *pre-ban* average impact of origin's and destination's GDP per capita on the export quantity of plastic scraps. η_2 and η_4 measure the *post-ban* change in the average impact of origin's and destination's GDP per capita on the quantity of plastic scrap. Similarly, η_5 and η_7 measure the *pre-ban* average impact of origin's and destination's EPI score (the proxy for disposal cost) on the export quantity of plastic scraps. η_6 and η_8 measure the *post-ban* change in the average impact of origin's and destination's EPI score on the export quantity of plastic scrap.

Model with bilateral WHH Variables

Model 1 helps answer questions about how country-specific characteristics may influence waste trade. For example, do wealthier countries export more plastic waste? Do countries with poorer environmental regulation quality import more plastic waste? These are meaningful questions but they do not adequately address the waste haven problem because they do not address how bilateral differences may *jointly* determine the waste trade. For example, does plastic waste tend to flow from richer to poorer countries? Does plastic waste tend to flow from countries with stronger environmental regulations to countries with weaker environmental regulations?

To address these questions, we make use of "gradient" forms of the waste haven variables, following Kellenberg (2012). Let x_{ot} be a time-varying characteristic of origin o and let x_{dt} be the same characteristic of destination d. The gradient of x, which is a time-variant bilateral variable,

[16] $\boldsymbol{G'\xi}$ includes country-specific GDP, pair-specific distance, bilateral tariffs on plastic scrap commodities ($\tau_{odt} = log(1 + \text{tariff}_{odt})$), and indicators of contiguity, common language, colonial relationship, common currency, common regional trade agreement. Note that some of these variables may be dropped in an estimation depending the set of fixed effects employed.

is defined as:

$$g(x)_{odt} = \frac{x_{ot} - x_{dt}}{(x_{ot} + x_{dt})/2}$$

In other words, the gradient of x is the origin-destination difference as a fraction of the pair average.

In his study, Kellenberg uses the gravity framework to analyze the trade flow of scrap commodities (including plastic and other scrap materials). He conducts a cross-section analysis in which the explanatory variable of interest is the environmental regulation gradient. The country-specific environmental regulation index is computed using data from the 2003–2004 Global Competitiveness Report. The gradient version of the index is interpreted as a measure of the average percentage difference in environmental regulation between the importer and the exporter, where larger positive values imply that the exporter has more stringent environmental regulation than the importer, and vice versa. Thus a positive coefficient is expected on the environmental regulation gradient variable.

In addition to capturing the effects of pair-specific characteristics, the gradient variant also addresses an identification issue in the previous model. Model 1 includes origin, destination, and pair fixed effects, thereby controlling for country-specific and pair-specific omitted variables. However, it is still possible that some time-variant country characteristics remain in the error term, causing omitted variable bias. The gradient model addresses this threat by replacing origin fixed effects and destination fixed effects with origin-year fixed effects and destination-year fixed effects. There is a cost, however: the application of country-year fixed effects rules out estimation of the effects of country-sepcific GDP per capita and EPI scores.

We define the two gradient variables — GDP per capita (w_{odt}) and EPI score (e_{odt}) as follows:

$$g(w)_{odt} = \frac{\text{GDP per Capita}_{ot} - \text{GDP per Capita}_{dt}}{(\text{GDP per Capita}_{ot} + \text{GDP per Capita}_{dt})/2}$$

$$g(e)_{odt} = \frac{\text{EPI}_{ot} - \text{EPI}_{dt}}{(\text{EPI}_{ot} + \text{EPI}_{dt})/2}$$

The MRF and reclaimer models suggest that higher disposal costs encourage exports of plastic scrap and discourage imports. Therefore, we expect positive coefficients on both the GDP per capita gradient and the EPI score gradient.

Analogous to the country-specific model, the pair-specific model includes fixed effects for year, destination-year, and country pairs. Standard errors are again clustered at the country pair level.

Model 2:

$$Q_{odt} = \lambda_1 g(w)_{odt} + \lambda_2 g(w)_{odt} \times post_t + \lambda_3 g(e)_{odt} + \lambda_4 g(e)_{odt} \times post_t + \boldsymbol{G'\xi} + \phi_{ot} + \phi_{dt} + \phi_{od} + \epsilon_{odt} \quad (2)$$

Model 2 decomposes the impact of GDP per capita gradient and EPI scores gradient into pre-period and post-period parts. There are four coefficients of interest. λ_1 and λ_2 measure the pre-ban and post-ban impacts of the GDP per capita gradient on the export quantity of plastic scrap. λ_3 and λ_4 measure the pre-ban and post-ban impact of the EPI score gradient on the export quantity of plastic scrap.

5.2 Estimation Results

Results from model 1 are reported in table 5 and those from model 2 are in table 6. In each table, columns (1) presents results from estimations that exclude the EPI score, and column (2) presents the full model.

5.2.1 Effect of GDP per Capita

Origin's GDP per Capita

We expect origin's GDP per capita to be positively correlated with the quantity of plastic scrap, for four reasons. Residents of wealthier countries consume more goods per capita, thereby generating more recyclable plastic waste; their countries are more likely to have legal requirements for recycling, allowing for better extraction of recyclable plastics from municipal solid waste; and residents likely have a higher willingness to pay for environmental regulation quality, which may lead to a preference for exporting scraps material to be handled elsewhere. Lastly, higher-income countries likely have higher labor costs. Recycling plastic waste requires some manual sorting, plastic recycling may be relatively costly in higher-income countries.

Model 1 estimation results indicate, as expected that higher GDP per capita in the origin country encourages more trade flow. The estimates show that in the pre-ban years, a 1% increase in the GDP per capita of origin increases quantity exported by 5.21% to 5.77%. The post-ban interaction term is not statistically significant, so this relationship was unaffected by the ban.

Destination's GDP per Capita

The sign on GDP per capita of destination countries cannot be unambiguously predicted. If plastic scrap is imported for use as raw material in the production of recycled primary form plastics to feed demand for raw materials from the domestic manufacturing sector, then industrializing middle-income countries may import more plastic scrap than high-income and low-income countries. In addition, while the sorting process is labor-intensive, the process of turning sorted scrap into primary-form plastic relies on machinery. Thus, low-income countries may not have the capacity for plastic recycling. For these reasons, the relationship between plastic scrap imports and GDP per capita may not be linear. It might follow an inverse U-shape curve, similar to the environmental Kuznets curve.

We find that a higher GDP per capita of the destination increases trade flow, but the interaction term indicates that this relationship weakens after the ban. This finding matches the real-world observation that lower-income countries started importing more plastic waste than did higher-income countries.

Gradient of GDP per Capita

We expect trade in plastic scrap to go from higher income origins to lower income destinations, so we expect the coefficient on the GDP per capita gradient variable to be positive. Table 6 confirms this expectation. The estimates are positive and statistically significant, and indicate that in the pre-ban period, for every 1% that an importer's GDP per capita is lower than an exporting partner, the importer will import 0.016% - 0.018% more waste from that exporter. Post-ban interactions are only weakly significant (Table 6, column 1) or not significant (column 2), so the positive relationship between GDP per capita gradient and plastic scrap trade did not change after the ban.

5.2.2 Effect of EPI Score

Origin's EPI Score

We expect the origin's EPI score to be positively correlated with export quantity, since EPI score is strongly correlated with effective waste management (Figure 1). We assume that a higher EPI score corresponds to a higher cost of waste disposal, which in turn increases costs for plastic reclaimers and material recovery facilities (MRF). Thus, a country with a higher EPI score may have less incentive to import plastic scraps and more incentive to export them.

Consistent with expectations, we find in Table 5 that for exporters, a higher EPI score is associated with higher trade volume. A one-unit increase in the origin's EPI score is associated with a 2.20% increase in the quantity of plastic scrap exported.[17] This relationship does not change after the ban.

Destination's EPI Score

We expect the destination's EPI score to be negatively correlated with traded quantity because plastic recycling is likely more profitable in countries with lower disposal costs.

[17] This elasticity is computed using the pre-period average EPI scores of origins (68.71).

We find as expected that for importers, a lower EPI score is associated with a higher trade volume. A one-unit increase in the EPI score of the destination country is associated with a 1.63% decrease in the quantity of plastic scrap imported.[18] This relationship does not change after the ban.

Gradient of EPI Score

We expect plastic scrap trade to flow from an origin with higher disposal costs to a destination with lower disposal costs, so we expect the coefficient on the GDP per capita gradient in Table 6 to be positive. The pre-ban estimate in Table 6 is not statistically significant which suggests that, in the pre-ban period, the EPI score gradient (disposal cost) has no impact on the quantity of plastic scrap traded between a pair of countries after controlling for GDP per capita and other variables. However, the post-ban estimate is positive and statistically significant. In teh post-ban period, for every 1% that an importer's EPI score decreases relative to that of an exporting partner, the importer will experience a 0.431% increase in waste imports from the exporter.[19] Alternatively, this estimate suggests that a one standard deviation (SD) increase in the gradient of the EPI score in 2016 (mean = 0.04, SD = 0.21) increases bilateral trade quantity by 9% in the post period.

5.2.3 Summary of Main Findings

GDP per capita of origin is positively correlated with trade quantity in the pre-period. This relationship remains unchanged in the post-period. GDP per capita of destination is positively correlated with trade quantity in the pre-period and decreases slightly in magnitude after the ban. The GDP per capita gradient has a positive impact on trade quantity in the pre-ban period, and this relationship remains unchanged in the post-period. Our analysis indicates that plastic scrap trade follows a waste haven pattern in which international trade allows for the negative externalities of plastic waste to be redistributed from wealthier to poorer countries. China's ban on imports of plastic scrap does not appear to change this pattern.

The EPI score of the origin country is positively correlated with trade quantity in the pre-period. This relationship remains unchanged in the post-period. EPI score of destination is negatively correlated with trade quantity in the pre-period. This relationship remains unchanged in the post-period. The EPI score gradient does not have a statistically significant relationship with the plastic scrap trade in the pre-ban period. However, the estimate of the post-ban relationship is positive and statistically significant. This suggests that the relative disposal cost between trading partners became an important determinant of the international flow of plastic waste after the China import ban was imposed.

[18] This elasticity is computed using the pre-period average EPI scores of destinations (67.89).

[19] The phrase "for every 1% an importer's EPI score decreases relative to an exporting partner" refers to $\%\Delta EPI_{orig} - \%\Delta EPI_{dest} = 1\%$. See appendix section A for discussion and examples.

Without considering the effect of the ban, we find that trade in plastic scrap follows a waste-haven-type pattern in the following ways. First, plastic waste flows more from a richer origin to a poorer destination, and countries with higher GDP per capita export more waste. This implies exportation of the negative externalities of their consumption that generated the waste. In terms of country characteristics, higher disposal costs in an exporting country are associated with higher trade volume whereas higher disposal costs in an importer are associated with smaller trade volume.

Considering the ban's impact, we find that the waste haven pattern in terms of GDP per capita observed in the pre-period persists in the post-period, while the waste haven pattern in terms of environmental quality becomes pronounced after the ban. This finding aligns with the hypothesis that, in the post-ban period, plastic scrap trade is increasingly driven by exporters' demand for disposal services. Because the measure of disposal cost (EPI score) is highly correlated with the share of poorly managed municipal solid waste (e.g. dumping, open burning, unsanitary landfills, etc.), it is reasonable to conclude that the environmental problem of plastic waste is likely higher under international trade than under a counterfactual in which exporting countries have to handle their waste locally.

6 Conclusion

in this study we explore the ex ante drivers of global trade in plastic waste and examine trends in global plastic waste trade following a policy ban on imports by the world's largest plastic waste importer, China. We find that the bilateral trade in plastic waste exhibits a waste-haven pattern. We find that bilateral differences in per capita GDP became stronger as determinants of trade after the China import ban came into effect. Bilateral differences in the stringency of environmental regulation emerged as significant drivers of trade after the ban.

While this study cannot address the distribution of the *net* benefit of the plastic scrap trade, it provides some information about the distribution of the environmental costs of processing plastic waste. The results provide empirical support for concerns that post-ban trade diversion may worsen global plastic waste pollution, because more waste gets diverted to countries with less stringent environmental regulation. If we assume that the recycling capacity of these new destinations cannot grow fast enough to accommodate all the diverted trade, then it is likely that some of the additional waste imports are simply dumped in the importing countries. This corresponds to documented cases where highly contaminated waste mislabeled as scraps was found in "new destination" countries, especially in Southeast Asia (Staub 2018 and Parker 2018). The Basel Convention amendments mandate that plastic waste be recycled or disposed of "as close as possible to source" and aim to regularize waste trade and international disposal through a "prior informed consent" procedure between exporters and importers (Benson and Mortensen, 2021). However, these measures were to be implemented only from 2021, so it is still to early to judge their efficacy.

The supply chain from recycling bins to PCR production is long and complex; no study can rigorously model all its links. We have modeled the immediate ex ante drivers of bilateral trade and estimated the structure and changes in that trade in light of a major policy shock. Related and ongoing work addresses empirical measures of reclaimers' demand for plastic scrap as raw material, for example recycling capacity (Kojima, 2020); this will facilitate estimation of the extent to which post-ban trade diversion is determined by demand for plastic scraps in importing countries. Similarly, a longer-run perspective will require examination of factors influencing post-ban investments in recycling capacity, waste disposal, and policy responses in the importing countries.

7 Tables

Table 1: Five countries with highest average EPI scores and five countries with lowest average EPI scores within each income group

High Income

Top 5		**Bottom 5**	
Country	Score	Country	Score
Switzerland	87.2	South Korea	65.0
Sweden	82.8	Saudi Arabia	61.8
Norway	81.1	UAE	59.5
Austria	80.1	Kuwait	57.0
France	79.7	Hong Kong	52.5

Upper-Middle Income

Top 5		**Bottom 5**	
Country	Score	Country	Score
Costa Rica	75.4	Namibia	58.9
Colombia	69.9	Guatemala	58.8
Albania	69.3	Botswana	55.6
Bulgaria	68.8	South Africa	53.8
Malaysia	67.4	China	52.5

Lower-Middle Income

Top 5		**Bottom 5**	
Country	Score	Country	Score
Tunisia	64.0	Indonesia	53.4
Egypt	63.7	Cote d'Ivoire	53.0
Philippines	62.7	Kenya	52.7
Morocco	62.2	Pakistan	45.0
El Salvador	60.7	India	43.4

Table 2: Pre-Ban vs. Post-Ban Averages of Bilateral Characteristics

Variable	**All** (1)	**Pre-Ban** (2)	**Post-Ban** (3)	**Difference** (3) - (2)	
Number of Country Pairs	2,888	2,888	2,858	30	
Trade Volume					
Export Quantity (Tons)	2,248.2	2,201.1	2,387.7	186.67	
Import Quantity (Tons)	2,433.7	2,487.4	2,274.6	-212.85	
Export Value ($1,000)	976.6	1,004.5	893.8	-110.65	
Import Value ($1,000)	985.2	1,038.9	826.2	-212.62	**
PHP Variables					
Difference in GDP per Capita (USD)	640	753	305	-448	
Difference in EPI Score	0.90	0.82	1.13	0.31	
Gradient of GDP per Capita†	3.39	3.78	2.22	-1.56	
Gradient of EPI Score†	1.41	1.28	1.81	0.53	
Gravity Variables: Contunous					
GDP of Origin in (Billion USD)	1,167	1,129	1,278	148.51	***
GDP of Destination in (Billion USD)	1,163	1,126	1,272	145.91	***
Distance (km)	6,123	6,126	6,115	-10.55	
Bilateral Tariff (%)	7.02	7.25	6.34	-0.91	***
Gravity Variables: Indicators					
Contiguity	0.06	0.06	0.06	-0.0009	
Common Language	0.13	0.13	0.13	0.0002	
Common Currency	0.07	0.07	0.07	0.0006	
Common Regional Trade Agreement	0.51	0.51	0.50	0.0038	
Orig is/was Colonizer of Dest	0.02	0.02	0.02	0.0001	
Dest is/was Colonizer of Orig	0.02	0.02	0.02	0.0003	

Stars indicate statistical significance of t-test of mean difference: *p<0.1; **p<0.05; ***p<0.01

†Let X_{it} be a time-varying country characteristic. The gradient of X, which is a bilateral time-variant variable, is defined as: $Grad(X)_{odt} = (X_{ot} - X_{dt})/((X_{ot} + X_{dt})/2)$. In other words, the gradient of X is the origin-destination difference as a fraction of the pair average.

Table 3: Average Characteristics of Net Importers vs. Net Exporters

Variable	**All**	**Net Importer**	**Net Exporter**	**Difference**	
	(1)	**(2)**	**(3)**	**(2) - (3)**	
(A) Whole Period: 2008-2019					
Number of Countries	74	51	65	-14	
Number of Import Partners	16.44	19.94	14.29	5.65	***
Number of Export Partners	19.51	19.20	19.70	-0.50	
Export Quantity (1,000 Tons)	86.00	43.23	112.29	-69.06	***
Import Quantity (1,000 Tons)	93.10	181.63	38.69	142.95	***
Net Import Quantity (1,000 Tons)	7.10	138.41	-73.60	212.00	***
GDP per Capita (1,000 USD)	23.76	19.98	26.07	-6.09	***
EPI Score	66.62	64.32	68.03	-3.71	***
Average Distance (1,000 km)	6.12	5.76	6.34	-0.68	***
GDP (Billion USD)	812.02	479.50	1,016.37	-536.87	***
(B) Pre-Ban Period: 2008-2016					
Number of Countries	74	45	63	-18	
Number of Import Partners	15.90	19.53	13.82	5.71	***
Number of Export Partners	18.84	18.87	18.83	0.05	
Export Quantity (1,000 Tons)	83.93	42.95	107.47	-64.52	***
Import Quantity (1,000 Tons)	94.85	199.07	34.97	164.10	***
Net Import Quantity (1,000 Tons)	10.92	156.13	-72.50	228.62	***
GDP per Capita (1,000 USD)	23.45	20.27	25.27	-5.00	***
EPI Score	66.99	65.33	67.95	-2.62	**
Average Distance (1,000 km)	6.13	5.76	6.34	-0.57	***
GDP (Billion USD)	788.08	462.57	975.08	-512.51	***
(C) Post-Ban Period: 2017-2019					
Number of Countries	74	40	50	-10	
Number of Import Partners	18.06	20.99	15.87	5.12	***
Number of Export Partners	21.50	20.03	. 22.60	-2.57	
Export Quantity (1,000 Tons)	92.22	43.94	128.33	-84.39	***
Import Quantity (1,000 Tons)	87.85	137.02	51.06	85.96	***
Net Import Quantity (1,000 Tons)	-4.37	93.08	-77.27	170.34	***
GDP per Capita (1,000 USD)	24.68	19.25	28.74	-9.50	***
EPI Score	65.50	61.75	68.32	-6.57	***
Average Distance (1,000 km)	6.11	5.76	6.37	-0.61	*
GDP (Billion USD)	883.85	522.82	1,153.90	-631.08	**

Stars indicate statistical significance of t-test of mean difference: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4: Countries that were net exporter in 2016 but became net importers in 2018

Country	Net Import 2016 (million tons)	Net Import 2018 (million tons)	2018/2016	2018-2016 (Δ)	Δ/2016
Thailand	−223.07	362.11	162%	585.17	262%
Indonesia	−82.61	221.94	269%	304.54	369%
South Korea	−149.23	83.81	56%	233.03	156%
Pakistan	−2.39	80.99	3394%	83.38	3494%
Denmark	−20.71	28.35	137%	49.06	237%
Egypt	−0.51	19.89	3908%	20.40	4008%
Poland	−73.42	7.11	10%	80.53	110%
South Africa	−11.96	6.69	56%	18.65	156%
Morocco	−0.07	5.42	8075%	5.49	8175%
Luxembourg	−0.49	3.10	629%	3.60	729%
Ecuador	−16.25	3.01	19%	19.26	119%
Brazil	−7.34	2.32	32%	9.66	132%
Botswana	−0.06	0.13	207%	0.19	307%
Paraguay	−0.19	0.01	5%	0.20	105%

Table 5: Pre-Post ban gravity analysis with country characteristics

Variable	**Dependent Variable: IHS(Tons of Plastic Scraps Traded)**	
	(1)	**(2)**
IHS(GDP per Capita of Orig)	5.309***	5.771***
	(1.275)	(1.286)
Post x ...	0.058	0.074
	(0.068)	(0.111)
IHS(GDP per Capita of Dest)	8.598***	8.198***
	(1.231)	(1.235)
Post x ...	−0.574***	−0.598***
	(0.066)	(0.100)
EPI Score of Orig		0.032***
		(0.007)
Post x ...		−0.011
		(0.010)
EPI Score of Dest		−0.024***
		(0.007)
Post x ...		0.611
		(0.009)
Log(1 + Tariff)	3.998**	4.261**
	(1.926)	(1.926)
Log(GDP of Orig)	−5.41***	−5.576***
	(1.195)	(1.209)
Log(GDP of Dest)	−7.879***	−7.687***
	(1.159)	(1.163)
Observations	33,969	33,969

*p<0.1; **p<0.05; ***p<0.01. All estimations include origin FE, destination FE, pair FE, and year FE. Standard errors clustered at pair level. Some gravity variables and the post-ban indicator are omitted from this table.

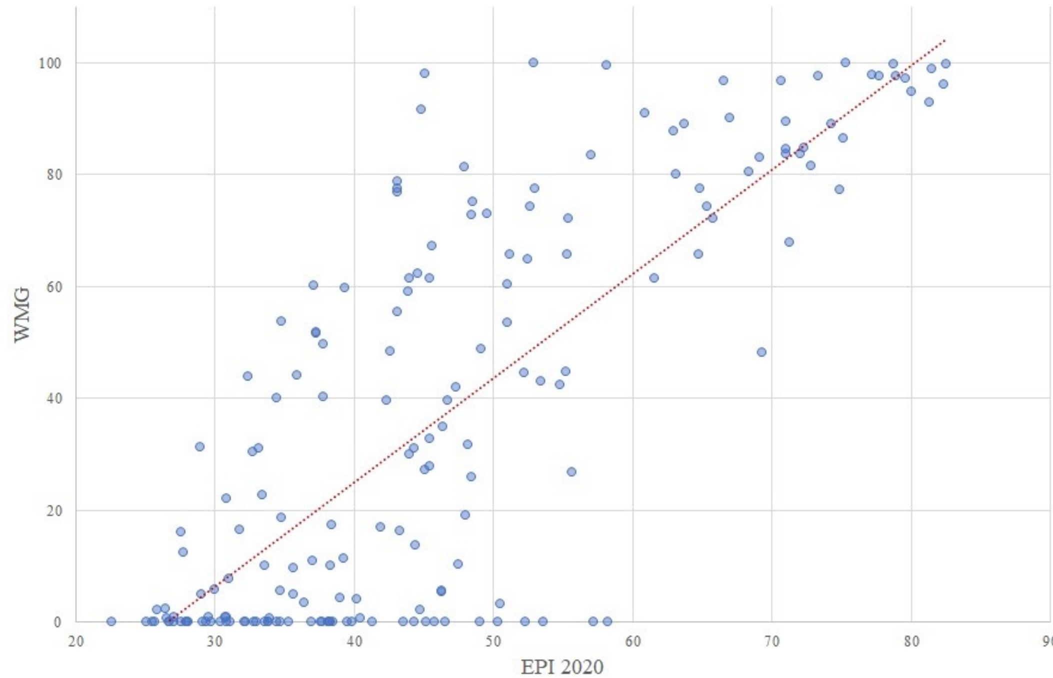
Table 6: Pre-post ban gravity analysis with pair gradient variables

Variable	**Dependent Variable: IHS(Tons of Plastic Scraps Traded)** (1)	(2)
Gradient(GDP per Capita)	0.016**	0.018**
	(0.008)	(0.008)
Post x ...	0.006*	0.002
	(0.004)	(0.004)
Gradient(EPI Score)		−0.069
		(0.140)
Post x ...		0.431**
		(0.199)
Observations	33,969	33,969

*p<0.1; **p<0.05; ***p<0.01. All estimations include origin-year FE, destination-year FE, and pair FE. Standard errors clustered at pair level. The inclusion of country-year FEs and pair FE causes all standard gravity control variables to be dropped out.

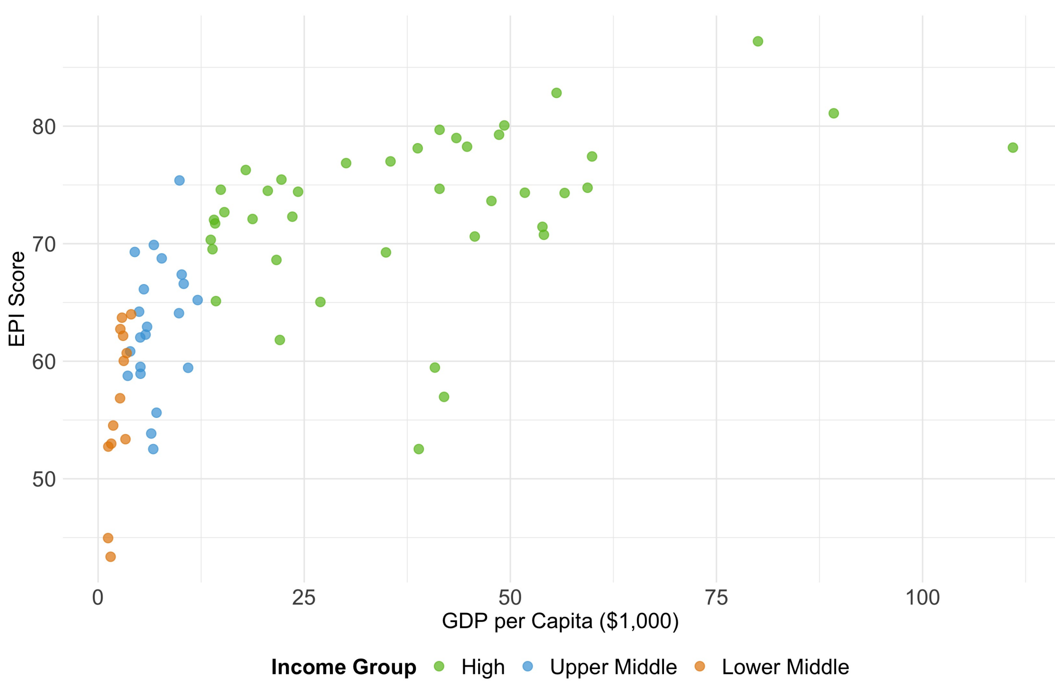
8 Figures

Figure 1: Correlation between overall 2020 EPI score and the share of properly managed waste



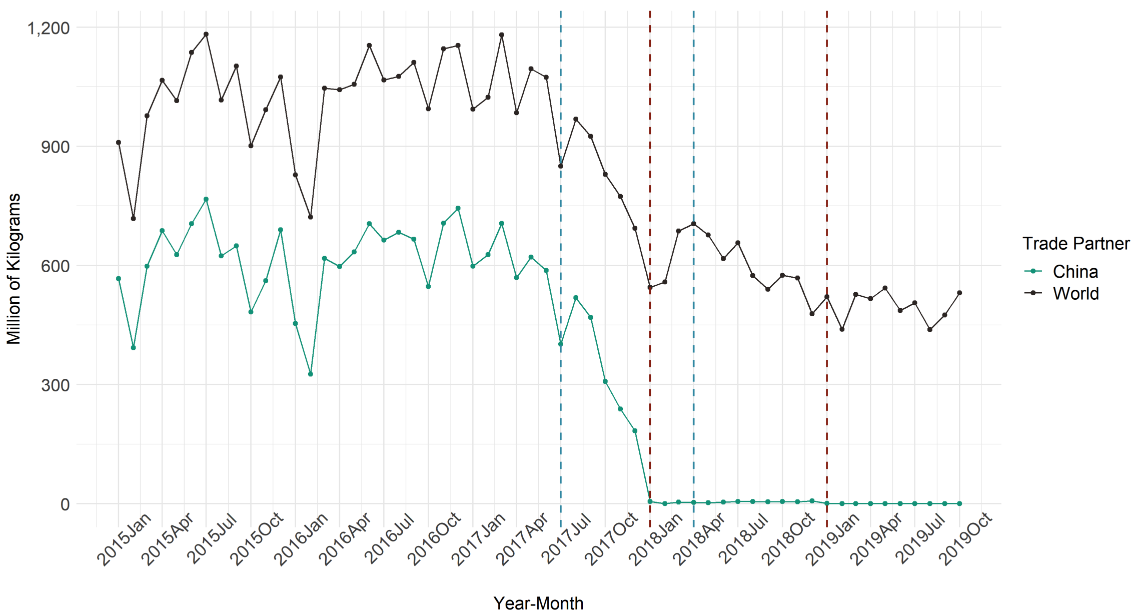
Note: What A Waste Global Database published by the World Bank.

Figure 2: Correlation between EPI score and GDP per capita by income group (2008-2018 average)



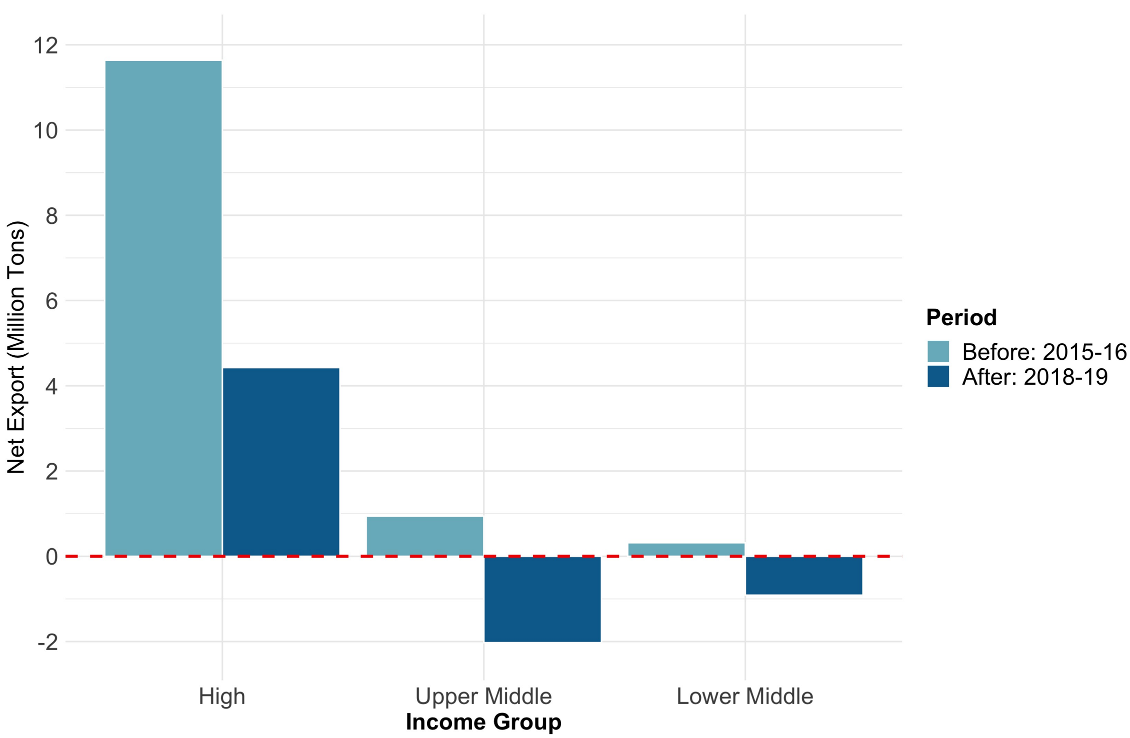
Note: GDP per capita data are from the World Bank. Environmental Performance Index (EPI) data are from NASA's Socioeconomic Data and Application Center (SEDAC).

Figure 3: Change in monthly quantity of plastic scraps imported by the world and china



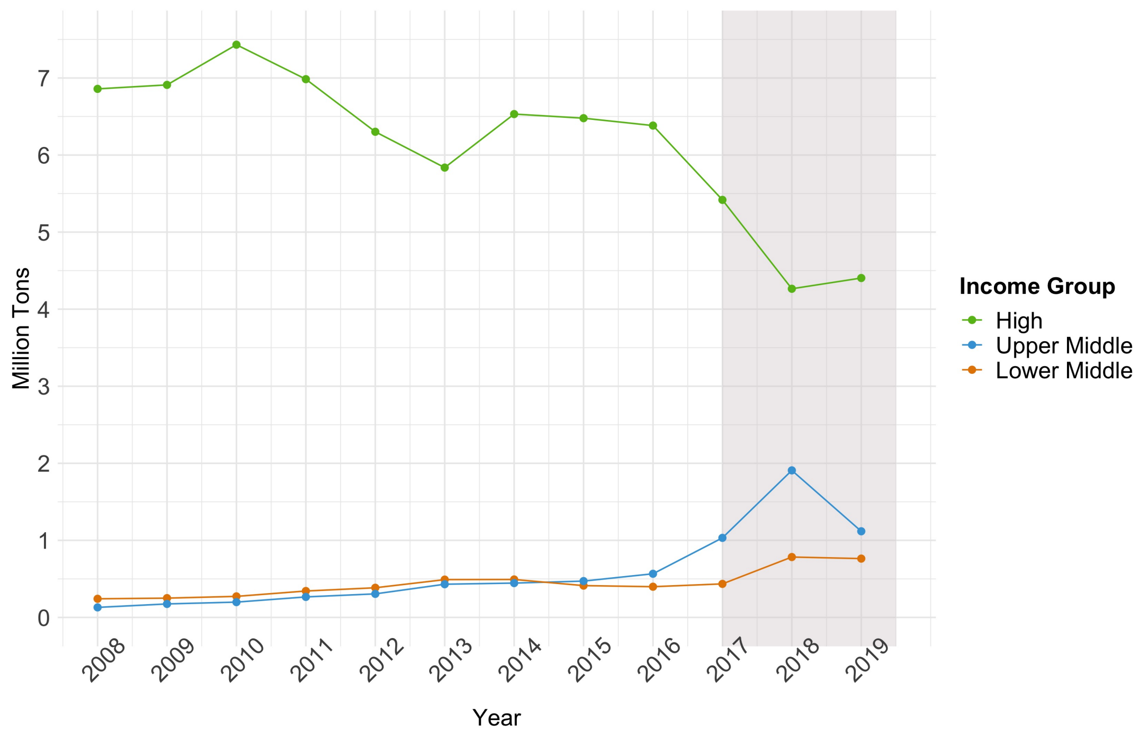
Note: Trade data are from UN Comtrade.

Figure 4: Change in net-export of plastic scraps by income group: before (2015-16 total) vs. after (2018-19 total) the ban



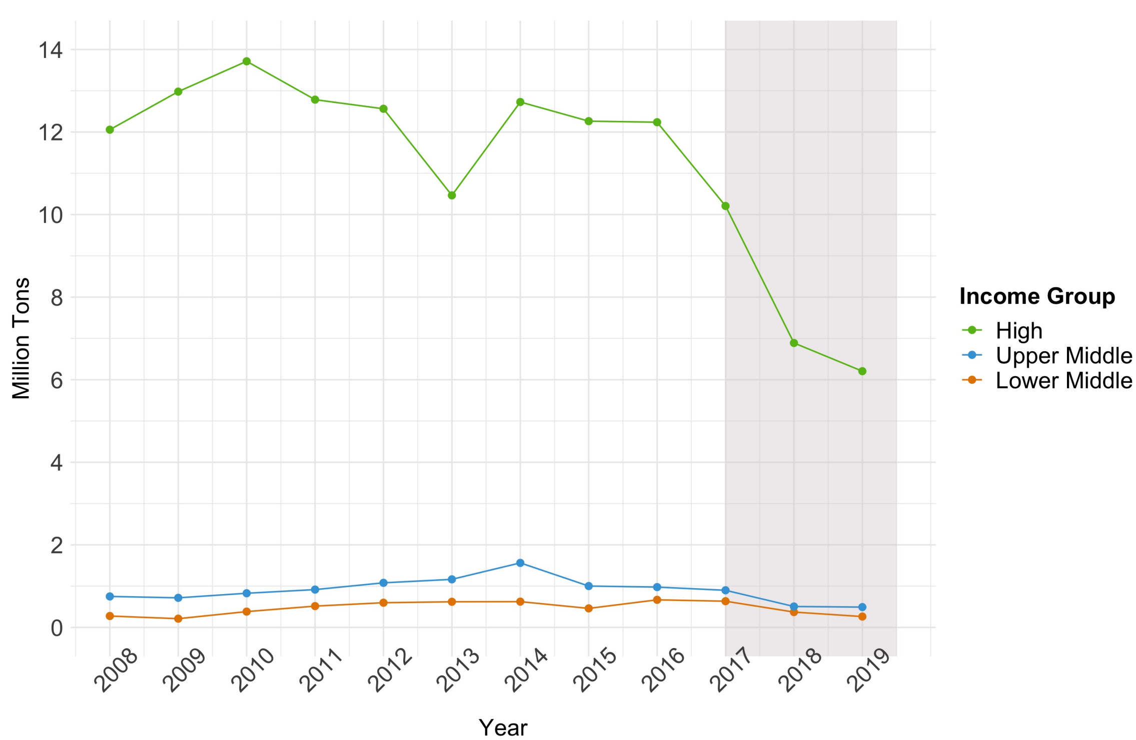
Note: Trade data are from UN Comtrade. Income group data are from UNCTAD

Figure 5: Annual import quantity of plastic scraps by Income Group



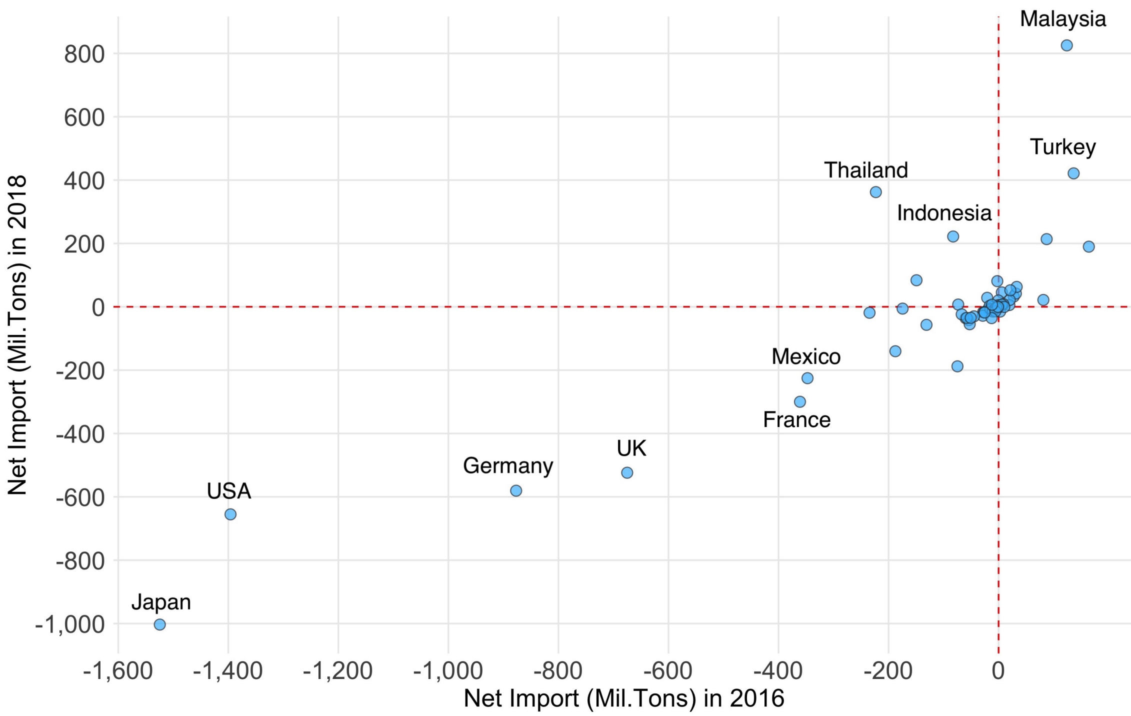
Note: Trade data are from UN Comtrade. Income group data are from UNCTAD

Figure 6: Annual export quantity of plastic scraps by income group



Note: Trade data are from UN Comtrade. Income group data are from UNCTAD

Figure 7: Relationship between net import quantities in 2016 and 2018



Note: Trade data are from UN Comtrade.

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Appendix

A Change in Gradient Variables

Let X_{it} be a time-varying country characteristic. The gradient of X is the origin-destination difference as a fraction of the pair average, which is a bilateral time-variant variable. The gradient of X is defined as:

$$Grad(X)_{odt} = \frac{X_{ot} - X_{dt}}{(X_{ot} + X_{dt})/2}$$

The coefficient estimates from the gradient regression analyses can be interpreted as, for example, for every 1% an importer's EPI score decreases relative to an exporting partner, the importer will experience a x% increase in waste imports from the exporter. From table **??**, the whole period estimate of x is 0.19%. And from table 6, the post-period estimate of the change in x is 0.43% (and the pre-period estimate is null).

The phrase "1% an importer's EPI score decreases relative to an exporting partner" refers to $\%\Delta EPI_{orig} - \%\Delta EPI_{dest} = 1\%$. This corresponds to an increase of 0.01 in the EPI gradient. Three tables below show three examples of how this 1% decrease in importer's EPI score relative to an exporting partner may occur.

Example 1: origin EPI = 80, destination EPI = 80, and gradient = 0.

Starting with origin EPI = 80, destination EPI = 80, and gradient = 0. If origin's EPI remains unchanged and destination's EPI decreases by 1% from 80 to 79.2, then the gradient increases from 0 to 0.01. If origin's EPI increases by 1% from 80 to 80.8 and destination's EPI remains at 80, then the gradient increases from 0 to 0.01. Similarly, if origin's EPI score increases by 5% from 80 to 84 and destination's EPI score increases by 4% from 80 to 83.2, then the gradient also increases from 0 to 0.01. All these cases correspond to a 1% decrease in importer's EPI score relative to an exporting partner may occur. Example 2 and 3 follow similarly, but with different reference EPI scores and gradient values.

Table 7: Example 1 of a change in EPI score gradient.

Orig %Δ EPI	**Dest %Δ EPI**	**Orig New EPI**	**Dest New EPI**	**Gradient New**	**Gradient Change**
0%	-1%	80.0	79.2	0.01	0.01
1%	0%	80.8	80.0	0.01	0.01
5%	4%	84.0	83.2	0.01	0.01
-1%	-2%	79.2	78.4	0.01	0.01
-5%	-6%	76.0	75.2	0.01	0.01

Example 2: origin EPI = 80, destination EPI = 70, and gradient = 0.13.

Table 8: Example 2 of a change in EPI score gradient.

Orig %Δ EPI	Dest %Δ EPI	Orig New EPI	Dest New EPI	Gradient New	Gradient Change
0%	-1%	80.0	69.3	0.14	0.01
1%	0%	80.8	70.0	0.14	0.01
5%	4%	84.0	72.8	0.14	0.01
-1%	-2%	79.2	68.6	0.14	0.01
-5%	-6%	76.0	65.8	0.14	0.01

Example 3: origin EPI = 70, destination EPI = 80, and gradient = -0.13.

Table 9: Example 3 of a change in EPI score gradient.

Orig %Δ EPI	Dest %Δ EPI	Orig New EPI	Dest New EPI	Gradient New	Gradient Change
0%	-1%	70.0	79.2	-0.12	0.01
1%	0%	70.7	80.0	-0.12	0.01
5%	4%	73.5	83.2	-0.12	0.01
-1%	-2%	69.3	78.4	-0.12	0.01
-5%	-6%	66.5	75.2	-0.12	0.01

B Recycler Model

B.1 Supply: Recyclers

We develop a model of a profit-maximizing plastic recycler to theoretically explore the determinants of the supply for plastic scraps. A detailed version of this model can be found in Chunsuttiwat (2022).

A profit-maximizing recycler takes in an exogenous quantity of waste (W) that was put in recycling bins as agreed upon in its contracts with municipalities. Let α denote the initial contamination rate of recyclable waste[20] which is exogenous to the recycler. A recycler charges a per-unit recycling fee of p_W and produces plastic scraps output by removing contamination. The contamination removal process requires effort (E), which has a unit cost of p_E. Let $r(\alpha; E)$ denote

[20]For example, the average contamination rate of the US is 25%, according to an article by Waste Management.

the contamination removal function, with $r(0) = 0$, $r'(E) > 0$, and $r''(E) < 0$. The contamination removal function depends on the initial contamination rate (α) which determines the upper bound of the removal function: $r(\alpha; E) \in [0, \alpha)\ \forall E$.

The contamination removal process separates total waste input (W) into two piles: the removed contamination, $r(E)W$, which must be disposed of at price p_D, and the plastic scraps, $[1-r(E)]W$, which is the output. The output quantity is decreasing in E. The contamination rate of the output (i.e. its quality) is the difference between the initial contamination rate and the the contamination removal rate: $c(E) = \alpha - r(E)$. If its output cannot be sold, the recycler must dispose of it at price p_D.

Let $\phi(c)$ be the market price of plastic scraps with $\phi'(c) < 0$. Let $\bar{c}$ be the maximum "marketable" contamination rate: $\phi(\bar{c}) = 0$ and $\phi(c) > 0\ \forall c < \bar{c}$, that is, scraps with $c > \bar{c}$ cannot be sold on the market. Let $\tau > 0$ be an exogenous transaction cost. Let $p(c) = \phi(c) - \tau$ be the unit "net price" of plastic scraps. $p(c) < 0$ if the market price is lower than the transaction cost. This is the gain/loss to a recycler from selling one unit of plastic scraps with a contamination rate c. Let $\tilde{c}$ be the "breakeven" contamination rate: $\phi(\tilde{c}) = \tau$ thus $p(\tilde{c}) = 0$. Any contamination rate that is greater than $\tilde{c}$ results in a negative net price.

A recycler can choose to exert no effort and dispose of all its recyclable waste. In this case, there is no output and the profit function is $\Pi^D = p_W W - p_D W$, which does not depend on effort or the price of plastic scraps. If a recycler chooses to exert effort and remove contamination, its profit function, Π^A, has a point of discontinuity at $\underline{\mathrm{E}}$ which satisfies $\alpha - r(\underline{\mathrm{E}}) = \bar{c}$.

$$\Pi^A(E) = \begin{cases} \Pi^L(E) = p_W W - p_D W - P_E E, & E \in [0, \underline{\mathrm{E}}) \\ \Pi^H(E) = p_W W - [\phi(\alpha - r(E)] - \tau][1 - r(E)]W - p_D r(E)W - P_E E, & E \geq \underline{\mathrm{E}} \end{cases}$$

If a recycler exerts effort $E < \underline{\mathrm{E}}$, the resulting contamination rate is higher than the marketable threshold: $c(E) = \alpha - r(E) > \bar{c}$. The output cannot be sold in the market and the profit function ($\Pi^L(E)$) depends on E but not $\phi(c)$. Notice that $\Pi^L(E)$ is minimized at $E = 0$ which renders it identical to Π^D.

If a recycler exerts effort $E \geq \underline{\mathrm{E}}$, then $c(E) = \alpha - r(E) \leq \bar{c}$. The output can be sold at price $\phi(c)$ and the profit function ($\Pi^H(E)$) depends both on E and $\phi(c)$. Whether Π^H lies below or above Π^L at $\underline{\mathrm{E}}$ depends on the relative magnitude of p_D and τ: if $p_D > \tau$ then $\Pi^H(\underline{\mathrm{E}}) > \Pi^L(\underline{\mathrm{E}})$ and if $p_D < \tau$ then $\Pi^H(\underline{\mathrm{E}}) < \Pi^L(\underline{\mathrm{E}})$. To find the optimal E, a recycler first finds E^H that maximizes Π^H then compares $\Pi^H(E^H)$ to Π^D. If $\Pi^H(E^H) < \Pi^D$, then it will choose to exert no effort and dispose of all W.

Model Prediction

Under the assumption that contamination removal technology and initial contamination rate is constant across all recyclers, the decisions of whether to exert effort at all and how much effort to exert depend on the relative magnitudes of disposal cost (p_D), effort cost (p_E), and the sale price of the plastic scrap ($\phi(c)$). The decision whether to exert effort at all depends on the relative magnitude of the per-unit disposal cost and per-unit *loss* from sorting and selling marketable plastic scraps (sale price net transaction cost and per-unit effort cost). A recycler will exert no effort only if the per-unit net loss is greater than per-unit disposal cost. The model thus implies that a recycler facing a higher disposal cost is more likely to be selling scraps in the market, even at a loss.

The decision of how much effort to exert is based on the cost-benefit tradeoff of exerting effort. Exerting additional effort allows for a cleaner scrap output which can be sold at a higher price. The marginal cost of exerting additional effort has three components: (1) the accruing effort cost, (2) the cost of disposing the additional contamination removed, (3) the reduction in the amount of salable scraps (with higher contamination rate) which could have been sold at a lower price. Thus, the faster the value of scrap rises with respect to its quality, the higher the incentive for recyclers to exert effort beyond the minimum amount required to produce salable scraps.

Consider a scenario in which initial contamination rate varies across recyclers. This likely have an important implication for the plastic waste trade. Recyclers in higher-income countries with a well-established municipal waste management system that requires the separation of recyclable waste are more likely to have a lower initial contamination rate. This means a smaller amount of effort may be required to achieve a minimal marketable effort level ($\underline{\mathrm{E}}$). The model thus predicts that, all else equal, recyclers with a low initial contamination rate are more likely to produce and sell plastic scraps.

The ban affects the plastic scrap price function. More specifically, the market becomes less tolerant to contamination. The maximum marketable contamination rate ($\bar{c}$) at least weakly decreases and the price at least weakly decreases at all contamination levels below the new $\bar{c}$.

The model predicts that recyclers that used to sell before the ban may keep selling or shift to disposal, whereas recyclers that chose disposal before the ban will continue with the same option (they will not switch from disposal to selling). As a result, the global quantity of plastic scrap traded decreases, and the total quantity of disposal increases, at least weakly in both cases.

As a result of the downward price shock, some recyclers may be forced to switch from selling to disposal ($\Pi^H(E^H) < \Pi^D$ under the post-ban price function). Recyclers that face a low disposal cost relative to effort cost are more likely to do this external margin adjustment. For recyclers that continue to sell (internal margin adjustment), those with a higher disposal cost are more likely to decrease effort and those with a lower disposal cost are more likely to increase effort after the ban.

If a recycler finds that $E = 0$ is the optimal choice, and if the resulting profit is negative ($\Pi^L(0) = \Pi^D < 0$), then it may be willing to pay for alternative disposal service with unit cost less than p_D. In countries where waste disposal is formalized, the disposal capacity may be more inelastic and the price may be more sensitive than in places where open dumping and other informal methods of disposal are widely practiced. For this reason, it may also be possible that p_D rises in response to the ban in some countries, and Π^D generates a greater loss for recyclers. To minimize loss, recyclers may seek alternative disposal options as described above. This corresponds to real-world observations where developing countries caught many shipments from developed countries labeled as recyclable scraps that were just trash or have a contamination rate that far exceeds the legal threshold (Law et al., 2020).

C Reclaimer Model

C.1 Demand: The Reclaimer

I develop a model of a profit-maximizing plastic reclaimer to theoretically explore the determinants of the demand for plastic scraps. A detailed version of this model can be found in Chunsuttiwat (2022).

A reclaimer uses plastic scraps to produce post-consumer resin (PCR) pellets. The output (Y) is sold at price p_Y. We assume that there is no quality variation in the PCR pellets and thus p_Y is an exogenous constant with respect to a reclaimer. A reclaimer uses plastic scraps (S), labor (L), and capital (K) as production inputs. The unit cost of labor is w and the unit cost of capital is r. Let us consider a vertically integrated production function scenario. The production of PCR involves two steps. First, the sorting process serves to remove contamination from the plastic scrap input. Second, the granulation process turns sorted plastic scraps into PCR pellets.

In the sorting process, a reclaimer buys plastic scraps S with contamination rate c at price $\phi(c)$. The first step of the production process is to remove all contamination (cS) and produce clean recyclable plastic scraps, denoted by $X = (1-c)S$. The contamination is disposed of at price p_D. Suppose that the sorting process only requires labor input. Let $h(c, S)$ be the amount of labor (e.g. labor hours) required to sort scraps quantity S with contamination rate c. For example, if each unit of contaminant requires one unit of labor, then $h(c, S) = cS$. The second step of the production process – the granulation process – converts the output of the sorting process into PCR granules (Y). Since all contaminants are removed in the first step, the granulating function does not depend on the contamination rate. Let $g(X, L, K) = g((1 - c)S, L, K)$ be the granulating function.

The profit function of a reclaimer is:

$$\Pi^R = \underbrace{p_Y g(\overbrace{(1-c)S}^{X}, L, K) - wL - rK}_{\text{the granulating process}} \underbrace{-wh(c,S) - p_D cS - \phi(c)S}_{\text{cost of the sorting step}} \tag{3}$$

The first term in the profit equation is the sales revenue. The second and the third terms are the labor cost and capital cost of the granulation process. The last three terms are the cost of the sorting process: $wh(c, S)$ is the total cost of labor, $p_D cS$ is the total cost of disposal, and $\phi(c)S$ is the total cost of scraps input. A reclaimer chooses c, S, L, and K to maximize profit.

C.1.1 Model Prediction

The ban affects reclaimers in two ways. First, it at least weakly decreases the input price (of plastic scraps). Second, it at least weakly increases the output price (of PCR). These changes encourage reclaimers to at least weakly increasing their output which requires input adjustments. Under some assumptions about the shapes of the sorting and granulation functions[21], capital, labor, and scrap input quantity weakly increases and the contamination rate of choice weakly decreases. There may be heterogeneity in the magnitude of adjustments in contamination rate and scrap input quantity due to variation in the wage rate. Whether a higher wage is associated with a larger magnitude of adjustment depends on the rate of change of the sorting function with respect to contamination rate and scrap input volume (h_{cc} and h_{SS}). There may be heterogeneity in output adjustment overall (which affects input adjustment) due to variation in transaction cost. Reclaimers who face a larger reduction in transaction cost post-ban have a greater incentive to increase output. Variation in granulation technology may also result in variation in reclaimers' magnitude of adjustment to the ban. This is true even when wage has no effect on the magnitude of adjustment (when $h_{cc} = h_{SS} = 0$).

[21] See Chunsuttiwat (2022).