Slow Violence of Waste: Evidence from Chinese Environmental Policy in Waste Trade

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Abstract

Since the 1990s, China has been the largest importer of waste in the world. However, China changed its environmental policy in 2018 not to import plastic, paper, and textile. This 2018 Chinese policy left questions regarding where the waste is exported to and which groups of countries are more affected by importing more waste. Using a difference-in-difference approach, this study analyzes the effects of the Chinese import ban on the extensive and intensive margins of waste exports and re-exports by country income level and region. The evidence is found that the effect of the Chinese waste import ban on waste exports is valid at both extensive and intensive margins, especially having substantial effects on the intensive margin of exports and re-exports to upper-middle-income countries and the East Asian & Pacific regions. Without the government's strict environmental regulations, people living in these regions will be affected by pollution.

Keywords: Trade and Environment Policies, Waste, Environment and Development
JEL codes: F13, F18, Q53, Q56

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1 Introduction

The emerging literature on waste movement indicates that less stringent environmental regulations ensuing cheaper waste disposal costs are one of the important factors that have made developing nations the ”waste haven” for the developed countries (Kellenberg (2012)). Similar to the concept of *pollution haven* effects, the movement of pollution-intensive industries to countries with lax environmental regulations, waste haven effects involve the direct movement of wastes across borders due to differences in environmental regulations. From an environmental perspective, the transboundary movement of waste has given rise to problems such as environmental pollution and public health concerns due to soil, water, and air contamination from disposing of waste into landfills or incineration. With respect to slow violence proposed by Nixon (2011), the detrimental effects of waste trade on humans are readily ignored because these effects occur gradually and out of sight.

The 2018 Chinese policy which started preventing waste imports excites rethinking of waste trading. China became the largest country importing waste as the demand for raw materials increased dramatically due to industrial development in the 1990s. However, the demands for sustainable development have increased as China achieves higher living standards. This induced the Chinese government to reduce hazardous waste imports and restrict imports to high-quality waste. The rich nations-including Canada, Germany, and the US-depended on China to discharge their waste had to find new trading partners.

This paper explores how the changes in the Chinese waste import ban in 2018 affected the amounts of waste exports and re-exports. Exploring the heterogeneous effects of the ban across countries, I narrow the importing countries down to four groups by their income level and seven groups by their region.

Wastes are secondary resources for importing countries, harvesting them is a significant economic activity such as converting waste materials into new products or creating jobs in the waste industry. For example, China, which consumes 43% of the world’s copper, obtains 50% of that sourced from scrap (Gregson and Crang (2015)). However, past economic research suggests that developing countries become destinations of global waste for several reasons. The business in developing countries is made more profitable by the cheap costs of shipping containers for empty spaces on the back run of global shipping routes or cheap labor to sort materials for recycling (Gregson and Crang (2015); Minter (2015)). Also, they have weaker environmental standards than their trade partners (Bernard (2015); Kellenberg (2012)). Developing countries readily import waste because they may simply discard unrecycled materials directly into the environment with few disposal restrictions.

More recent papers explored how the Chinese waste import bans change waste trade. Using the historical data (1988-2016), Brooks, Wang and Jambeck (2018) predicted the changes in the plastic waste trade and found that imports of plastic waste are almost evenly split between high-income countries and upper-middle-income countries which collectively account for 96% of all imports. On the other hand, Tian et al. (2021) analyzed the impact of the Chinese ban on scrap copper waste imports. They reported that the ban has promoted the development of regional trade and improved the quality of scrap copper in international trade. However, their studies are limited by focusing on a specific type of waste and testing prediction not the casual.

My contributions to the literature are twofold. First, this study contributes to the trade, environmental, and development literature by empirically analyzing the impacts of the new Chinese environmental policy on bilateral waste trade. Previous studies of this policy's impact on trade are focused on one specific type of waste, such as scrap copper (Tian et al. (2021)) or a specific region (Kumamaru and Takeuchi (2021)). General-science contributions on this topic focus on the changes in the plastic waste trade or its environmental effects (Brooks, Wang and Jambeck (2018)). In contrast, this study focuses on trade flows for all types of waste covered in China's waste import ban and for 88 countries.

Second, this study is the first to examine the bilateral trade of waste re-exports. Re-exports have an important implication in the waste trade. Re-exports are goods exported in the same state as previously imported, and it happens when waste is imported illegally or the initial importing countries raise an import barrier. It implies that re-exported waste is less likely to be desired. This study will answer where less preferred waste is exported to and which groups of countries are more affected by importing it.

To assess the impacts of the 2018 Chinese waste import ban, I use a panel data set which includes 16 years (2005-2020) and 88 exporting countries and their pairs with 87 importing countries. Using a difference-in-difference (DiD) approach, I estimate waste export and re-export changes after the ban by country income level and region at extensive and intensive margins. The treatment group is 18 waste commodities banned by the 2018 Chinese policy including plastic, paper, textile, and vanadium slag (PPTV), and the control group is 40 waste commodities that have never been banned by the policy in 2018-2020. The weights of corresponding waste in each group are aggregated respectively in the analysis. Also, the year 2018 and after are defined as the post-treatment period.

The analysis shows that the effect of the 2018 Chinese waste import ban on waste trade is valid at the extensive margin (e.g., more countries started importing waste) as well as at the intensive margin (e.g., increasing trade volumes of already existing export lines). I find that the extensive margins of PPTV waste exports and re-exports are significant but small. At the intensive margin, the 2018 Chinese waste import ban increased volumes of PPTV waste exported to high-income countries by 23.6%, middle-income countries by 35.8%, and low-income countries by 16.8%. But, the results of the pre-trends analysis suggest that the estimate for low-income countries may be overestimated. With respect to waste re-export, the ban led to 2.8-8.8% increase in PPTV waste re-export to upper-middle income countries at the intensive margins, suggesting that the waste, denied entry to a receiving country, is re-exported to upper-middle-income countries after the ban.

In terms of region, the probability that PPTV waste are re-exported to the East Asian & Pacific and Europe & Central Asian regions increased by 4.5% and 2.5%, respectively. More importantly, intensive margins are much more pronounced. The ban led to an increase in PPTV waste re-exports to the East Asian & Pacific region by 64.7% and to Europe & Central Asia region by 30.8%. But, the pre-trends analysis suggests that the estimates may be overestimated.

The remainder of this paper is organized as follows. Section 2 provides background information about global waste trade and the Chinese waste import ban. Section 3 presents the empirical framework. Section 4 describes data and provides descriptive statistics. Section 5 presents the empirical results, and Section 6 describes robustness checks and extensions. Section 7 concludes with a discussion of the findings.

2 Waste trade and Chinese waste import ban

2.1 Global waste trading

The flow of waste for a country is described by Kellenberg (2012) as shown in Figure 1. In general, domestic waste is produced as a result of the domestic economy (a). Domestic waste has three potential disposal options: it can be recycled (b), exported to other countries (c), or disposed of domestically (d). Recycled materials are returned to the domestic economy to be reprocessed or consumed (e) or ended up back in the domestic waste stream because few waste products are fully recyclable.

The main trade flows of interest are waste exports (c) and waste re-exports (m and n). Domestic wastes are exported to a foreign country (c) if it is less costly to send domestic trash abroad than to recycle or dispose of it in their own country. In most cases, developed countries need to pay higher costs for recycling due to the expensive labor to perform sorting, or high construction expenses for recycling facilities. They are also likely to face high costs for disposal because these countries have strict regulations on waste disposal to protect the environment and public health, or land is scarce, and thus finding suitable sites for waste disposal is a challenge.

Although a country exports waste overseas, this waste can be re-exported to the country of origin (m) or to another country (n). Re-exports are goods exported in the same state as previously imported. Importing countries re-export goods when they have defaulted

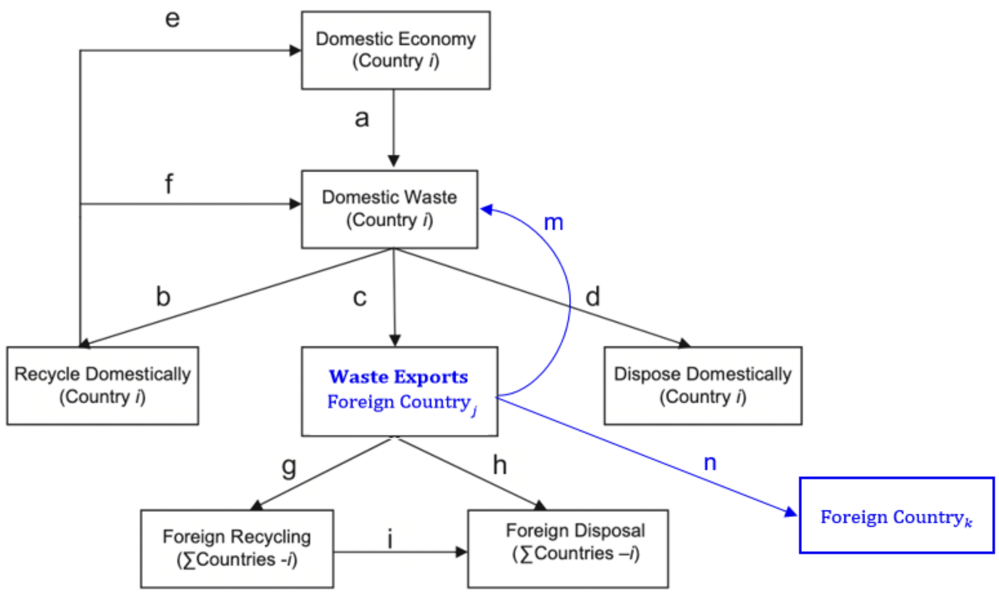


FIGURE 1: **Global Waste Trading**

Source: Kellenberg (JEEM 2012), edited by author

on payments, the exported goods are defective, or the authorities have imposed an import barrier (UN Trade Statistics (2016)). If waste is re-exported, it implies that the exported waste no longer meets an importing country's standard. Another reason for re-exports of waste is that the illegal plastic waste imports have to be returned to their countries of origin following international norms and the Basel Convention which has been ratified by 187 countries (Basel Convention (2021)).

Given these characteristics of re-exported waste, this waste is more likely to be contaminated than waste that has not been re-exported but only exported (Gillespie (2015);Hartono et al. (2021)). For example, the Philippines sent tonnes of household waste to Canada mislabelled as recyclable plastics, and Malaysia sent back containers of plastic waste to Spain after it was found to be contaminated (BBC (2019)). Morever, some re-exported waste does not arrive in the country of origin but is diverted to other developing countries. This phenomenon suggests less-preferred waste arrives in more economically disadvantaged countries, contaminating land, air, and water as well as human health. For instance, it was discovered that in 2020 wastes sent from Germany to Turkey ended up being re-exported to Vietnam because the Turkish importer lost its license to import waste after the Turkish government began to crack down on mixed and dirty plastic waste imports and Germany refused to repatriate the wastes (The Guardian (2021)). The re-exports have especially an important implication in waste trade because re-exported waste is more likely to be contaminated and less preferred.

2.2 Chinese waste import ban

Since the 1990s, China has been the largest importer of waste products in the world, accounting for 43% of the world's imports of used paper and 45% of plastic waste in 2016 (UN Comtrade (2022)). As their economy developed, Chinese living standards have increased, and the demand for goods have simultaneously increased as well. However, China lacked raw materials while the quality and cost of the existing raw materials did not meet the standards and needs to produce goods. As an alternative, China has increased their imports of waste products and recycled them, thereby using the recycled materials as an input in the production process. Chinese businesses imported large amounts of waste from overseas because it was often of a higher quality than what was available domestically. For example, China imported 0.655 million tonnes of plastic waste in 1998 and increased their imports to 8,8 million tonnes in 2016 which was a 1,255% increase over 18 years (UN Comtrade (2022)).

Chinese Waste imports skyrocketed after China joined the World Trade Organization (WTO) in 2001. As the country's manufacturing industry was experiencing rapid growth and exporting more manufactured goods on enormous container ships, shipping companies ended up with thousands of empty shipping containers to carry back. Logistics companies saw that it was inexpensive to fill empty containers with low-value products such as recyclable items (Matsuda, Hanaoka and Kawasaki (2020)). Figure 2 shows that the increasing trend of plastic waste imports moves similar to that of total Chinese exports implying recyclable trash fills the empty space in containers that were available on return trips.

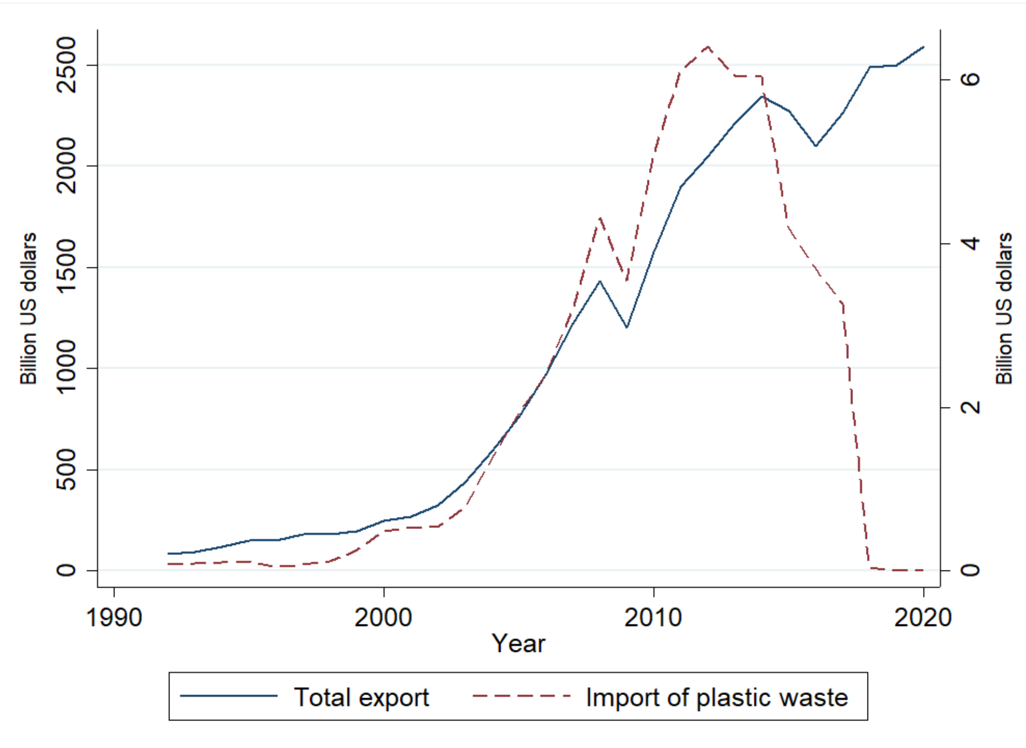


FIGURE 2: **The Trend of China's Total Export and Plastic Waste Import in Value**

Source: UN Comtrade database (UN Comtrade (2022)). Plastic waste is identified under HS code category 3915.

Although imported waste is recyclable and can potentially mitigate the shortage of resources in China, it has caused significant environmental impacts from disposal processes, in addition to the fact that waste can contain hazardous materials (Chen et al. (2019)). Much of the waste was contaminated which makes it difficult to be recycled, leading to high levels of pollution and health risks for workers in the recycling industry as well as residents living close to recycling sites. Contaminated or unsorted waste requires extra efforts to sort and increase the costs of recycling. In 2016, China imported 8.88 million tons of plastic waste, 70.6% of which was buried or mismanaged, causing a series of environmental problems (Chen et al. (2019)).

In addition to poor quality and contaminated waste shipments, waste smuggling also became issues for waste imports (Balkevicius, Sanctuary and Zvirblyte (2020)). Approximately 180 countries are members of the Basel Convention which aims to prevent illegal traffic of waste. Although illegal shipments to Asia accounted for 20 percent of the violations, China and including Hong Kong were the preferred destinations for illegal shipments (Rucevska et al. (2015)).

As a part of the response, China started to regulate solid waste imports by implementing policies such as the Operation Green Fence (OGF) of 2013 and the recent National Sword of 2017. The former policy attempted to increase the quality of imported waste through the strict inspections of every container that arrived in China. Balkevicius, Sanctuary and Zvirblyte (2020) found that OGF resulted in a 26% reduction in low-quality waste exports from developed countries to China. Because this policy was only implemented for nine months in 2013, and Tran, Goto and Matsuda (2021) argued that the impact of OGF on the reduction of low-quality waste was short-lived.

To combat illegal traffic of waste and impose higher restrictions on the waste import, the National Sword policy was launched in February 2017. In July 2017, China notified the WTO that they would forbid the import of plastics waste from living sources, unsorted waste paper, waste textile materials, and vanadium slag[1] on January 1, 2018 (WTO (2017)).[2] of Appendix

Aiming to ban most waste imports, the Chinese government announced that 16 waste materials (equivalent to 5 unique 6-digit HS codes) would be banned in 2019, including metal and electrical appliance scraps and scrap vessels. They also announced that another 16 materials (equivalent to 11 unique 6-digit HS codes) would be banned in 2020. These materials are wood wastes and other metal wastes. A list of wastes materials banned in 2019 and 2020 is available in Tables B.2 and B.3 of Appendix, respectively.

An abrupt announcement of the waste import ban created a disruption to the recycling industry and global waste trade. For example, in the domestic paper market in southern China, the price of finished paper doubled from 3,000 yuan per ton to 6,000 yuan ($902) af-

[1]Vanadium slag is a solid by-product releasing from iron- and steel-making plants, and is used for producing a vanadium redox flow battery (Lee et al. (2021)). This type of batteries helps to average out highly variable generation sources such as wind or solar power.

[2]China has forbidden imports of 4 classes, 24 kinds of solid wastes which are equivalent to 18 6-digit Harmonized System (HS) codes. A full list of these 18 HS codes is available in Table B.1.

ter China announced the National Sword policy (Reuters (2017)). As the amounts of waste paper pulp produced from imported waste paper shortened, supplies of raw materials for the paper industry shrunk. Thus, paper mills in China faced higher prices of raw materials and thus produced finished papers at higher prices inevitably.

Moreover, the National Sword policy also changed the global waste trade. This policy pushed many companies to resort to shipping trash bins via a black market. Some firms, unable to find an importing partner or wanted to export waste at a lower price, shipped waste illegally. INTERPOL (2020) reported that an emerging criminal trend in the global plastic waste market started in January 2018 and documented an increase in illegal plastic waste imports in South and Southeast Asian countries as well as in Eastern European countries. INTERPOL (2020) pointed out that countries were re-routing illegal waste shipments to camouflage the origin of the waste shipment. The policy also appears to change the geography of global waste trade. According to Wen et al. (2021), the major export destinations were swiftly switched to Southeast Asian countries such as Thailand, Indonesia, Vietnam, Malaysia, and the Philippines.

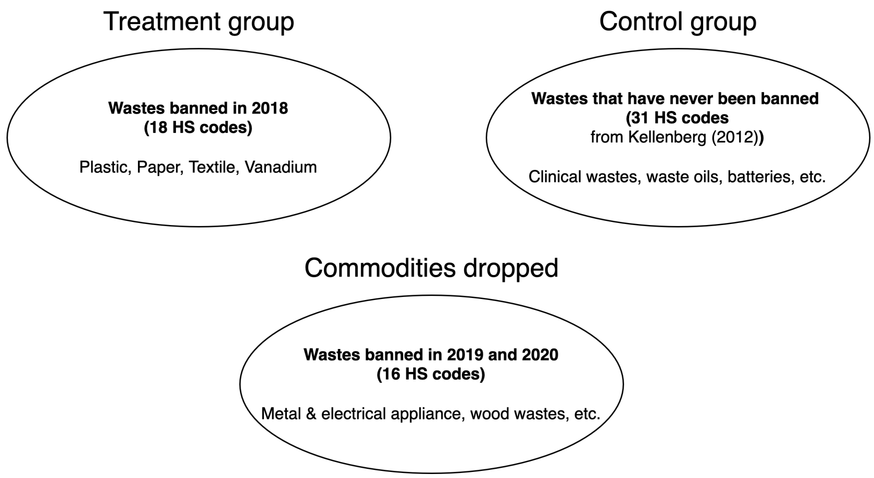
3 Empirical Model

The empirical approach in estimating the effect of the 2018 Chinese waste import ban on global waste exports/re-exports is based on the difference-in-difference (DiD) approach. I identify the effects of the 2018 Chinese waste import ban on trade by comparing PPTV waste exports to exports of other waste that have never been prohibited by the 2018-2020 Chinese waste import bans.

3.1 Treatment and Control Groups

Figure 3 presents which waste categories are classified as the treatment and control groups. The treatment group in the main analysis is four types of waste (plastic, paper, textile, and vanadium slag waste) regulated by the 2018 Chinese waste import ban, consisting of 18

FIGURE 3: **Treatment and Control Groups in the DiD Estimation**



6-digit HS categories. The control group is the wastes that have never been prohibited to import by Chinese waste import bans in 2018-2020, accounting for 31 6-digit HS categories. I exclude the wastes banned by China in 2019 and 2020 from the control group because these became treated in the post-period and thus will not generate a reliable counterfactual for the treatment group. Total bilateral waste trade of the treatment and control groups is the aggregated weight of waste across the corresponding HS categories, respectively. The descriptions of HS codes for the treatment and control group are available in Tables B.1 and B.4 of Appendix.

3.2 Difference-in-differences Model

To estimate the impact of the 2018 Chinese waste import ban on extensive margins of exports (the probability that waste is exported), I perform the following regression:

$$\begin{aligned} I(Export_{ijt,k} > 0) = \alpha_1 + \beta_1 Treat_k + \beta_2 Post_t + \beta_3 (Treat_k * Post_t) + X_{ij}\gamma_1 + X_{it}\gamma_2 + X_{jt}\gamma_3 \\ + X_{ijt}\gamma_4 + \delta_i + \delta_j + \epsilon_{ijt,k} \end{aligned} \tag{1}$$

where i represents exporter, j represents importer, t represents time, and k represents the treatment or control group. $Export_{ijt,k}$ represents exports/re-exports from country i to country j during time t in a k group. I is equal to 1 if $Export_{ijt,k} > 0$, and zero otherwise. $Treat_k$ is an indicator variable for the treated state, and $Post_t$ is an indicator variable of the post-treatment period (1 if year >= 2018). The control variables based on the gravity model are included. X_{ij} includes the distance between countries i and j and whether two countries use the same official language, share a common border, and have a colonial tie. X_{it} and X_{jt} indicate a country i's or j's time-varying controls including GDP, ratification of Basel Ban Amendment[3], and EU and WTO memberships in year t. X_{ijt} indicates whether countries i and j have a bilateral or regional trade agreement in year t. Detailed information about control variables is explained in Section 4. δ_i and δ_j are country fixed effects controlling for numerous time-invariant characteristics of the country. $\epsilon_{ist,k}$ denotes an error term. Throughout, the standard errors are clustered at a country-pair to allow for correlated shocks in the residuals, $\epsilon_{ist,k}$, which could reflect unobserved political or economic forces between countries.

I estimate the impact of the 2018 Chinese waste import ban on intensive margins of trade (the quantity of waste exports) with the following equation:

$$\begin{aligned} IHS(Export_{ijt,k}) = \alpha_2 + \eta_1 Treat_k + \eta_2 Post_t + \eta_3 (Treat_k * Post_t) + X_{ij}\theta_1 + X_{it}\theta_2 + X_{jt}\theta_3 \\ + X_{ijt}\theta_4 + \iota_i + \iota_j + \epsilon_{ijt,k} \end{aligned} \tag{2}$$

where $Export_{ijt,k}$, an outcome variable, is transformed by the inverse hyperbolic sine function. The motivation to use this transformation is to allow for a zero value (Bellemare and Wichman (2020)). Waste trade includes many zero trade weights, which are infeasible for the use of the log-linearized estimation method. This process is potentially important for the waste trade data employed in this paper, where 83% of the bilateral country observations have zero trade weights. The variables included in the right-hand side of Equation (2) are identical to the ones in Equation (1).

The semi-elasticities are obtained from adopting inverse hyperbolic sine transforma-

[3]A detailed information about Basel Ban Ammendent is available in Section 4.1

tion to approximate a logarithm and interpret coefficients as they would for a logarithmic equation. The resulting approximation is calculated using the following equation proposed by Bellemare and Wichman (2020):

$$\tilde{P}(\cdot)/100 \approx exp(\eta_3) - 1 \tag{3}$$

3.3 Evaluation of pre-trends

In Equations (1) and (2), I assume that exports/re-exports of waste in the control group serve as a valid counterfactual. The underlying assumption is that controlling for other determinants of trade, exports in PPTV waste (the treatment group) should experience the same trends as those expereienced by other waste that have never been prohibited by the 2018-2020 Chinese waste import bans (the control group), in the absence of the 2018 ban. The true counterfactual is unknowable, but the comparison group can be supported as a valid proxy counterfactual by looking at trends before the 2018 Chinese trash import ban. To evaluate pre-trends of extensive margin waste exports, I perform an event study using the following regression:

$$\begin{aligned} I(Export_{ijt,k} > 0) = \alpha_3 + \sum_{\substack{d=-13 \\ d\neq -1}}^{2} \kappa_d Treatment_k * I[Post_t = d] + X_{ij}\lambda_1 + X_{it}\lambda_2 + X_{jt}\lambda_3 \\ + X_{ijt}\lambda_4 + \mu_i + \mu_j + \epsilon_{ijt,k} \end{aligned} \tag{4}$$

where $I[Post_t = d]$ indicates that the event occurred in year d relative to the year of the Chinese waste import ban in 2018 with the exclusion of the first-year lag, used as a reference category. The main explanatory variables ($Treatment_k * I[Post_t = d]$) are a series of binary indicators that take the value of one for treatment group k in relative year d ($= t - 2018$). The coefficients of interest κ_d are identified as the average effect of the 2018 Chinese waste import ban on the treatment group relative to their control group, d periods after the event year 2018. To assess pre-trends of intensive margin waste exports, I replace $I(Export_{ijt,k} > 0)$ in the left-hand side with $IHS(Export_{ijt,k})$.

3.4 Robustness checks

As mentioned, analyzing re-exports of waste is essential to understand which countries are more likely to receive less-preferred waste. However, the re-export data from UNComtrade is not available for all countries because not all countries record/provide re-exports data, and some countries include re-exports in their export statistics. Since the zero weight of re-exports could not be a valid value (i.e., missing), I define a subset of my sample to include countries that have re-exported any waste since 2005 and report results.

Also, as alternative specifications, I run Equations 1 and 2 without control variables or time-variant control variables with country-pair fixed effects.

One potential threat to identification is a violation of the stable unit treatment value assumption (SUTVA; see Pearl (2009)). In this context, the SUTVA states that the 2018 Chinese waste import ban imposed on PPTV waste should have no impact on exports of other waste. The 2018 ban was placed on unsorted waste paper (HS 470790) but not on other types of waste paper (i.e. HS 470710, 470720, and 470730[4]). However, these four HS codes are classified as "waste and scrap of paper or paperboard" (HS 4707). As Figure A.2 of Appendix shows, since 2018, China has decreased their import of those three types of waste paper although they were not restricted by the ban. To partially control for violations of the SUTVA, I create two datasets: 1) excluding them from the control group, meaning they are excluded from the dataset, and 2) assigning the three types of waste paper to the treatment group as well.

[4]HS 470710 indicates Recovered (waste & scrap) unbleached kraft paper/paperboard; HS 470720 indicates recovered (waste & scrap) paper/paperboard mainly of bleached chemical pulp; HS 470730 indicates recovered (waste scrap) paper/paperboard made mainly of mechanical pulp.

4 Data

4.1 Datasets

The bilateral waste trade data comes from the United Nations Comtrade Database (UN-Comtrade) for 88 countries [5] over 16 years (2005-2020). This database contains trade flows reported up to the 6-digit level of the Harmonized System (HS) classification. Waste trade exports and re-exports are defined as all 6-digit HS categories where waste and/or scrap is the only categorization of a product or material. This yields 62 6-digit HS categories of waste as Kellenberg (2012) defined and 12 additional categories the Chinese waste import ban have prohibited. The descriptions of those 74 HS categories can be found in Tables B.1-B.4 in Appendix along with the country list for the sample in Table B.5. Total bilateral waste trade of the treatment group is defined as the total weight of waste (in kilograms) traded between countries aggregated across the 18 HS categories forbidden to import under the 2018 Chinese import ban. Similarly, total bilateral waste trade of the control group is the aggregated total weight of waste across 40 HS categories that have never been prohibited by China since 2018. Thus, total observations are 244,992 (=88*87*16*2).

UNComtrade reports both trade weight in kilograms and trade value in US dollars (i.e., weight times price). I will use the weight of waste rather than the value of waste as the outcome variable As Kellenberg (2012) explains, the magnitude of physical waste is more important from an environmental perspective. This is because a large volume of waste creates environmental problems by contaminating land, air, and water with toxins and greenhouse gas. Because waste is a high-weight but low-value product, the trade value of waste is defined in terms of the recyclability of the materials and the expected resale price of its recycled materials. Therefore, trade value itself cannot clearly take a role in estimating its harmful effect on the environment. In fact, the simple correlation between weight and

[5] I include all countries which Kellenberg (2012) studied in his paper except for four countries (Romania, Serbia and Montenegro, China, and Hong Kong). It is because the gravity-related control variables are not available for Romania, and Serbia and Montenegro does not exist after 2006 due to the dissolution of that country into its two separate nations. China and Hong Kong are omitted because my main interest is how the Chinese waste import ban redirects waste trade flows to other countries.

value measures is 0.8, indicating that most variations in the value can be explained by changes in weights.

Additional control variables that have been shown to be important in the international trade literature are included as well. Based on a standard gravity model, time-invariant variables include the distance between two countries and whether two countries have the same official language, share a common border, have had a common colonizer after 1945, and have ever had a colonial link. Time variant variables include whether two countries have bilateral or regional trade agreements and belong to WTO or European Union, and their gross domestic product (GDP) per capita in billions of US dollars. The GDP data is obtained from the International Monetary Fund (2021) website while the other control variables are collected from the CEPII (2021) website.

Moreover, the Basel Ban Amendment is an additional important factor to control for. The Basel convention aims to reduce trade of international hazardous waste for its member countries. At the present, most countries around the world have signed the convention. Among 88 countries, all countries except the United States ratified the convention after 2012. Previous studies have controlled for the Basel Convention effect in reducing international waste trade (Baggs (2009); Kellenberg (2012); Kellenberg and Levinson (2014)). However, the Basel convention merely requires a notification and consent system for the movement of waste. Following the convention's initial adoption, some least-developed countries and environmental organizations argued that a more restrictive ban was needed including exports for recycling and waste exports from developed countries to developing countries. To meet this demand, the Basel Ban Amendment was adopted in 1995, and 63 countries of 88 countries have ratified this amendment by 2020. Data on the Basel Ban Amendment membership comes from the Basel Convention (2021) website.

4.2 Descriptive statistics

Descriptive statistics for all variables can be found in Table 1. The waste categories that were banned in 2018 and have never been banned since 2018 are of main interest. The

TABLE 1: **Descriptive Statistics**

Dependent variables	Obs.	Mean	Std. dev.	Min.	Max.
I(Waste exports>0)	244,992	0.158	0.365	0.000	1.000
IHS(Waste exports in kg)	244,992	1.902	4.712	0.000	24.744
I(Waste re-exports>0)	244,992	0.006	0.076	0.000	1.000
IHS(Waste re-exports in kg)	244,992	0.054	0.760	0.000	18.871
Control variables					
$CommonLanguage$	244,992	0.133	0.340	0.000	1.000
$Border$	244,992	0.027	0.163	0.000	1.000
$Colony$	244,992	0.020	0.141	0.000	1.000
$CommonColony$	244,992	0.047	0.212	0.000	1.000
$ln(Distance_{km})$	244,992	8.677	0.892	4.088	9.892
$ln(GDP_{per\ capita,exporter})$	244,992	9.062	1.426	5.107	11.699
$ln(GDP_{per\ capita,importer})$	244,992	9.062	1.426	5.107	11.699
$Basel_{exporter}$	244,992	0.558	0.497	0.000	1.000
$Basel_{importer}$	244,992	0.558	0.497	0.000	1.000
RTA	244,992	0.330	0.470	0.000	1.000
EU	244,992	0.082	0.275	0.000	1.000
WTO	244,992	0.938	0.241	0.000	1.000

Notes: I(·) is an indicator variable which is one if a country exports waste, and 0 otherwise. IHS(·) is waste exports/re-exports weight in kg transformed by the inverse hyperbolic sine (IHS). Total observations are 244,992 (=88*87(countries do not trade with themselves)*16*2). Waste trade flows (dependent variables) come from (UN Comtrade (2022)), GDP and Basel Ban Amendment data are obtained from IMF and Basel Convention websites, and the other control variables come from the CEPII.

indicator variable of I(·) is one if a country exports waste and zero otherwise. As expected, a few countries engage in the trade of waste. 15.8% of the bilateral country observations over 16 years in the dataset have non-zero export weight. This trend is more pronounced for re-exports, showing only 0.6% of the bilateral country observations record non-zero export weight. The reason for having many zero re-export counts is either many countries do not re-export waste at all or they do not record or report re-export trade to the United Nations. Thus, these zero counts could be actual zeros or missing values. If they are not true zeros, this dataset could be unreliable. As a robustness check, I include only countries which have ever re-exported waste over 16 years in the dataset.

All control variables except for three log-transformed variables ($ln(Distance_{km})$, $ln(GDP_{per\ capita,exporter})$, $ln(GDP_{per\ capita,importer})$) are indicator variables. 13.3% of the country pairs share a common official or primary language, 2.7% are contiguous, 2% are or were in a colonial relationship post 1945, and 4.7% share a common colonizer post 1945. Using the original scale instead of log transformation, the average distance between most populated cities in country pairs is 5,866km, and the average GDP per capita was 8,621 US dollars. On average, 55.8% of countries have ratified the Basel Ban Amendment, 33% of country pairs have bilateral or regional trade agreements, 8.2% of country pairs are European Union members, and 93.8% of country pairs are WTO members.

4.3 Which countries export and import most waste?

High-income countries are the major importers of plastic, paper, textile, and vanadium slag (PPTV) waste in 2017 (see Table 2). Six of the top ten countries importing PPTV waste are high-income countries. The other two countries are upper-middle-income countries (China and Malaysia) and the last two are lower-middle income countries (India and Vietnam). Considering 90 countries (including China and Hong Kong), high-income countries imported 61% of all PPTV waste, upper-middle-income countries imported 29%, lower-middle-income countries imported 9%, and low-income countries 1%.[6] Countries import waste to recycle or turn waste into electricity. For example, Germany imported 85% of all PPTV waste from EU countries in 2017. Plants in Germany were left short millions of tonnes of garbage and had to import waste from their neighboring countries to get burned and converted to electricity (WSJ (2015)).

In 2017 before the Chinese waste import ban was implemented, China was the largest importer of PPTV waste making up 21.6%[7] of all imports of the 90 countries. Collectively, China and Hong Kong imported 25.5% of all imports, approximately a quarter of all imports. In the next year, China and Hong Kong reduced their PPTV waste imports enormously by 81% and 60%, respectively, meaning the Chinese waste import ban was implemented effectively. In 2018, the year that the Chinese waste import ban was imposed, around 17% of waste imports dropped on average because countries who normally ex-

[6] Appendix Table B.7 provides a full list of countries and their statistics are available in Appendix Table 2.
[7] =3,452.148/15,966.207*100

TABLE 2: Top 10 Importing Countries, Volume of Four Types of Waste Prohibited By China's Waste Import Ban in 2017 and 2018

Rank in 2017	Country	Country income group[a]	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
1	China	upper	3,452.148	642.369	-81
2	Netherlands	high	1,442.479	1,286.892	-11
3	Germany	high	1,382.609	1,238.508	-10
4	France	high	922.605	1,006.521	9
5	USA	high	890.767	991.956	11
6	United Kingdom	high	685.870	470.601	-31
7	Hong Kong	high	622.322	245.836	-60
8	India	lower	577.182	714.162	24
9	Malaysia	upper	517.369	656.590	27
10	Vietnam	lower	417.826	473.962	13
Total 90 countries including China and Hong Kong			15,966.207	13,279.444	-17

Notes: [a] Country income group consists of four categories: high-income countries (high), upper-middle-income countries (upper), lower-middle-income countries (lower), and low-income countries (low) based on 2020 gross national income per capita following the World Bank classification. Source: UN Comtrade (2022)

ported waste to China could not find their trading partners in that short time.

High-income countries have overwhelmingly been the primary exporters of PPTV waste in 2017, consisting of all the top 10 countries exporting waste as presented in Table 3. This result goes along with Brooks, Wang and Jambeck (2018)'s finding that high-income countries have been the major exporters of plastic waste since 1988. High-income countries contributed to 88% of all exports at 14,051 thousand tonnes, calculated using Appendix Table B.6 having a full list of all 90 countries. Although they imported a considerable portion of PPTV waste at 61%, they exported more waste than they imported, being net exporters. Kellenberg (2015) also find a similar result that although developed countries import a greater quantity of waste in an absolute sense, their share of world waste imports is lower than their share of world waste exports. The top five countries and the United Kingdom decreased their waste exports sharply in 2018 by 14%-34% because they were the major trading partners of China (see Figure A.1 in Appendix), the most affected countries by the

TABLE 3: Top 10 Exporting Countries, Volume of Four Types of Waste Prohibited By China's Waste Import Ban in 2017 and 2018

Rank in 2017	Country	Country income group[a]	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
1	Germany	high	3,500.386	3,026.363	-14
2	Canada	high	1,827.947	1,523.695	-17
3	France	high	1,410.462	1,205.063	-15
4	Japan	high	1,054.388	697.086	-34
5	USA	high	889.069	630.698	-29
6	Belgium	high	773.031	778.028	1
7	United Kingdom	high	547.979	425.198	-22
8	Hong Kong	high	504.172	59.986	-88
9	Australia	high	463.176	468.289	1
10	Austria	high	376.364	360.794	-4
Total 90 countries including China and Hong Kong			15,966.207	13,279.444	-17

Notes: [a] Country income group consists of four categories: high-income countries (high), upper-middle-income countries (upper), lower-middle-income countries (lower), and low-income countries (low) based on 2020 gross national income per capita following the World Bank classification. Source: UN Comtrade (2022)

Chinese policy change. Hong Kong reduced its waste exports remarkably by 88% because they act as an entry port into China, with most of the waste imported to Hong Kong going directly to China as an export, accounting for around 95% of waste export arriving in China in 2017.

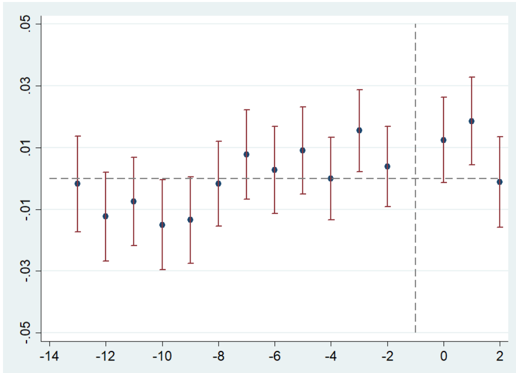
5 Results and Discussion

5.1 Pre-trend testing

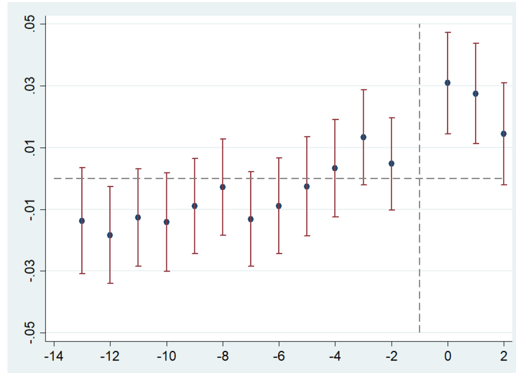
My results of the event study are presented in Figures 4 and 5 with respect to the extensive and intensive margins, respectively. These figures show the coefficients of pre- and post-treatment periods with their corresponding confidence intervals for each year. Prior to the ban, waste exports to high-income (Panel A), upper-middle-income (Panel B), and low-income countries (Panel D) have a similar trend across treatment and control groups. However, the values of the coefficients are increasingly positive over time, and statistically significant during the five years before the implementation of the ban. If this trend extends beyond the pre-treatment period, the DiD estimator is upward biased, meaning that the true effect is smaller than the estimated coefficient. The issue of pre-trends observed in lower-middle-income countries is also detected in the event study of an intensive margin (see Figure 5). Panel C shows that the coefficients are positive and increasing over time during the pre-treatment periods. This result implies that waste exports to lower-middle-income countries are increasingly faster than the average of exports of the other waste, even prior to the import ban. The results of pre-trend testing with respect to waste re-export are reported in Appendix A.1. The estimates overall remain insignificant for pre-treatment periods except for negative and statistically significant coefficients of the 5th- and 6th-year lags for lower-middle-income countries (Panel C).

5.2 Waste export and re-export by income level

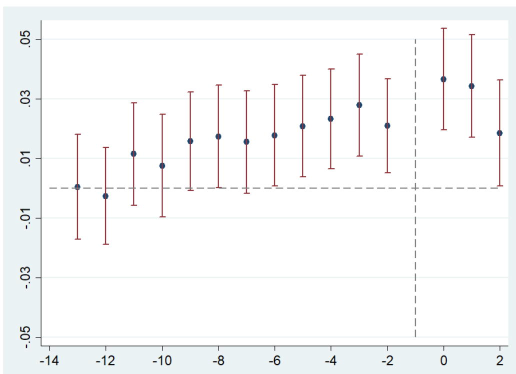
With respect to an extensive margin waste export (Table 4), my results suggest that the 2018 Chinese waste import ban increases the probability of exporting PPTV waste relative to exporting other waste to high-income countries by 1.7%, upper-middle-income countries by 2.6%, and lower-middle-income countries by 1.5%. But, the result of the pre-trend analysis suggests that the coefficient of lower-middle-income countries is overestimated. The results imply that countries that did not export PPTV waste before 2018 started exporting this waste, especially to upper-middle-income countries. This trend is more pronounced in the intensive margin.



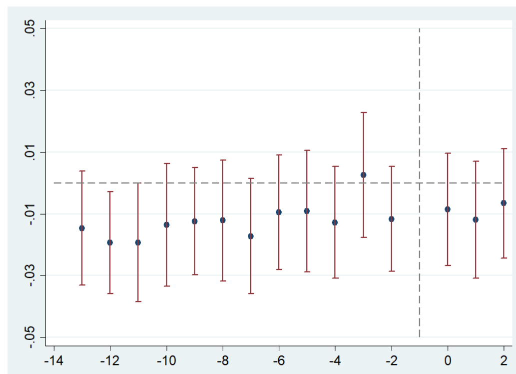
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle income countries



Panel D: Low-income countries

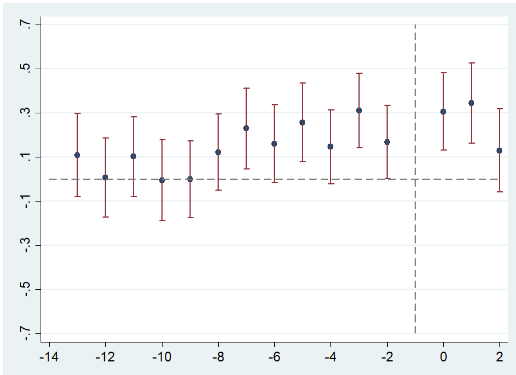
FIGURE 4: Extensive margin waste exports - event analysis

Note: These figures report coefficients from the estimation of Equation 4 serving the probability of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the beginning of the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.

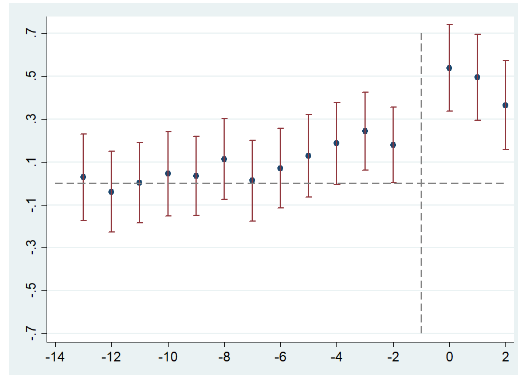
TABLE 4: Extensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ° *Post*	0.017***	0.026***	0.015***	0.005
	(0.005)	(0.006)	(0.006)	(0.006)
R^2	0.451	0.347	0.341	0.248
Covariates	Yes	Yes	Yes	Yes
Observations	108,576	64,032	55,680	16,704

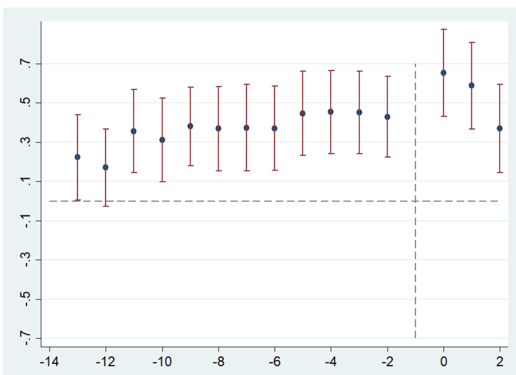
Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.



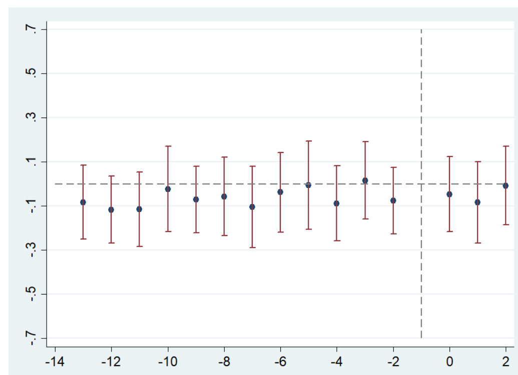
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle income countries



Panel D: Low-income countries

FIGURE 5: Intensive margin waste exports - event analysis

Note: These figures report coefficients from the estimation of Equation 4 serving the volume of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.

For the intensive margin, I find evidence of statistically significant increases in PPTV waste exports to upper-middle-income countries by 35.8% in response to the 2018 Chinese waste import ban (see Table 5). More volumes of PPTV waste arrived in upper-middle-income countries compared to those arriving in high-income and lower-middle-income countries. But, the true effect for lower-middle-income countries may be lower than 16.8% given that the pre-trend analysis implies that the coefficient is upward biased.

TABLE 5: Intensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ° Post	0.212***	0.306***	0.155**	0.034
	(0.063)	(0.068)	(0.073)	(0.049)
R^2	0.514	0.347	0.355	0.279
Covariates	Yes	Yes	Yes	Yes
Observations	108,576	64,032	55,680	16,704
Calculated (semi-)elasticities:				
$\tilde{P}(\cdot)/100$	0.236***	0.358***	0.168**	0.035
	(0.078)	(0.092)	(0.085)	(0.051)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

These results indicate that more waste is exported to upper-middle-income and high-income countries than that to lower-middle-income countries. I do not find a statistically significant effect on low-income countries. This result implies that low-income countries lack a proper waste infrastructure to properly manage and dispose of imported waste. They may not have the financial resources to invest in the infrastructure and regulations needed to manage waste imports effectively.

In contrast to changes in the waste export pattern, the 2018 Chinese waste import ban did not change the re-export patterns to high-income and low-income countries but to middle-income countries. The probability of exporting PPTV waste to upper-middle and low-income countries increases similarly by about 0.2-0.7% but small (see Table 6). However, estimates for intensive margin change are larger in magnitude than the estimates for extensive margin change. The 2018 Chinese waste import ban leads to an increase of 2.8-8.5% in the waste exports to upper-middle-income countries and 2.2-6.8% to lower-middle-income countries (Table 7). Although lower-middle-income countries lack recycling or waste-to-energy facilities, they end up in the destinations of waste re-exports due to their lax environmental regulations, where non-recyclable items can be melted, dumped, or burned.

TABLE 6: Extensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ° Post	0.001	0.002	0.002*	0.007*	0.002*	0.006*	0.003	0.008
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.002)	(0.006)
R^2	0.106	0.140	0.112	0.124	0.042	0.054	0.044	0.056
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE 7: Intensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ° Post	0.014	0.043	0.028**	0.085**	0.022*	0.068*	0.007	0.020
	(0.013)	(0.039)	(0.013)	(0.040)	(0.013)	(0.040)	(0.009)	(0.027)
R^2	0.102	0.152	0.104	0.125	0.041	0.055	0.036	0.046
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408
Calculated (semi-)elasticities:								
$\tilde{P}(\cdot)/100$	0.014	0.044	0.028**	0.088**	0.023*	0.070	0.007	0.021
	(0.013)	(0.041)	(0.014)	(0.044)	(0.014)	(0.043)	(0.009)	(0.027)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1

5.3 Waste export and re-export by region

Table 8 shows the quantity change of PPTV waste relative to other waste exported to seven different regions from 88 countries excluding China and Hong Kong. After 2018, the probability of exporting PPTV waste to the East Asian & Pacific and Europe & Central Asian regions increased by 4.5% and 2.5%, respectively, while the coefficients of other regions are not statistically different from zero. This result indicates that exporters search for a new destination, especially in the East Asian & Pacific and Europe & Central Asian regions. Chinese waste import ban causes re-routing of PPTV waste imports to Asia the re-routing of plastic waste from the developed to less-developing nations, especially Southeast Asian ones, has increased tremendously (represented in the illustration below), where the impacts are manifold and the potential to safeguard is min

TABLE 8: Extensive margin waste exports by region (excl. China and Hong Kong), 2005-2020

	East Asia & Pacific	South Asia	Europe & Central Asia	North Amer.	Latin Amer. & Carib.	Middle East & North Afr.	Sub-Saharan Afr.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat ˚ Post	0.045***	-0.002	0.025***	0.000	0.009*	0.017	0.004
	(0.010)	(0.016)	(0.006)	(0.027)	(0.005)	(0.012)	(0.005)
R^2	0.455	0.408	0.474	0.512	0.405	0.346	0.259
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

The volume of waste exports is also substantially concentrated in the aforementioned two regions. The Chinese waste import ban leads to the increase of 64.7% and 30.8% in the flow of waste to the East Asian & Pacific and Europe & Central Asian regions, respectively (Table 9). Similarly, Tran, Goto and Matsuda (2021) reported sizable effects on these two regions, presenting that there is an increase in the import of waste plastics and used paper considerably compared to other regions. Although these regions could be an ideal alternative destination because of its close proximity to China as Tran, Goto and Matsuda (2021) showed, the import shares of these regions before the ban were much less than those of China. These imply that these two regions do not have enough recycling capacity to absorb the waste flow diverted from China given a spike in the import volume in a short time.

The pre-trend tests of extensive and intensive margins for the East Asia & Pacific and Europe & Central Asia regions are presented in Figures A.5 and A.6 of Appendix. The results show that more PPTV waste was exported to these two regions than other waste a few years before the ban, but the point estimates are substantial in magnitude from the onset of the treatment, especially for the East Asia & Pacific regions. The coefficients from regressing Equations 1 and 2 may be overestimated due to the pre-trends, but it appears that the ban increased PPTV waste exports, especially to the East Asian & Pacific regions.

TABLE 9: Intensive margin waste exports by region (excl. China and Hong Kong), 2005-2020

	East Asia & Pacific (1)	South Asia (2)	Europe & Central Asia (3)	North Amer. (4)	Latin Amer. & Carib. (5)	Middle East & North Afr. (6)	Sub-Saharan Afr. (7)
Treat ˚ *Post*	0.647***	-0.173	0.308***	0.078	0.091	0.047	0.051
	(0.137)	(0.218)	(0.071)	(0.308)	(0.058)	(0.129)	(0.049)
R^2	0.494	0.449	0.546	0.612	0.453	0.341	0.275
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976
Calculated (semi-)elasticities:							
$\tilde{P}(\cdot)/100$	0.909***	-0.159	0.361***	0.082**	0.095	0.049	0.053
	(0.260)	(0.183)	(0.097)	(0.333)	(0.064)	(0.135)	(0.052)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

With respect to waste re-exports' extensive and intensive margins, my results are statistically insignificant coefficients across all regions, except for the positive but small coefficient of extensive margin to Sub-Saharan Africa (0.2%) and the intensive margin to Europe & Central Asia (2.4%). My result tables are available in Tables B.1 of Appendix.

6 Robustness and Extensions

Alternative specifications are run to test the robustness of the results and presented in Appendix B.2. The results of an estimator obtained without control variables or time-variant control variables with country-pair fixed effects are robust, having only different R-squared values across specifications.

The results for testing SUTVA violations are presented in Appendix C. I estimated Equations 1 (extensive margin) and 2 (intensive margin) using two adjusted datasets: 1) excluding three types of waste paper from the control group, and 2) assigning them to the treatment group. I find that the coefficients are overall larger than those obtained from the main analysis (Section 5.2). PPTV waste exports to high-, upper-middle-, lower-middle-, and low-income countries for the extensive margin is 2-2.1%, 3.4-3.5%, 1.8-1.9%, and 0.5%, respectively (Table C.2). PPTV waste exports to each group for the intensive margin is 34-35%, 57-58.7%, 22-23%, and 3.1%, respectively (Table C.2). However, the results of the pre-trend analysis suggest that these estimates may be overestimated given that the values of the coefficients are increasingly positive over time (Figures C.1 and C.2).

6.1 Quantity Changes in Waste Exports/Re-exports By Country's Environmental Stringency

I also find that countries export waste to others with less stringent environmental standards, similar to the results of Kellenberg (2012). The probability of exporting PPTV waste (relative to other waste) to countries with low environmental protection control standards (extensive margin) increases more than that of its counterpart (Table D.1) and the volume of PPTV waste exports to low environmental regulation countries (intensive margin) increased by 23.4%, higher than those to counterpart (D.2). In terms of re-export, I observe statistically positive extensive and intensive margin effects only to countries with lax environmental regulations. Further details on the definition of high and low environment regulations, data source, and result tables are provided in Appendix D.

7 Concluding Remarks

Since 2018, China no longer imports plastic waste from living sources, paper waste, textile waste, and vanadium slag (PPTV). I examined the impact of the 2018 Chinese waste import ban on trade flows to countries by their income level and region. Using UNComtrade data on bilateral trade, my difference-in-difference estimates suggest that the ban lead to a higher increase in the extensive and intensive margin of waste exports to upper-middle-income countries and the East Asian & Pacific regions. I also found that the ban had a positive impact on the extensive and intensive margin of waste re-exports to upper-middle-income countries. This implies that waste, denied entry to a receiving country, is re-exported to upper-middle-income countries. Moreover, PPTV waste flows to countries with relatively weak environmental regulations.

Future work can expand on this finding using waste prices. A higher unit price of waste indicates that the waste may have a higher quality or be more easily recycled and processed into new products. This may help explain the heterogeneous effects of the ban on waste exports across different types of waste and why upper-middle-income countries become destinations of waste.

China implemented the waste import bans to avoid low-quality waste and protect Chinese health and ecosystems. This policy also changed the global patters of waste trade. Since most countries cannot significantly decrease waste discharges in a short period, waste should be exported to other countries if they cannot recycle the waste domestically or if they do not have land to bury their garbage. Businesses in upper-middle-income countries import more waste to recycle, and use recycled materials in the production of new products. In this circumstance, if the countries have loose environmental regulations, unrecycled materials can be easily burned, buried, or discharged into the oceans. People living close to those sites are the ones who are immediately impacted by harmful gases, contaminated water, and polluted soil. Improving waste management infrastructure in upper-middle-income countries that increase their waste import substantially is paramount and will require substantial resources and time. While such infrastructure is being developed, high-income countries that export more than half of PPTV waste can take immediate action by reducing waste and using more recyclable products.

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Appendix

A Figures

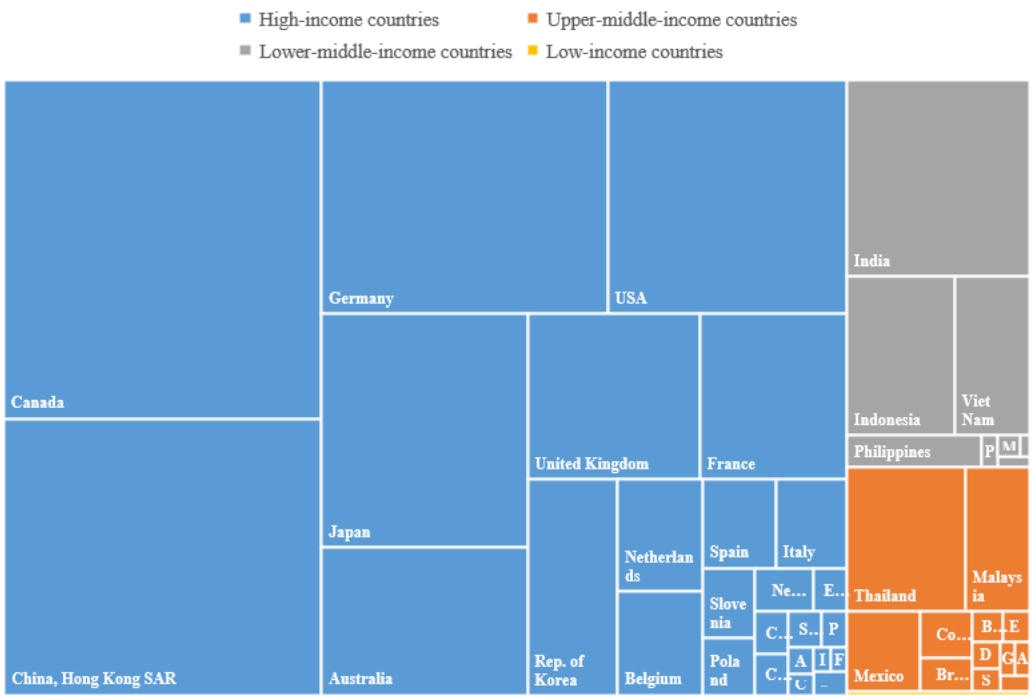


FIGURE A.1: **Exports of Plastic, Paper, Textile, and Vanadium Slag Waste to China, 2017**

Note: The size of the square indicates the sum of weights of plastic, paper, textile, and vanadium slag waste exported to China. Source: UN Comtrade (2022).

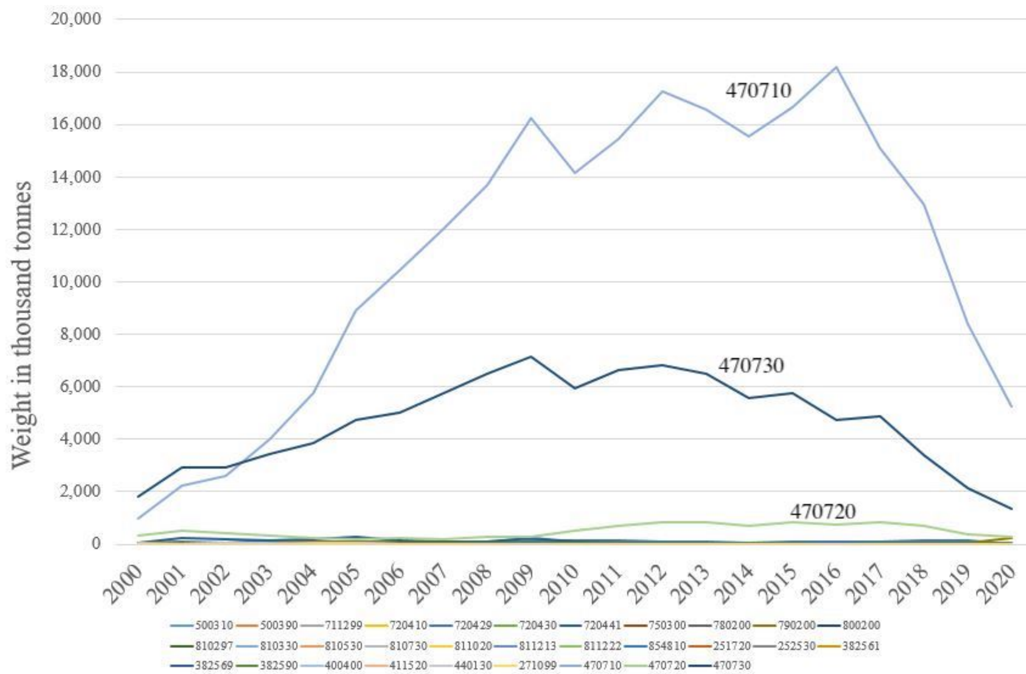
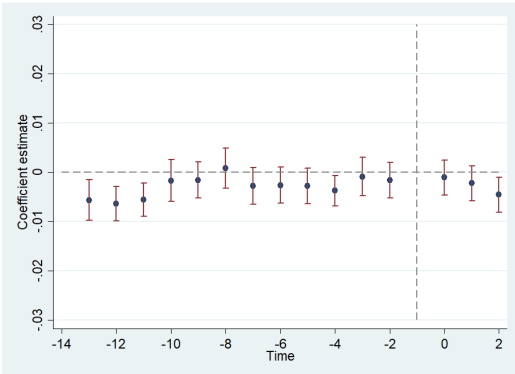


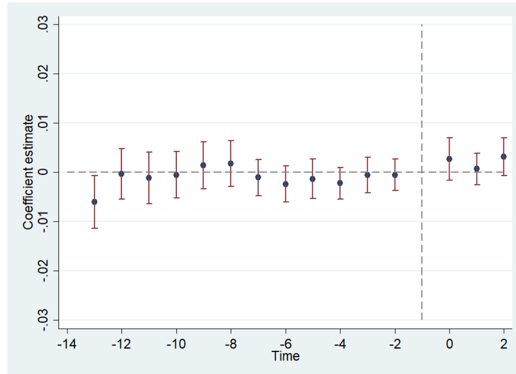
FIGURE A.2: **The trend of China's waste imports that have never been banned**

Source: UN Comtrade (2022).

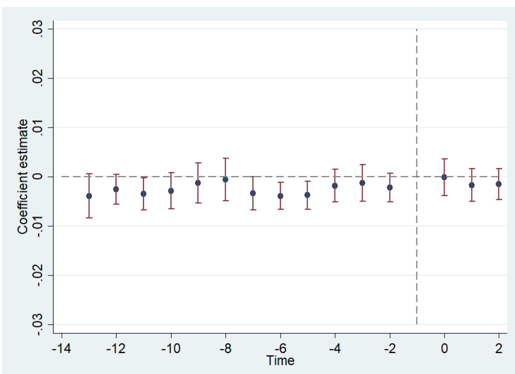
A.1 Pre-trend testing – waste re-exports



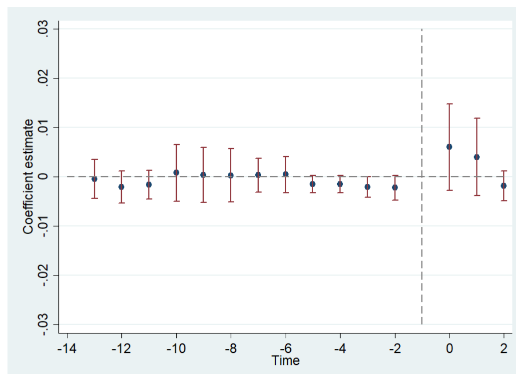
Panel A: High-income countries



Panel B: Upper-middle-income countries



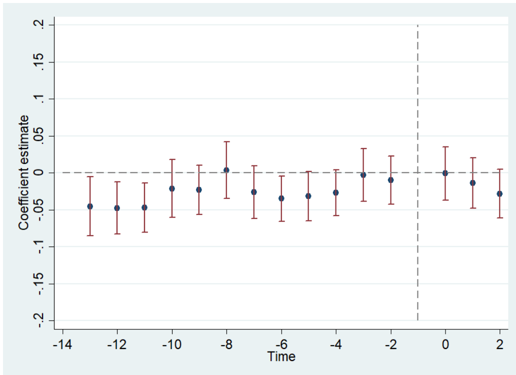
Panel C: Lower-middle income countries



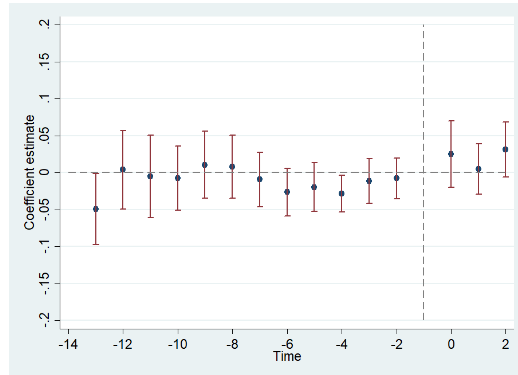
Panel D: Low-income countries

FIGURE A.3: Extensive margin waste re-exports - event analysis

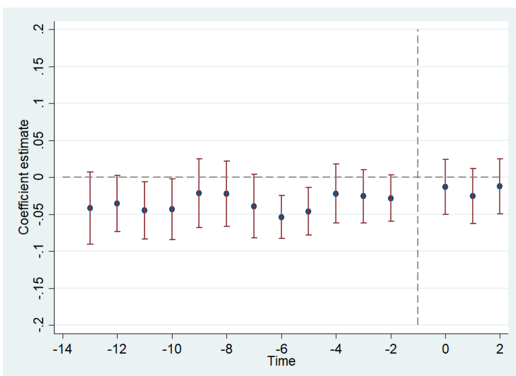
Note: These figures report coefficients from the estimation of Equation 4 serving the probability of re-exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the beginning of the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.



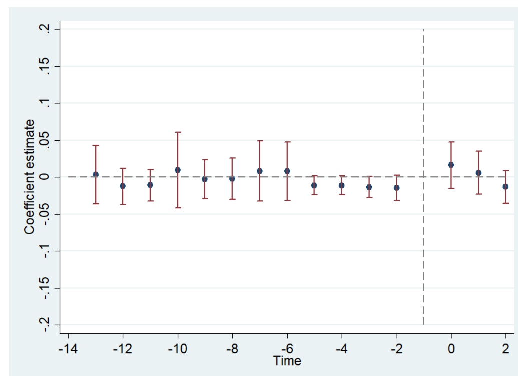
Panel A: High-income countries



Panel B: Upper-middle-income countries



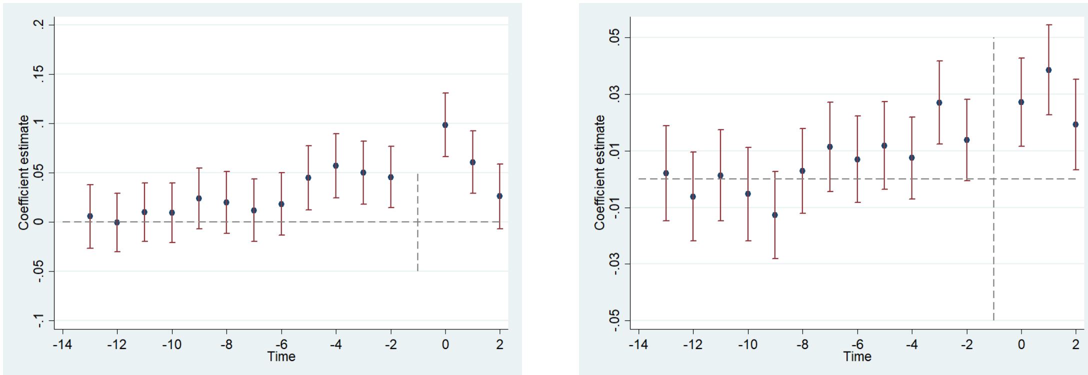
Panel C: Lower-middle income countries



Panel D: Low-income countries

FIGURE A.4: Intensive margin waste re-exports - event analysis

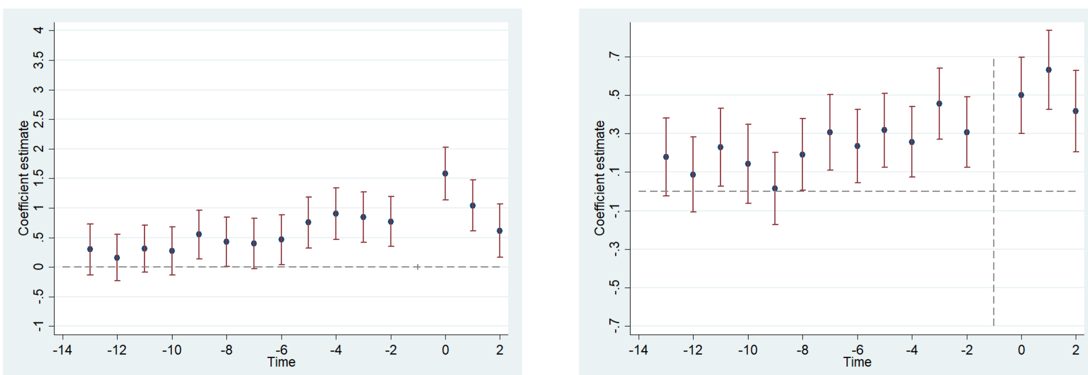
Note: These figures report coefficients from the estimation of Equation 4 serving the volume of re-exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.



Panel A: East Asia & Pacific   Panel B: Europe & Central Asia

FIGURE A.5: Extensive margin waste exports - event analysis by region

Note: These figures report coefficients from the estimation of Equation 4 serving the probability of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the beginning of the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.



Panel A: East Asia & Pacific   Panel B: Europe & Central Asia

FIGURE A.6: Intensive margin waste exports - event analysis by region

Note: These figures report coefficients from the estimation of Equation 4 serving the volume of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.

B Tables

TABLE B.1: A list of 18 HS codes and commodity description (2018 treatment group)

HS code	Commodity description
Vanadium slag	
261900	Slag, dross (excluding granulated slag), scalings & other waste from the manufacture of iron or steel
262099	Ash & residues others (excluding iron and steel), containing metals or metallic compounds
Plastic waste from living sources	
391510	Waste, parings & scrap, of polymers of ethylene
391520	Waste, parings & scrap, of polymers of styrene
391530	Waste, parings & scrap, of polymers of vinyl chloride
391590	Waste, parings & scrap, of plastics n.e.s.
Unsorted waste paper	
470790	Paper or paperboard; waste and scrap of paper or paperboard n.e.c. and of unsorted waste and scrap
Waste textile materials	
510310	Wool and hair; noils of wool or of fine animal hair, including yarn waste, but excluding garnetted stock
510320	Wool and hair; waste of wool or of fine animal hair, including yarn waste, but excluding garnetted stock and noils of wool or of fine animal hair
510330	Wool and hair; waste of coarse animal hair, including yarn waste, but excluding garnetted stock
510400	Wool and hair; garnetted stock of wool or of fine or coarse animal hair
520210	Cotton; yarn waste (including thread waste)
520291	Cotton; garnetted stock waste
520299	Cotton; waste other than garnetted stock and yarn (including thread) waste
550510	Fibres; waste (including noils, yarn waste and garnetted stock), of synthetic fibres
550520	Fibres; waste (including noils, yarn waste and garnetted stock), of artificial fibres
631010	Rags; used or new, scrap twine, cordage, rope and cables and worn out articles of twine, cordage, rope or cables, of textile materials; sorted
631090	Rags; used or new, scrap twine, cordage, rope and cables and worn out articles of twine, cordage, rope or cables, of textile materials; other than sorted

TABLE B.2: A list of 5 HS codes and commodity description (2019 treatment group)

HS code	Commodity description
Ores, slag and ash	
261800	Slag, granulated (slag sand); from the manufacture or iron or steel
Iron and steel	
720449	Ferrous waste and scrap; n.e.c. in heading no. 7204
Copper and articles	
740400	Copper waste and scrap
Aluminium and articles	
760200	Aluminium waste and scrap
Ships, boats, and floating structures	
890800	Vessels and other floating structures; for breaking up

TABLE B.3: A list of 11 HS codes and commodity description (2020 treatment group)

HS code	Commodity description
Wood and articles of wood	
440131	Wood pellet
440139	Other sawdust, wood waste and scrap
Cork and articles of cork	
450190	Cork waste
Iron and steel	
720421	Waste and scrap of stainless steel
Metals n.e.c.	
810197	Tungsten wastes and scraps
810420	Magnesium wastes and scraps
810600	Other unwrought bismuth wastes and scraps
810830	Titanium wastes and scraps
810930	Zirconium wastes and scraps
811292	Gallium, germanium, hafnium, indium, niobium (columbium), rhenium and vanadium; articles thereof, unwrought, including waste and scrap, powders
811300	Cermets; articles thereof, including waste and scrap

TABLE B.4: A list of 40 HS codes and commodity description (control group)

HS code	Commodity description
Salt; sulphur; earths and stone; plastering materials, lime and cement	
251720	Macadam of slag/dross/sim. industrial waste
252530	Mica waste
Ores, slag and ash	
262110	Ash & residues from the incineration of municipal waste
Mineral fuels, mineral oils and products of their distillations	
271091	Waste oils cont. polychlorinated biphenyls (PCBs)
271099	Waste oils other than those cont. polychlorinated biphenyls (PCBs)
Pharmaceutical products	
300680	Waste pharmaceuticals
Miscellaneous chemical products	
382510	Municipal waste
382530	Clinical waste
382541	Halogenated waste organic solvents
382549	Waste organic solvents other than halogenated waste organic solvents
382550	Wastes of metal pickling liquors, hydraulic fluids, brake fluids, etc.
382561	Wastes from chem./allied industries, mainly cont. organic constituents
382569	Wastes from chem./allied industries, n.e.s. in Ch.38
382590	Residual prods. of the chem./allied industries, n.e.s. in Ch.38
Rubber and articles thereof	
400400	Waste, parings & scrap, of rubber (excl. hard rubber)
Raw hides and skins (other than furskins) and leather	
411520	Parings & oth. waste of leather/composition leather, not suit. for mfr.
Wood and articles of wood	
440130	Sawdust & wood waste & scrap
Pulp of wood or of other fibrous cellulosic material; waste and scrap of paper or paperboard	
(Unsorted waste paper)	
470710	Recovered (waste & scrap) unbleached kraft paper/paperboard
470720	Recovered (waste & scrap) paper/paperboard mainly of bleached chem.
470730	Recovered (waste & scrap) paper/paperboard made mainly of mech. Pulp
Silk	
500310	Silk waste, not carded or combed (incl. cocoons unsuit. for reeling, yarn waste & garnetted stock)

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Table B.4 – continued from previous page

HS code	Commodity description
500390	Silk waste, carded or combed (incl. cocoons unsuit. for reeling, yarn waste & garnetted stock)
Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery; coin	
711291	Waste & scrap of gold, incl. metal clad with gold
711299	Waste & scrap of precious metal/metal clad with precious metal
Iron and steel	
720410	Waste & scrap of cast iron
720429	Waste & scrap of alloy steel other than stainless steel
720430	Waste & scrap of tinned iron/steel
720441	Ferrous turnings, shavings, chips, milling waste, sawdust, filings
Nickel and articles thereof	
750300	Nickel waste & scrap
Lead and articles thereof	
780200	Lead waste & scrap
Zinc and articles thereof	
790200	Zinc waste & scrap
Tin and articles thereof	
800200	Tin waste
scrap	
Metals n.e.c.	
810297	Molybdenum waste & scrap
810330	Tantalum waste & scrap
810530	Cobalt waste & scrap
810730	Cadmium waste & scrap
811020	Antimony waste & scrap
811213	Beryllium waste & scrap
811222	Chromium waste & scrap
Electrical machinery and equipment and parts thereof	
854810	Waste & scrap of primary cells, primary batteries

TABLE B.5: A List of 90 countries

High-income countries (40)				
Australia	Estonia	Ireland	Malta	Slovenia
Austria	Finland	Israel	Netherlands	Spain
Belgium	France	Italy	New Zealand	Sweden
Canada	Germany	Japan	Norway	Switzerland
Chile	Greece	Korea, Rep.	Poland	Trinidad and Tobago
Croatia	Hong Kong	Latvia	Portugal	United Kingdom
Czech Republic	Hungary	Lithuania	Singapore	United States
Denmark	Iceland	Luxembourg	Slovak Republic	Uruguay
Upper-Middle-income countries (23)				
Argentina	Dominican Republic	Malaysia	Panama	Thailand
Brazil	Ecuador	Mauritius	Paraguay	Turkey
Bulgaria	Guatemala	Mexico	Peru	Venezuela
Colombia	Jamaica	Namibia	Russian Federation	
Costa Rica	Jordan	North Macedonia	South Africa	
Lower-Middle-income countries (20)				
Algeria	Honduras	Morocco	Philippines	Ukraine
Bangladesh	India	Nicaragua	Senegal	Vietnam
Bolivia	Indonesia	Nigeria	Sri Lanka	Zambia
El Salvador	Kenya	Pakistan	Tunisia	Zimbabwe
Low-income countries (6)				
Ethiopia	Madagascar	Malawi	Mali	Mozambique
Uganda				

Source: World Bank (2022)

TABLE B.6: Import volume of four types of waste before and after the 2018 Chinese waste import ban

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
1	China	upper	3,452.148	642.369	-81
2	Netherlands	high	1,442.479	1,286.892	-11
3	Germany	high	1,382.609	1,238.508	-10
4	France	high	922.605	1,006.521	9
5	USA	high	890.767	991.956	11
6	United Kingdom	high	685.870	470.601	-31
7	Hong Kong	high	622.322	245.836	-60
8	India	lower	577.182	714.162	24
9	Malaysia	upper	517.369	656.590	27
10	Vietnam	lower	417.826	473.962	13
11	Luxembourg	high	356.693	169.153	-53
12	Austria	high	348.149	329.091	-5
13	Italy	high	339.126	322.435	-5
14	Belgium	high	338.343	368.459	9
15	Japan	high	300.376	235.278	-22
16	Spain	high	282.459	328.924	16
17	Thailand	upper	281.560	395.888	41
18	Poland	high	278.385	319.191	15
19	Rep. of Korea	high	221.400	177.849	-20
20	Indonesia	lower	213.459	401.350	88
21	Slovenia	high	211.752	223.632	6
22	Switzerland	high	192.057	141.086	-27
23	Mozambique	low	165.988	161.432	-3
24	Philippines	lower	134.549	133.951	0
25	Sweden	high	131.005	128.751	-2
26	Slovakia	high	119.174	132.192	11
27	Czechia	high	95.296	108.808	14
28	Norway	high	88.039	193.353	120
29	Canada	high	87.892	97.633	11
30	Turkey	upper	79.785	225.211	182
31	Ireland	high	55.764	70.088	26
32	Bulgaria	upper	55.697	76.917	38
33	Colombia	upper	54.914	57.130	4
34	Hungary	high	54.280	49.694	-8
35	Mexico	upper	52.316	78.664	50
36	Latvia	high	49.847	42.267	-15
37	Lithuania	high	45.951	61.690	34
38	Israel	high	45.598	52.619	15
39	Finland	high	35.225	45.290	29
40	Croatia	high	33.861	20.820	-39
41	Portugal	high	28.522	27.426	-4
42	Denmark	high	27.700	27.082	-2
43	Ukraine	lower	25.887	33.510	29

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Table B.6 – continued from previous page

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
44	Pakistan	lower	24.569	39.870	62
45	Ecuador	upper	23.130	19.884	-14
46	Singapore	high	17.611	23.169	32
47	Bangladesh	lower	17.184	51.616	200
48	Greece	high	14.847	7.960	-46
49	South Africa	upper	10.096	6.133	-39
50	Peru	upper	10.027	7.869	-22
51	Honduras	lower	9.867	11.976	21
52	Chile	high	9.667	4.006	-59
53	Russian Federation	upper	9.026	5.658	-37
54	New Zealand	high	8.064	4.022	-50
55	El Salvador	lower	7.800	14.443	85
56	Brazil	upper	7.657	16.154	111
57	Estonia	high	7.438	7.908	6
58	Guatemala	upper	6.315	8.090	28
59	Iceland	high	6.279	20.541	227
60	Bolivia	lower	4.396	4.674	6
61	Tunisia	lower	3.910	0.487	-88
62	Australia	high	3.840	6.260	63
63	Algeria	lower	3.663	0.975	-73
64	Morocco	lower	2.399	1.938	-19
65	Zimbabwe	lower	2.364	1.838	-22
66	Nigeria	lower	1.944	2.181	12
67	Namibia	upper	1.931	0.086	-96
68	Costa Rica	upper	1.832	2.204	20
69	Paraguay	upper	1.810	10.849	499
70	Dominican Rep.	upper	1.150	0.843	-27
71	Sri Lanka	lower	1.041	0.527	-49
72	Panama	upper	0.734	0.348	-53
73	Malta	high	0.697	0.700	0
74	Uruguay	high	0.621	0.672	8
75	North Macedonia	upper	0.585	0.162	-72
76	Nicaragua	lower	0.332	0.783	136
77	Trinidad and Tobago	high	0.249	0.023	-91
78	Malawi	low	0.244	0.224	-8
79	Zambia	lower	0.219	0.231	5
80	Kenya	lower	0.112	0.464	314
81	Argentina	upper	0.083	0.444	434
82	Madagascar	low	0.068	0.048	-29
83	Venezuela	upper	0.047	12.101	25,427
84	Mauritius	upper	0.047	0.052	12
85	Ethiopia	low	0.041	0.086	112
86	Mali	low	0.039	0.071	82
87	Jordan	upper	0.003	0.003	-5
88	Senegal	lower	0.002	16.583	774,074

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Table B.6 – continued from previous page

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
89	Uganda	low	0.001	0.000	-100
90	Jamaica	upper	0.001	0.024	4163
Total 90 countries including China and Hong Kong			15,966.207	13,279.444	-17

TABLE B.7: Export volume of four types of waste before and after the 2018 Chinese waste import ban

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
1	Germany	high	3,500.386	3,026.363	-14
2	Canada	high	1,827.947	1,523.695	-17
3	France	high	1,410.462	1,205.063	-15
4	Japan	high	1,054.388	697.086	-34
5	USA	high	889.069	630.698	-29
6	Belgium	high	773.031	778.028	1
7	United Kingdom	high	547.979	425.198	-22
8	Hong Kong	high	504.172	59.986	-88
9	Australia	high	463.176	468.289	1
10	Austria	high	376.364	360.794	-4
11	Czechia	high	353.959	370.441	5
12	India	lower	333.054	160.656	-52
13	Poland	high	331.057	297.998	-10
14	Denmark	high	312.996	247.175	-21
15	Turkey	upper	252.454	283.201	12
16	Rep. of Korea	high	233.298	93.698	-60
17	Netherlands	high	213.081	191.765	-10
18	Spain	high	210.752	113.194	-46
19	Italy	high	197.772	210.469	6
20	Norway	high	192.453	214.165	11
21	South Africa	upper	175.850	164.738	-6
22	Indonesia	lower	164.753	158.163	-4
23	Thailand	upper	125.447	143.896	15
24	Mexico	upper	123.786	118.324	-4
25	Malaysia	upper	86.407	37.631	-56
26	China	upper	82.353	108.120	31
27	Switzerland	high	77.445	105.462	36
28	Greece	high	76.611	74.584	-3
29	Vietnam	lower	72.281	127.796	77
30	Ukraine	lower	67.729	48.244	-29
31	Slovenia	high	63.178	52.913	-16

Continued on next page

Table B.7 – continued from previous page

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
32	Russian Federation	upper	63.003	74.809	19
33	Portugal	high	59.971	63.318	6
34	Algeria	lower	55.969	0.000	-100
35	Costa Rica	upper	55.571	56.670	2
36	Croatia	high	54.690	54.089	-1
37	Estonia	high	53.173	55.540	4
38	Dominican Rep.	upper	48.580	40.348	-17
39	Sweden	high	44.237	50.613	14
40	Bulgaria	upper	38.614	24.082	-38
41	New Zealand	high	37.508	16.610	-56
42	Luxembourg	high	34.602	21.648	-37
43	Finland	high	34.122	33.653	-1
44	Morocco	lower	27.845	53.903	94
45	El Salvador	lower	27.679	26.612	-4
46	Israel	high	26.679	5.606	-79
47	Philippines	lower	24.560	16.173	-34
48	Brazil	upper	24.130	36.164	50
49	Singapore	high	20.045	29.690	48
50	Ecuador	upper	18.896	8.021	-58
51	Slovakia	high	17.543	24.825	42
52	Chile	high	14.616	15.847	8
53	Ireland	high	14.361	11.885	-17
54	Hungary	high	13.273	13.324	0
55	Latvia	high	8.036	8.296	3
56	Guatemala	upper	7.237	7.006	-3
57	Lithuania	high	6.926	6.512	-6
58	Sri Lanka	lower	6.691	0.000	-100
59	Argentina	upper	6.377	1.557	-76
60	Pakistan	lower	5.676	4.512	-21
61	Ethiopia	low	5.466	3.672	-33
62	Tunisia	lower	3.187	2.827	-11
63	Bolivia	lower	2.344	0.961	-59
64	Colombia	upper	2.064	1.595	-23
65	Paraguay	upper	1.816	0.646	-64
66	Malta	high	1.473	0.775	-47
67	Jamaica	upper	1.229	3.155	157
68	Mauritius	upper	1.200	1.658	38
69	Peru	upper	0.648	0.190	-71
70	Nicaragua	lower	0.540	0.864	60
71	Iceland	high	0.475	0.178	-62
72	Honduras	lower	0.451	0.059	-87
73	Nigeria	lower	0.229	0.104	-54
74	Malawi	low	0.219	0.103	-53
75	Zambia	lower	0.197	0.189	-4
76	Namibia	upper	0.117	0.176	51

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Table B.7 – continued from previous page

Rank in 2017	Country	Country income group	Weight in 2017 (thousand tonnes)	Weight in 2018 (thousand tonnes)	% change
77	Uruguay	high	0.101	0.226	124
78	Mozambique	low	0.050	0.000	-100
79	Zimbabwe	lower	0.046	0.027	-42
80	North Macedonia	upper	0.024	2.809	11655
81	Jordan	upper	0.020	0.026	32
82	Panama	upper	0.012	0.000	-100
83	Kenya	lower	0.001	0.000	-100
84	Madagascar	low	0.000	0.024	7821
85	Bangladesh	lower	0.000	0.000	0
86	Mali	low	0.000	0.000	0
87	Senegal	lower	0.000	0.035	.
88	Trinidad and Tobago	high	0.000	0.000	0
89	Uganda	low	0.000	0.000	0
90	Venezuela	upper	0.000	0.000	0
Total 90 countries including China and Hong Kong			15,966.207	13,279.444	-17

B.1 Waste re-exports by region

Result tables for extensive and intensive waste re-exports by region should be included here.

B.2 Results with different specifications

TABLE B.8: Extensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – without control variables

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ˚ *Post*	0.017***	0.026***	0.015***	0.005
	(0.005)	(0.006)	(0.006)	(0.006)
R^2	0.000	0.001	0.001	0.001
Covariates	No	No	No	No
Observations	108,576	64,032	55,680	16,704

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.9: Extensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ˚ *Post*	0.017***	0.026***	0.015***	0.005
	(0.005)	(0.006)	(0.006)	(0.006)
R^2	0.596	0.519	0.525	0.355
Covariates	Yes	Yes	Yes	Yes
Observations	108,576	64,032	55,680	16,704

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.10: Intensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – without control variables

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ˚ Post	0.212***	0.306***	0.155**	0.034
	(0.063)	(0.068)	(0.073)	(0.049)
R^2	0.001	0.002	0.003	0.000
Covariates	No	No	No	No
Observations	108,576	64,032	55,680	16,704
Calculated (semi-)elasticities:				
$\tilde{P}(\cdot)/100$	0.236***	0.358***	0.168**	0.035
	(0.078)	(0.092)	(0.085)	(0.051)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.11: Intensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Treat ˚ Post	0.212***	0.306***	0.155**	0.034
	(0.063)	(0.068)	(0.073)	(0.049)
R^2	0.682	0.580	0.586	0.441
Covariates	Yes	Yes	Yes	Yes
Observations	108,576	64,032	55,680	16,704
Calculated (semi-)elasticities:				
$\tilde{P}(\cdot)/100$	0.236***	0.358***	0.168**	0.035
	(0.078)	(0.092)	(0.085)	(0.051)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (2)-(4) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.12: Extensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020 – without control variables

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ Post	0.001	0.002	0.002*	0.007*	0.002*	0.006*	0.003	0.008
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.002)	(0.006)
R^2	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.002
Covariates	No	No	No	No	No	No	No	No
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.13: Extensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ Post	0.001	0.002	0.002*	0.007*	0.002*	0.006*	0.003	0.008
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.002)	(0.006)
R^2	0.304	0.294	0.274	0.268	0.186	0.182	0.128	0.130
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.14: Intensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020 – without control variables

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ Post	0.014	0.043	0.028**	0.085**	0.022*	0.068*	0.007	0.020
	(0.013)	(0.039)	(0.013)	(0.040)	(0.013)	(0.040)	(0.009)	(0.027)
R^2	0.000	0.001	0.000	0.000	0.001	0.002	0.000	0.000
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408
Calculated (semi-)elasticities:								
$\tilde{P}(\cdot)/100$	0.014	0.044	0.028**	0.088**	0.023*	0.070	0.007	0.021
	(0.013)	(0.041)	(0.014)	(0.044)	(0.014)	(0.043)	(0.009)	(0.027)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1

TABLE B.15: Intensive margin waste re-exports by country income level (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ Post	0.014	0.043	0.028**	0.085**	0.022*	0.068*	0.007	0.020
	(0.013)	(0.039)	(0.013)	(0.040)	(0.013)	(0.040)	(0.009)	(0.027)
R^2	0.362	0.354	0.343	0.337	0.198	0.194	0.128	0.127
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	35,872	64,032	21,088	55,680	18,368	16,704	5,408
Calculated (semi-)elasticities:								
$\tilde{P}(\cdot)/100$	0.014	0.044	0.028**	0.088**	0.023*	0.070	0.007	0.021
	(0.013)	(0.041)	(0.014)	(0.044)	(0.014)	(0.043)	(0.009)	(0.027)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Column (1) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. As robustness checks, even columns represent estimated results from using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1

TABLE B.16: Extensive margin waste exports by region (excl. China and Hong Kong), 2005-2020 – without control variables

	East Asia & Pacific (1)	South Asia (2)	Europe & Central Asia (3)	North Amer. (4)	Latin Amer. & Carib. (5)	Middle East & North Afr. (6)	Sub-Saharan Afr. (7)
Treat ° Post	0.045***	-0.002	0.025***	0.000	0.009*	0.017	0.004
	(0.010)	(0.016)	(0.006)	(0.026)	(0.005)	(0.012)	(0.005)
R^2	0.003	0.004	0.001	0.001	0.000	0.001	0.002
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.17: Extensive margin waste exports by region (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	East Asia & Pacific (1)	South Asia (2)	Europe & Central Asia (3)	North Amer. (4)	Latin Amer. & Carib. (5)	Middle East & North Afr. (6)	Sub-Saharan Afr. (7)
Treat ° Post	0.045***	-0.002	0.025***	0.000	0.009*	0.017	0.004
	(0.010)	(0.016)	(0.006)	(0.027)	(0.005)	(0.012)	(0.005)
R^2	0.525	0.508	0.602	0.564	0.532	0.448	0.412
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.18: Intensive margin waste exports by region (excl. China and Hong Kong), 2005-2020 – without control variables

	East Asia & Pacific	South Asia	Europe & Central Asia	North Amer.	Latin Amer. & Carib.	Middle East & North Afr.	Sub-Saharan Afr.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat ˚ Post	0.647***	-0.173	0.308***	0.078	0.091	0.047	0.051
	(0.136)	(0.217)	(0.071)	(0.308)	(0.058)	(0.129)	(0.049)
R^2	0.006	0.007	0.002	0.001	0.000	0.000	0.001
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976
Calculated (semi-)elasticities:							
$\tilde{P}(\cdot)/100$	0.909***	-0.159	0.361***	0.082**	0.095	0.049	0.053
	(0.260)	(0.183)	(0.097)	(0.333)	(0.064)	(0.135)	(0.052)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE B.19: Intensive margin waste exports by region (excl. China and Hong Kong), 2005-2020 – with country pair fixed effects

	East Asia & Pacific	South Asia	Europe & Central Asia	North Amer.	Latin Amer. & Carib.	Middle East & North Afr.	Sub-Saharan Afr.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat ˚ Post	0.647***	-0.173	0.308***	0.078	0.091	0.047	0.051
	(0.137)	(0.218)	(0.071)	(0.308)	(0.058)	(0.129)	(0.049)
R^2	0.578	0.571	0.688	0.666	0.612	0.473	0.470
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,840	11,136	89,088	5,568	55,680	16,704	38,976
Calculated (semi-)elasticities:							
$\tilde{P}(\cdot)/100$	0.909***	-0.159	0.361***	0.082**	0.095	0.049	0.053
	(0.260)	(0.183)	(0.097)	(0.333)	(0.064)	(0.135)	(0.052)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Columns represent waste exports from 88 countries (excluding China and Hong Kong) to the corresponding region. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

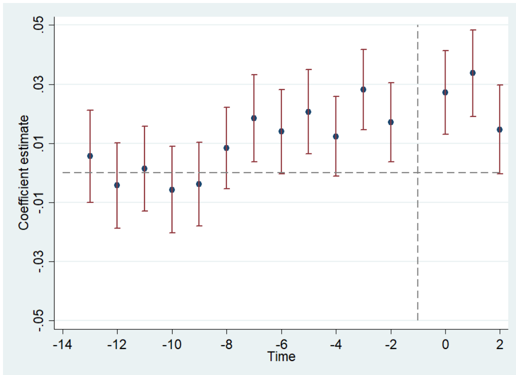
C Testing for SUTVA violations

C.1 Extensive margins

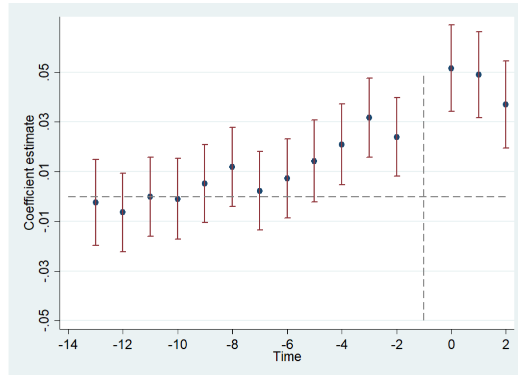
TABLE C.1: Extensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – testing for SUTVA violations

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ *Post*	0.020***	0.021***	0.034***	0.035***	0.019***	0.018***	0.005	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.444	0.447	0.323	0.333	0.328	0.331	0.248	0.247
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	108,576	64,032	64,032	55,680	55,680	16,704	16,704

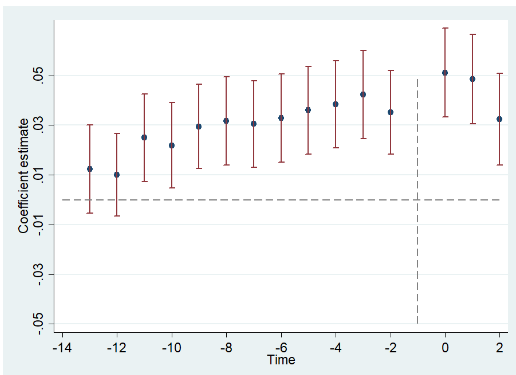
Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Odd columns present an analysis that drops three types of paper waste that were not imposed under the 2018 Chinese import ban from data while even columns present an analysis that assigns three types of paper waste as the treatment group. Column (1-2) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3-4), (5-6), and (7-8) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.



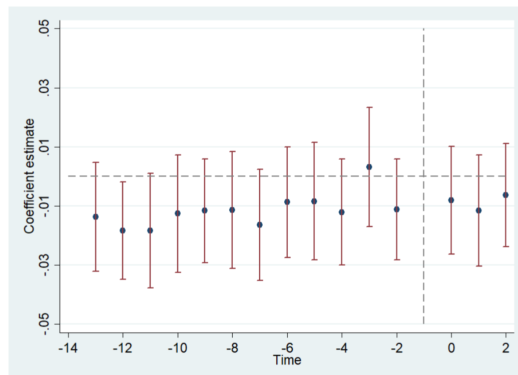
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle income countries



Panel D: Low-income countries

FIGURE C.1: Extensive margin waste exports - event analysis (testing for SUTVA violations)

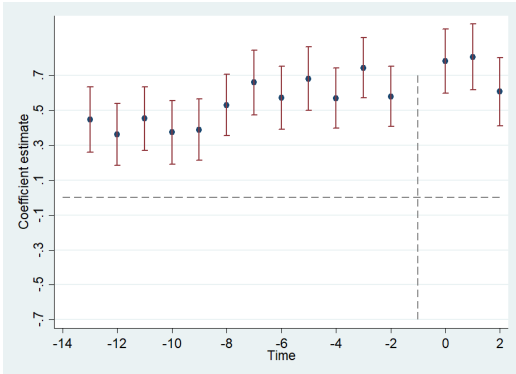
Note: These figures report coefficients from the estimation of Equation 4 serving the probability of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the beginning of the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.

C.2 Intensive margins

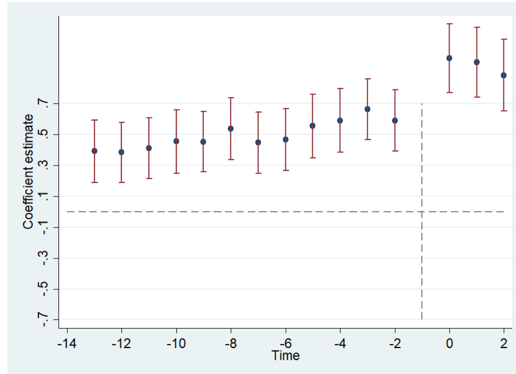
TABLE C.2: Extensive margin waste exports by country income level (excl. China and Hong Kong), 2005-2020 – testing for SUTVA violations

	High Income Countries		Upper-Middle Income Countries		Lower-Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ˚ Post	0.020***	0.021***	0.034***	0.035***	0.019***	0.018***	0.005	0.005
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.444	0.447	0.323	0.333	0.328	0.331	0.248	0.247
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108,576	108,576	64,032	64,032	55,680	55,680	16,704	16,704

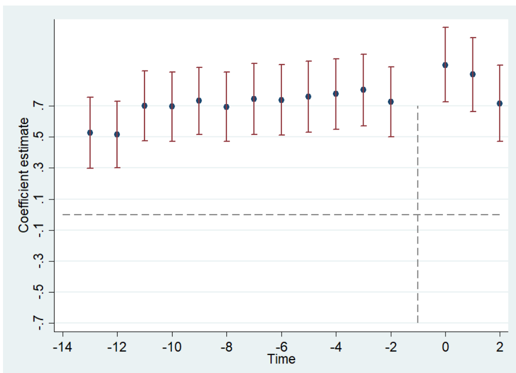
Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Odd columns present an analysis that drops three types of paper waste that were not imposed under the 2018 Chinese import ban from data while even columns present an analysis that assigns three types of paper waste as the treatment group. Column (1-2) represents waste exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3-4), (5-6), and (7-8) represent waste exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low income countries, respectively. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.



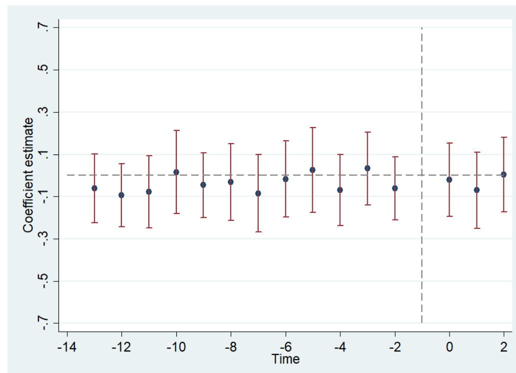
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle income countries



Panel D: Low-income countries

FIGURE C.2: Intensive margin waste exports - event analysis (testing for SUTVA violations)

Note: These figures report coefficients from the estimation of Equation 4 serving the volume of exporting PPTV waste to the corresponding countries as the outcome variable. The coefficients represent the change in outcomes for PPTV waste exports relative to other waste exports in the 13 years before and 3 years after the 2018 Chinese waste import ban, as compared to the year immediately prior to the ban. Red bars refer to 99% confidence intervals. Control variables are based on the gravity model and the full list of control variables is in Table 1.

D Quanty Changes in Waste Exports By EPI Level

I provide an additional test whether relative levels of environmental regulation across countries are an important determinant of waste trade. To measure stringency of environmental regulation across countries, I use the Environment Performance Index (EPI) obtained from the Universities of Yale and Columbia[8]. The EPI quantifies the environmental performance of a country's policies including 11 issue categories [9] such as air quality, heavy metals, waste management, and pollution emissions. The EPI includes waste management issues only in 2020 but is still a good index to measure waste regulations in that waste products are often either incinerated (affecting air quality) or dumped in unlined landfills (affecting water quality).

The EPI has been reported biennially in even-numbered years since 2006 and covers around 180 countries, which facilitates cross-country comparisons over years. But, to divide countries into two groups having higher and lower environmental regulations, I use the 2020 EPI. The EPI ranges from 0 to 100 with high scorers exhibiting long-standing policies and programs to protect public health, preserve natural resources, and decrease greenhouse gas emissions. To assign countries to high or low environmental regulations, I use a medium value of 88 countries' EPI scores excluding China and Hong Kong which is 51.7 as a threshold. Thus, 44 countries having a 2020 EPI higher than 51.7 are defined as having higher environmental regulations. Figure D.1 shows the relationship between the 2020 EPI Score and GDP per capita with Denmark having the highest score (82.5) in 2020 and Madagascar the lowest (26.5). A country's environmental regulation and GDP per capita have a positive correlation, although many countries out- or underperform their economic peers. This relationship implies that good policy results are associated with wealth, meaning that economic prosperity makes it possible for nations to invest in policies and programs that lead to better public and environmental health.

[8] https://epi.yale.edu/

[9] Eleven issue categories include air quality, sanitation and drinking water, heavy metals, waste management, biodiversity and habitat, ecosystem services, fisheries, climate change, pollution emissions, agriculture, and water resources.

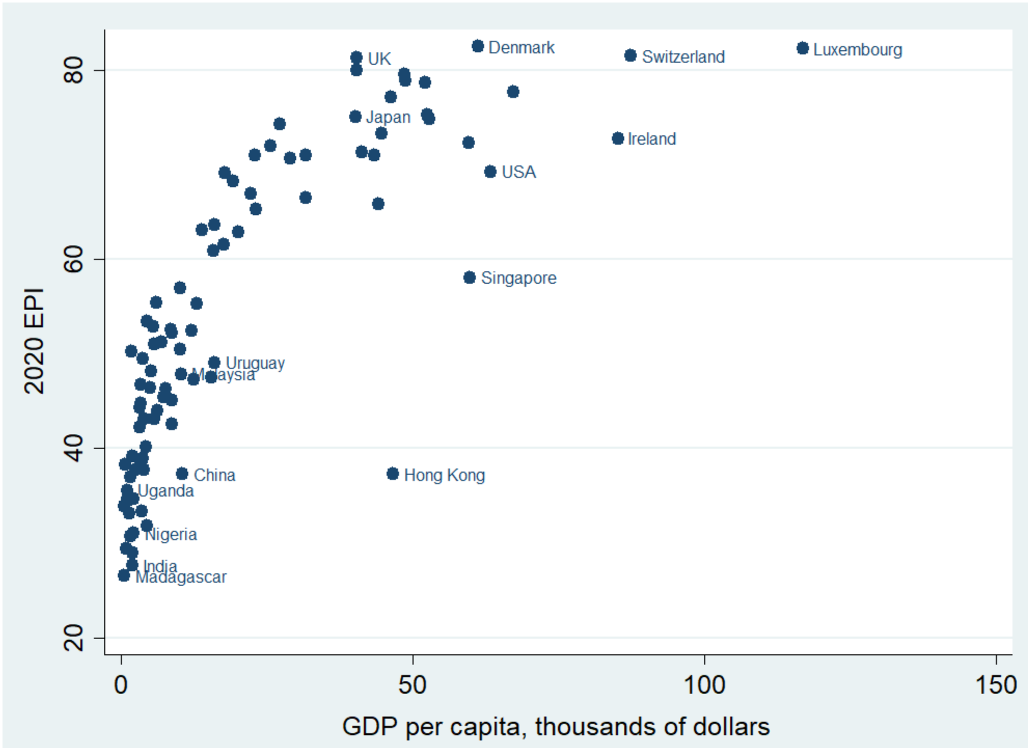


FIGURE D.1: **Relationship between EPI and GDP per capita, 2020**

Note: The EPI of Hong Kong is not available and is replaced by the EPI of China. Source: Universities of Yale and Columbia.

TABLE D.1: Extensive margin Waste exports/re-exports by country's EPI level (excl. China and Hong Kong), 2005-2020

	Export		Re-export			
	High EPI	Low EPI	High EPI		Low EPI	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ° *Post*	0.017***	0.019***	0.001	0.003	0.002***	0.007***
	(0.005)	(0.004)	(0.001)	(0.004)	(0.001)	(0.002)
R^2	0.442	0.323	0.114	0.155	0.053	0.062
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,496	122,496	122,496	40,480	122,496	40,256

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 High (low) EPI means waste exports/re-exports to countries having higher (lower) EPI scores than the median. Columns (1) and (3) represent waste exports and re-exports from 88 countries (excluding China and Hong Kong) to 44 countries having high EPI, respectively. Similarly, Columns (2) and (5) represent waste exports and re-exports from 88 countries to 44 countries having low EPI, respectively. Columns (4) and (6) are presented as robustness checks for columns (3) and (5), respectively using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.

TABLE D.2: Intensive margin Waste exports/re-exports by country's EPI level (excl. China and Hong Kong), 2005-2020

	Export		Re-export			
	High EPI	Low EPI	High EPI		Low EPI	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat ˚ *Post*	0.189***	0.234***	0.015	0.046	0.023***	0.070***
	(0.058)	(0.046)	(0.012)	(0.036)	(0.009)	(0.026)
R^2	0.500	0.339	0.111	0.171	0.046	0.056
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,496	122,496	122,496	40,480	122,496	40,256
Calculated (semi-)elasticities:						
$\tilde{P}(\cdot)/100$	0.208***	0.264***	0.015	0.047	0.023***	0.073**
	(0.071)	(0.058)	(0.012)	(0.038)	(0.009)	(0.028)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 High (low) EPI means waste exports/re-exports to countries having higher (lower) EPI scores than the median. Columns (1) and (3) represent waste exports and re-exports from 88 countries (excluding China and Hong Kong) to 44 countries having high EPI, respectively. Similarly, Columns (2) and (5) represent waste exports and re-exports from 88 countries to 44 countries having low EPI, respectively. Columns (4) and (6) are presented as robustness checks for columns (3) and (5), respectively using subsamples that have re-exported any waste for 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese waste import ban. *Post* indicates the post-treatment time periods (equal to one for years 2018-2020). Control variables are based on the gravity model and the full list of control variables is in Table 1.