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, in 2018, China changed its policy to prohibit the import of plastic, paper, and textile waste. This policy change raises the question about where the waste will go now. Using a difference-in-difference approach, I analyze the effects of the 2018 Chinese policy change on global waste exports and re-exports.[1] The evidence suggests that the policy has a positive impact on both the extensive margin (probability of waste export) and the intensive margin (quantity of waste export), particularly with substantial effects on the intensive margin of exports and re-exports to upper-middle-income countries and the East Asian & Pacific regions. I also uncover evidence of pollution haven effects, indicating that waste is exported to countries with lax environmental regulations, potentially affecting residents in those regions.

Keywords: Trade and Environment Policies, Waste, Pollution Haven Hypothesis
JEL codes: F13, F18, Q53, Q56

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[1] Re-export refers to the exportation of goods or products that were initially imported into a country without undergoing any processing or modification in that importing nation (UN Statistics, 2022). Countries re-export waste when trade regulations change or return goods when they are discovered to be mislabeled or imported illegally. It has an important implication in waste trade as re-exported items are often considered low-quality waste, given that they are not recyclable (Priyanti et al., 2023)

1 Introduction

"[Slow violence] occurs gradually and out of sight, a violence of delayed destruction that is dispersed across time and space, an attritional violence that is typically not viewed as violence at all" (p.2)

— *Rob Nixon, Slow Violence and the Environmentalism of the Poor*

This quote from Rob Nixon (2011) highlights the importance of recognizing the slow and cumulative nature of environmental damage, as it can lead to profound consequences for communities. From an environmental perspective, the transboundary movement of waste has given rise to problems such as environmental pollution and public health concerns related to exposure to hazardous substances and emissions from incinerators and landfill sites (Giusti, 2009; Hoornweg and Bhada-Tata, 2012). Waste disposal plays a central role in these issues, as they can lead to soil, water, and air contamination. While recyclable waste can serve as an input for producing goods, a low recycling rate inevitably results in the disposal of residual waste in landfills.

Previous studies have investigated the factors shaping global waste trade, emphasizing the role of environmental regulations in inhibiting the cross-border movement of waste materials. One strand of literature on waste movement indicates that less stringent environmental regulations are important factors that have made developing nations destinations for waste from developed countries (Kellenberg, 2012, 2015; O'Neill, 2000). Developing countries might find it economically advantageous to import waste due to lower waste disposal costs and minimal pressure from environmentalists at the domestic level. On the other hand, another body of literature suggests that environmental regulations may not be the primary determinant of the direction of waste trade (Baggs, 2009; Higashida and Managi, 2014). These studies propose that factors such as material demand, including recycled materials, or distance costs play a more substantial role in influencing the direction and scale of waste trade. Given the disparate findings from two distinct bodies of literature, it becomes imperative to investigate how different national responses to environmental problems influence the patterns and directions of waste trade.

The recent Chinese policy change that prevented waste imports leads us to question how this policy change shapes the routes and directions of waste trade. China became the largest country importing waste as the demand for raw materials increased dramatically due to its 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 waste imports to those that are high-quality. Thus, in 2018, China started banning the import of four types of waste: plastic, paper, textile, and vanadium slag[2] (PPTV) (herein referred to as "the 2018 Chinese policy"). Rich nations, such as Canada, Germany, and the US, relied on China for waste disposal but had to seek new trading partners following the policy change. Consequently, the Chinese policy change raises the question of where the waste will go now.

First, this paper explores how the 2018 Chinese policy change affected global waste exports and re-exports. I classify trading partners into different groups based on income and region to assess the spillover effects of Chinese policy on countries with varying economic development levels and geographical regions. Consequently, I investigate the export of waste to four income-level groups and seven regional groups of countries. In addition to examining exports, I also analyze re-exports due to their crucial implications in waste trade. Re-exports refer to exporting goods in the same condition as when initially imported, often occurring in cases of illegal exportation or when importing countries impose import barriers (UN Statistics, 2022). For example, the Philippines imported plastic waste from Canada but later returned it, claiming it was mislabeled as plastic recycling in 2013 and 2014, and Malaysia sent back plastic waste to Spain after it was found to be contaminated in 2019 (BBC, 2019). This suggests that re-exported waste is more likely to be contaminated, less preferred, and more environmentally damaging (Priyanti et al., 2023).

Second, I conduct tests to determine the validity of pollution haven effects, an eco-

[2] Vanadium slag is a solid by-product generated from iron- and steel-making plants. It finds application in the production of vanadium redox flow batteries (Lee et al., 2021). These batteries contribute to stabilizing the output from intermittent energy sources such as wind or solar power.

nomic theory suggesting that industries and businesses may relocate from countries with stringent environmental regulations to those with less stringent standards. By categorizing countries into two groups based on their environmental regulations—relatively stringent and lax—I investigate the patterns of waste exportation to each group of countries.

Previous studies explored how the Chinese waste import ban changes waste trade. Using historical data from 1988 to 2016, Brooks, Wang and Jambeck (2018) predicted changes in the plastic waste trade, finding that 96% of all imports of plastic waste are almost evenly split between high-income countries and upper-middle-income countries. On the other hand, Tian et al. (2021) analyzed the impact of the China 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, these studies are limited by focusing on a specific type of waste and testing the prediction not causality. It is important to understand the comprehensive effects of policy changes and their causal impacts on waste trading.

To assess the impacts of the 2018 Chinese policy on waste export, I employ a panel data set spanning 16 years (2005-2020) and encompassing 88 exporting countries along with their paired 87 importing countries, excluding China and Hong Kong from the analysis[3]. Using a difference-in-difference (DiD) approach, I estimate changes in waste export and re-export, considering an importing country's income level and region across both extensive and intensive margins. The treatment group comprises PPTV waste prohibited by the 2018 Chinese policy. In contrast, the control group consists of 40 waste commodities unaffected by the 2018-2020 policy. The respective weights of the waste materials within each group are aggregated for analysis. Additionally, the period from 2018 onward is designated as the post-treatment period.

The analysis reveals that the impact of the 2018 Chinese policy on waste trade is evident both at the extensive margin (i.e., more countries initiating waste imports) and at

[3] I exclude China and Hong Kong from the analysis because my primary interest is understanding how the Chinese policy change redirects waste trade flows to other countries. The reason for excluding Hong Kong is that it serves as a crucial trans-shipment port for waste entering China. For instance, in 2016, Hong Kong exported 99.74% of PPTV waste to China.

the intensive margin (i.e., increased trade volumes for existing export lines). The extensive margins of PPTV waste exports and re-exports show significance, albeit with small magnitudes. Examining the intensive margin, the 2018 Chinese policy resulted in a significant increase in the volumes of PPTV waste, in comparison to other types of waste, exported from all 88 countries to different income groups: 23.6% to high-income countries, 35.8% to upper-middle-income countries, and 16.8% to lower-middle-income countries. However, the pre-trend analysis suggests a potential overestimation in the estimate for lower-middle-income countries.

In terms of regions, the probability of PPTV waste being exported to the East Asian & Pacific and Europe & Central Asian regions increased by 4.5% and 2.5%. Notably, the impact is more pronounced at the intensive margins. The policy change resulted in a substantial rise in PPTV waste exports to the East Asian & Pacific region by 90.9% and to the Europe & Central Asia region by 36.1%. However, the pre-trend analysis suggests a potential overestimation of the coefficients.

Finally, I find a high probability of waste being exported to countries with weak environmental regulations, accompanied by a higher volume of waste being exported to these nations. Specifically, the 2018 Chinese policy resulted in a 20.8% increase in PPTV waste exports to countries with stringent environmental regulations, while the increase to countries with weak environmental regulations was about 26.4%. This trend is more pronounced in waste re-export. While the difference is not substantial, there is a higher likelihood for waste to be directed to countries with weak environmental regulations.

My contributions to the literature are threefold. First, this study contributes to the literature linking the fields of environmental, international, and development economics. Specifically, it explores how domestic environmental policies impact international trade. Additionally, I examine whether changes in trade patterns disproportionately affect countries based on their income levels. While other studies have investigated the effects of the Chinese waste import ban, many focus on specific waste types (Brooks, Wang and Jambeck, 2018; Tian et al., 2021) or recycling market in a certain region (Kumamaru and

Takeuchi, 2021). I go a step further to investigate trade flows that encompass all types of waste covered by China's waste import ban, accounting for a collective total of 88 countries. This broader perspective enhances our understanding of the global implications of such policies.

Second, this study examines the bilateral trade of waste re-exports. Re-exported waste may consist of materials that are less preferred in terms of recycling or disposal methods. This could result in increased difficulty in managing and processing the waste in an environmentally friendly manner. Understanding and addressing the environmental impacts of waste re-export is crucial for implementing effective waste management strategies and promoting sustainable practices on a global scale.

Third, my paper contributes to the literature on the pollution haven hypothesis. The primary reason for the relocation of polluting industries to countries with lax environmental regulations is the desire to reduce production costs, particularly those associated with environmental compliance. The pollution haven hypothesis was initially proposed by Copeland and Taylor (1994), who linked the environmental regulation stringency and trade patterns with the level of pollution in a country. Although there are analytical theories examining the environmental impacts of trade, the empirical evidence remains inconclusive (Cole and Elliott, 2003; Frankel and Rose, 2005; Jaffe et al., 1995; Levinson and Taylor, 2008; Tobey, 2001). In the literature on waste trade, Kellenberg (2012) further explores this hypothesis, highlighting that countries with lax environmental regulations become appealing destinations for waste disposal or recycling industries. This paper contributes to the expanding body of literature on the pollution haven hypothesis by presenting evidence that domestic environmental policies serve as a factor influencing the global movement of waste.

The remainder of this paper is organized as follows. Section 2 provides background information about global waste trade and the Chinese policy changes. Section 3 describes data and provides descriptive statistics, and Section 4 presents the empirical strategy. Section 5 presents the empirical results, and Section 6 describes robustness checks. Section 7

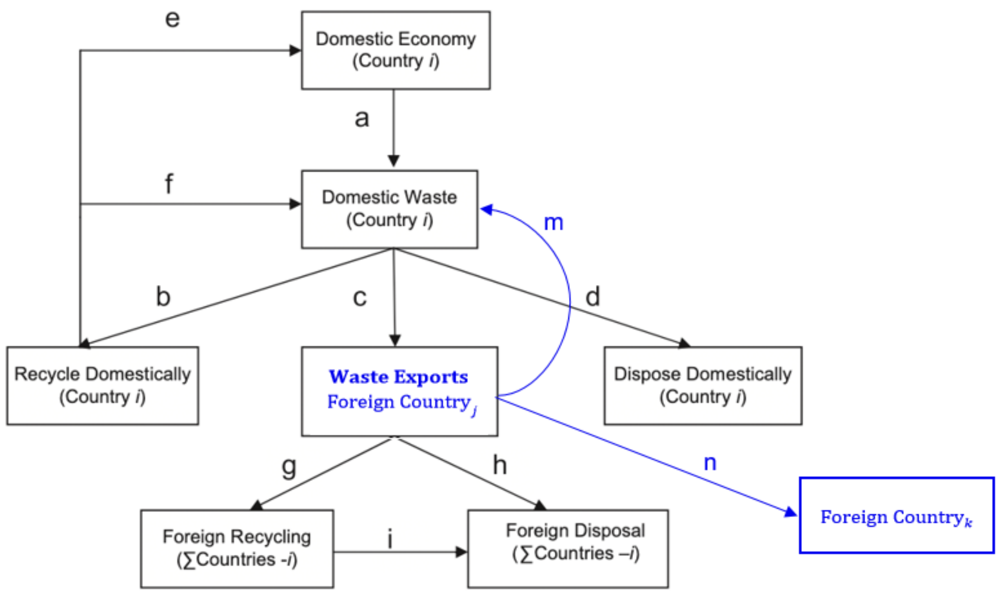


FIGURE 1: **Global waste trading**

Source: Kellenberg (2012), edited by author

concludes with a discussion of the findings.

2 Waste Trade and Chinese Policy Changes in 2018-2020

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 end 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 waste is 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 required for 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 on payments, when the exported goods are defective, or when authorities have imposed import barriers (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 illegal 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). Moreover, some re-exported waste does not arrive in the country of origin but is diverted to other developing countries. This phenomenon suggests that less-preferred waste arrives in more economically disadvantaged countries, contaminating land, air, and water as well as impacting human health. For instance, it was discovered that in 2020, waste 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 cracking down on mixed and dirty plastic waste imports, and Germany refused to repatriate the wastes(The Guardian, 2021). The re-exports have important implications in waste trade because re-exported waste is more likely to be contaminated and less preferred.

2.2 Chinese policy changes in 2018-2020

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 (UNComtrade, 2022). As their economy developed, Chinese living standards have increased, and the demand for goods has risen simultaneously as well. However, China lacked raw materials and 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 its 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 (UNComtrade, 2022).

Chinese waste imports skyrocketed after China joined the World Trade Organization (WTO) in 2001. As the country's manufacturing industry experienced rapid growth and increased exports of manufactured goods via enormous container ships, shipping companies ended up with thousands of empty shipping containers to carry back. Logistics companies found 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.

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). Waste heavily contaminated by chemicals or oils, along with materials that are challenging to separate, can result in elevated pollution levels and health risks for both recycling industry workers and residents living in proximity to recycling facilities. The existence of

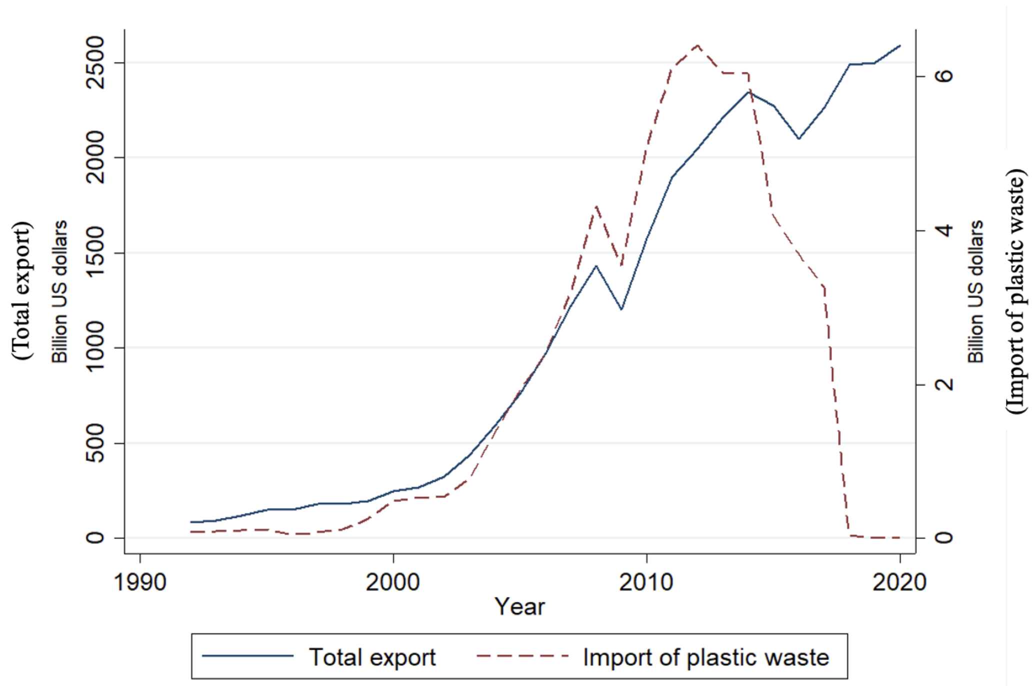


FIGURE 2: **The trend of China's total export and plastic waste import in value**

Source: UNComtrade database (UNComtrade, 2022). Plastic waste is identified under the HS code category 3915.

contaminated or unsorted waste demands extra sorting efforts, ultimately increasing the overall recycling costs. In 2016, China imported 8.88 million tonnes 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 an issue for waste imports (Balkevicius, Sanctuary and Zvirblyte, 2020). Approximately 180 countries are members of the Basel Convention, which aims to prevent the illegal trafficking of waste. Although illegal shipments to Asia accounted for 20 percent of the violations, China and Hong Kong were the preferred destinations for illegal shipments (Rucevska et al., 2015).

As part of its response, China began regulating solid waste imports by implementing the Operation Green Fence (OGF) policy in 2013. OGF aimed to enhance the quality of imported waste by implementing rigorous inspections for every container arriving in China.

Balkevicius, Sanctuary and Zvirblyte (2020) discovered a 26% reduction in low-quality waste exports[4] from developed countries to China due to OGF. However, OGF's impact on reducing low-quality waste was considered short-lived, as it was only in effect for nine months in 2013 (Tran, Goto and Matsuda, 2021).

To address illegal waste trafficking and impose stricter restrictions on waste imports, the Operation National Sword (ONS) policy was launched in February 2017. In July of the same year, China notified the World Trade Organization (WTO) that it would prohibit the import of plastics waste from living sources, unsorted waste paper, waste textile materials, and vanadium slag, starting on January 1, 2018 (WTO, 2017).[5]

Aiming to ban most waste imports, the Chinese government announced the prohibition of 16 waste materials (equivalent to 5 unique 6-digit Harmonized System (HS) codes[6]) would be banned in 2019, including metal and electrical appliance scraps and scrap vessels. They also announced that an additional 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 banned materials in 2019 and 2020 is available in Tables B.2 and B.3 of Appendix, respectively.

The sudden announcement of the waste import ban caused disruptions to the recycling industry and global waste trade. For instance, 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) after the National Sword policy was announced (Reuters, 2017). The reduction in waste paper pulp produced from imported waste paper led to a shortage of raw materials for the paper industry, resulting in higher prices for finished papers.

Furthermore, the National Sword policy had a significant impact on global waste trade, prompting some companies to resort to illegal methods such as shipping trash bins via the

[4]Low-quality waste typically refers to materials that are considered less suitable for recycling or reuse due to contamination, poor condition, or a lack of economic value in the recycling process.

[5]China has banned the import of four classes and 24 types of solid waste, equivalent to 18 6-digit Harmonized System (HS) codes. The complete list of these 18 HS codes is provided in Table B.1 of Appendix.

[6]Harmonized System codes are a standardized nomenclature that identifies product categories and specific products using a two- to six-digit code.

black market. INTERPOL (2020) reported a criminal trend emerging in the global plastic waste market since January 2018, documenting an increase in illegal plastic waste imports in South and Southeast Asian countries and Eastern European countries. Countries were found to be rerouting illegal waste shipments to conceal the origin of the waste. The policy also altered the geography of global waste trade, with major export destinations shifting to Southeast Asian countries such as Thailand, Indonesia, Vietnam, Malaysia, and the Philippines (Wen et al., 2021).

3 Data

3.1 Datasets

The bilateral waste trade data comes from the United Nations Comtrade Database (UN-Comtrade) for 88 countries [7] over 16 years (2005-2020). This database includes trade flows reported up to the 6-digit level of the Harmonized System classification. Waste trade exports and re-exports are defined as all 6-digit HS categories where waste and/or scrap is the sole categorization of a product or material. This results in 62 6-digit HS categories of waste, as defined by Kellenberg (2012), and an additional 12 categories prohibited by the Chinese waste import ban. Descriptions of these 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. The 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 for import under the 2018 Chinese import ban. Similarly, the 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, the total observations amount to 244,992

[7] I include all countries that Kellenberg (2012) studied in his paper, except for four countries (Romania, Serbia and Montenegro, China, and Hong Kong). This exclusion is due to the unavailability of gravity-related control variables for Romania, the non-existence of Serbia and Montenegro after 2006 following the dissolution of that country into its two separate nations. Additionally, China and Hong Kong are omitted because my main focus is to comprehend how the Chinese policy alters the direction of waste trade to other nations.

(=88 countries*87 country-pair*16 years*2 groups).

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 explained by Kellenberg (2012), where the magnitude of physical waste is more critical from an environmental perspective. A large volume of waste creates environmental problems by contaminating land, air, and water with toxins and greenhouse gases. As 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 play a role in estimating its harmful effect on the environment. In fact, the simple correlation between weight and value measures is 0.8, indicating that most variations in value can be explained by changes in weights.

Additional control variables, demonstrated to be important in the international trade literature, are also included. Time-invariant variables include the distance between two countries, whether two countries share 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 the European Union, along with 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 the trade of international hazardous waste for its member countries. Currently, most countries around the world have signed the Convention. Among the 88 countries, all except the United States ratified the Convention after 2012. Previous studies have controlled for the Basel Convention effect when examining 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 the 88 countries have ratified this Amendment by 2020. Data on the Basel Ban Amendment membership comes from the Basel Convention (2021) website.

3.2 Descriptive statistics

Descriptive statistics for all variables can be found in Table 1. The indicator variable I(·) is one if country i exports/re-exports waste to country j in year t 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 run separate regressions using only countries that reported they have ever re-exported waste over the 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 5,866 km, 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.

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
$\ln(\text{Distance}_{km})$	244,992	8.677	0.892	4.088	9.892
$\ln(\text{GDP}_{per\ capita,exporter})$	244,992	9.062	1.426	5.107	11.699
$\ln(\text{GDP}_{per\ capita,importer})$	244,992	9.062	1.426	5.107	11.699
$\text{Basel}_{exporter}$	244,992	0.558	0.497	0.000	1.000
$\text{Basel}_{importer}$	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 country i exports/re-exports waste to country j in year t, and 0 otherwise. IHS(·) represents the weight of waste exports or re-exports in kilograms 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 UNComtrade (2022), GDP and Basel Ban Amendment data are obtained from IMF and Basel Convention websites, and the other control variables come from the CEPII.

3.3 Which countries import and export most waste?

Table 2 presents the leading ten countries among 90 countries[8] in terms of importing plastic, paper, textile, and vanadium slag waste. As shown in the table, high-income countries were the major importers of PPTV waste in 2017. Six out of the top ten countries in PPTV waste imports belong to the high-income category. In addition, two countries fall under the upper-middle-income countries (China and Malaysia), while the remaining two are classified as lower-middle-income countries (India and Vietnam). Considering a total of 90 countries, including China and Hong Kong, high-income countries accounted for 61% of all PPTV waste imports. Upper-middle-income countries followed with 29%, lower-middle-income countries with 9%, and low-income countries with 1%.[9] The importation

[8]In this section, I include China and Hong Kong to highlight that China was the largest waste importer. It is important to note that in my main analysis, these two countries are not included.

[9]Appendix Table B.6 provides a full list of countries and their statistics.

TABLE 2: **Top 10 importing countries in 2017, volume of four types of waste prohibited by the 2018 Chinese policy**

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: UNComtrade (2022)

of waste serves the purpose of recycling or converting waste into electricity. For instance, in 2017, Germany imported 85% of its PPTV waste from EU countries due to a shortage of garbage for their plants, necessitating the importation of waste from neighboring countries for incineration and energy conversion (WSJ, 2015).

Before the implementation of the Chinese waste import ban, China stood as the largest importer of PPTV waste, accounting for 21.6%[10] of all imports among the 90 countries. When combined with Hong Kong, they collectively represented 25.5% of all imports. However, in 2018, both China and Hong Kong significantly reduced their imports of PPTV waste by 81% and 60%, respectively, indicating the effective implementation of the Chinese waste import ban. Consequently, there was an average drop of approximately 17% in waste imports in 2018, as countries that typically exported waste to China faced challenges in finding alternative trading partners in a short time.

[10]=3,452.148/15,966.207*100

Table 3 shows the top ten countries out of 90 in terms of exporting PPTV waste. In 2017, high-income countries overwhelmingly dominated as the primary exporters of PPTV waste, comprising all the top 10 countries. This finding aligns with the results of Brooks, Wang and Jambeck (2018) who found that high-income countries had been the major exporters of plastic waste since 1988. High-income countries contributed to 88% of PPTV waste exports, totaling 14,051 thousand tonnes, as calculated using data from Appendix Table B.7, which provides a comprehensive list of all 90 countries. Despite importing a substantial portion of PPTV waste at 61%, high-income countries exported more waste than they imported, positioning themselves as net exporters. Kellenberg (2015) also corroborates this trend, indicating that although developed countries import a greater quantity of waste in absolute terms, their share of world waste imports is lower than their share of world waste exports. Notably, the top five PPTV waste-exporting countries and the United Kingdom experienced a significant decline in waste exports in 2018, ranging from 14% to 34%, primarily due to their status as major trading partners with China (see Figure A.1 in Appendix). Hong Kong, functioning as an entry port into China, exported approximately 95% of PPTV waste in 2017 but significantly decreased its waste exports by 88%.

3.4 Environmental regulations

I conduct an additional test to examine whether the relative levels of environmental regulation across countries are an important determinant of waste trade. To measure the stringency of environmental regulations, I use the Environment Performance Index (EPI) obtained from the Universities of Yale and Columbia.[11] The EPI assesses a country's environmental performance across 11 issue categories,[12] including air quality, heavy metals, waste management, and pollution emissions.

The EPI serves as a valuable index for measuring waste regulations since waste prod-

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

[12] 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.

TABLE 3: **Top 10 exporting countries in 2017, volume of four types of waste prohibited by the 2018 Chinese policy**

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: UNComtrade (2022)

ucts are often either incinerated (impacting air quality) or disposed of in landfills (affecting water quality). The EPI, reported biennially in even-numbered years since 2006, covers approximately 180 countries, allowing for cross-country comparisons over the years. I chose the year 2020 to categorize countries into groups with higher and lower environmental regulations. This decision is based on the inclusion of waste management issues in the EPI, expanding its scope beyond the existing 11 issue categories, starting from that year.

The EPI ranges from 0 to 100, with higher scores indicating robust policies and programs aimed at protecting public health, preserving natural resources, and reducing greenhouse gas emissions. Using a threshold of 51.7, which is the median value of EPI scores for 88 countries (excluding China and Hong Kong), 44 countries with a 2020 EPI higher than 51.7 are classified as having stringent environmental regulations.

Figure 3 shows the relationship between the EPI score and GDP per capita for 88 countries in 2020. Denmark, with the highest score of 82.5 in 2020, contrasts with Madagascar,

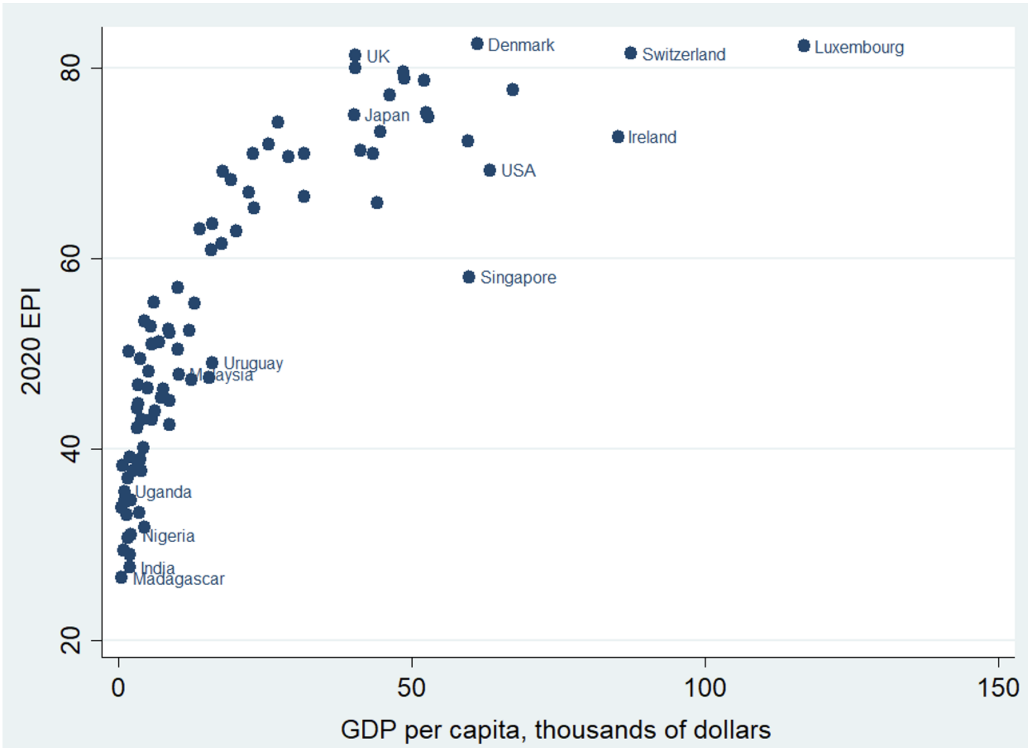


FIGURE 3: **Relationship Between EPI and GDP per capita, 2020**
Source: Universities of Yale and Columbia (https://epi.yale.edu/).

which has the lowest score of 26.5. The figure demonstrates a positive correlation between a country's environmental regulation and GDP per capita, although many countries either outperform or underperform their economic peers. This correlation suggests that economic prosperity enables nations to invest in policies and programs that contribute to better public and environmental health.

4 Empirical Methodology

The empirical approach in estimating the effect of the 2018 Chinese policy on global waste exports/re-exports is based on the difference-in-difference approach. I identify the effects of the policy on trade by comparing PPTV waste exports to the exports of other waste categories that have not been prohibited by the 2018-2020 Chinese waste import bans.

4.1 Difference-in-differences approach

To estimate the impact of the 2018 Chinese policy on the extensive margins of exports (the probability that waste is exported), I use 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. Given my interest in examining the impact of the Chinese policy change across different groups of countries, I categorize importing nations into four groups based on their income level or seven groups by their region. In each sample, I include all 88 countries as exporters (i) but limit the importers (j) to only the corresponding countries. The treatment group comprises four waste types (plastic, paper, textiles, and vanadium slag waste), while the control group consists of waste materials that were not subject to the Chinese waste import ban from 2018 to 2020. A more detailed explanation of how waste is assigned to the treatment and control groups can be found in Section 4.2. $Export_{ijt,k}$ represents exports/re-exports from country i to country j during time t in 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 $\geq$ 2018).

The control variables based on the gravity model are included in the regression. The inclusion of gravity model-based control variables in empirical analyses, particularly in the context of international trade, is grounded in economic theory and empirical evidence. The gravity model is a widely used framework in international economics, and it suggests that the volume of trade between two countries is proportional to their economic sizes (measured by GDP), inversely proportional to the distance between them, and influenced by other factors like language, border sharing, and historical relationships. 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 and ratification of Basel Ban Amendment[13]. X_{ijt} indicates whether countries i and j have a bilateral or regional trade agreement and both had EU or WTO memberships in year t. Detailed information about control variables is explained in Section 3. δ_i and δ_j are country fixed effects controlling for numerous time-invariant characteristics of the country. $\epsilon_{ijt,k}$ denotes an error term. Throughout, the standard errors are clustered at a country-pair to allow for correlated shocks in the residuals, $\epsilon_{ijt,k}$, which could reflect unobserved political or economic forces between countries.

To estimate the impact of the 2018 Chinese policy on intensive margins of trade (the quantity of waste exports), I employ the following equation:

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

where $Export_{ijt,k}$, an outcome variable, is transformed by the inverse hyperbolic sine function. This transformation is defined as $IHS(Export) = log(Export + \sqrt{Export^2 + 1})$. 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 because 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 transformation 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):

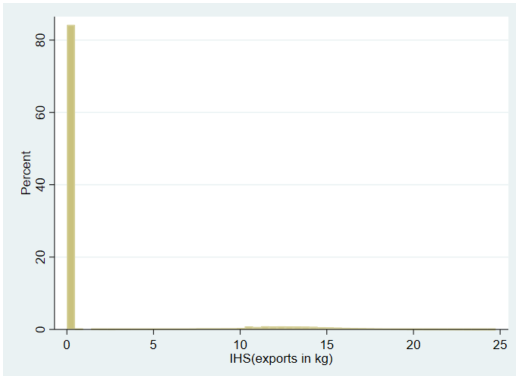
[13] A detailed information about Basel Ban Amendment is available in Section 3.1

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

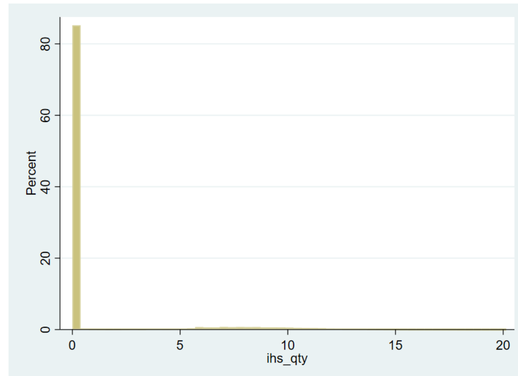
However, recent papers have raised concerns about using the inverse hyperbolic sine transformation because estimated coefficients and elasticities can be sensitive to the units of the outcome variable (Aihounton and Henningsen, 2021; De Brauw and Herskowitz, 2021). It means that if the export volume is measured in kilograms versus thousand kilograms, the estimated percentage increase in export after the Chinese policy change can vary. Recent working papers by Chen and Roth (2023) and Mullahy and Norton (2022) highlight that different choices of units for the outcome variable alter the weighting of the extensive margin effect and intensive margin effect. To examine the distribution of waste exports with varying units, Figure 4 displays the distribution of waste exports. Shifting to larger units (i.e., dividing the variable by 100 and 10,000) brings the nonzero values closer to zero values. However, since the outcome variable contains numerous zero values, the distributions of the outcome variable do not appear to differ significantly when using different units. As a robustness check, I repeat the regression with different units of measurement to assess the sensitivity of the results.

4.2 Treatment and control groups

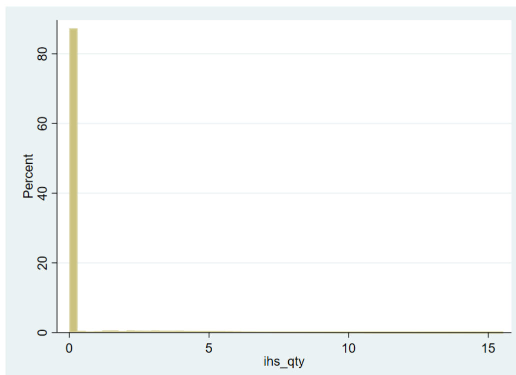
Figure 5 presents which waste categories are classified as the treatment and control groups. The treatment group in the main analysis consists of four types of waste (plastic, paper, textile, and vanadium slag waste), regulated by the 2018 Chinese policy, encompassing 18 6-digit HS categories. The control group comprises waste materials that were never prohibited by Chinese waste import bans in 2018-2020, totaling 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. The total waste exports of the treatment and control groups are the aggregated weight of waste across the corresponding HS categories, respectively. The



Panel A: IHS(export weights in kg)



Panel B: IHS(export weights in 100 kg)



Panel C: IHS(export weights in 10,000 kg)

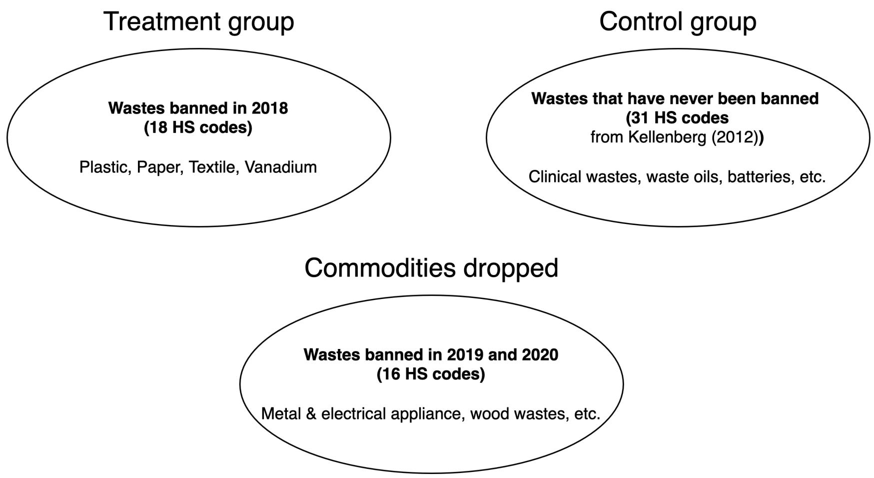
FIGURE 4: **Histogram of IHS-transformed waste exports with y-axis as percentage**

descriptions of HS codes for the treatment and control group are available in Tables B.1 and B.4 of Appendix.

4.3 Identification strategy

One potential threat to the validity of the results is measurement errors. As mentioned earlier, re-export data from UNComtrade is unavailable for all countries because not all countries record or provide re-export data, and some countries include re-exports in their export statistics. Given that a zero weight for re-exports may not be a valid value in in-

FIGURE 5: **Treatment and control groups in the DiD estimation**



stances where countries simply did not report, I establish a subset of my sample that includes countries reporting any waste re-exported since 2005 and then proceed to report the results.

In the case of unobserved heterogeneity, I include country-pair fixed effects instead of controlling for time-invariant country-pair characteristics, such as distance between countries, shared borders, and colonial ties. Country-pair fixed effects eliminate the correlation between the error term and the treatment variable by accounting for factors that persist within a country-pair (e.g., the unique relationship between countries influencing the Chinese policy change). As an alternative specification, I run Equations 1 and 2 with country-pair fixed effects.

Lastly, a potential threat to identification arises from a violation of the stable unit treatment value assumption (SUTVA, see Pearl 2009). In this context, SUTVA states that the 2018 Chinese waste import ban imposed on PPTV waste should not influence exports of other types of waste. While the ban specifically targeted unsorted waste paper (HS 470790), other types of waste paper (i.e., HS 470710, 470720, and 47073014) remained unaffected. However, it is noteworthy that all four HS codes fall under the category 'waste and scrap of paper or paperboard' (HS 4707). As illustrated in Appendix Figure A.2, China has reduced its imports of these three types of waste paper since 2018, even though they were not restricted by the ban. To address potential violations of the SUTVA, I create two datasets and conduct regressions: 1) by excluding these three waste paper types from the control group, and 2) by incorporating the three types of waste paper into the treatment group.

4.4 Evaluation of pre-trends

The underlying assumption is that, when controlling for other determinants of trade, exports in PPTV waste (the treatment group) should experience the same trends as those observed in other waste that has never been prohibited by the 2018-2020 Chinese waste import ban (the control group), in the absence of the 2018 Chinese policy. The true counterfactual is unknowable, but the comparison group can be considered a valid proxy counterfactual by examining trends before the 2018 Chinese policy. To evaluate pre-trends of extensive margin waste exports, I conduct 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 policy 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 policy on the treatment group relative to their control group in d periods after the event year 2018. To assess pre-trends of intensive margin waste exports, I replace $I(Export_{ijt,k} > 0)$ on the left-hand side with $IHS(Export_{ijt,k})$.

TABLE 4: **Extensive margin of waste exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)				
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 policy. *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 Estimation Results and Discussion

5.1 Waste export and re-export by importing country's income level

The extensive margin of waste export is presented in Table 4. Column (1) includes the sample with all 88 countries as exporters but only high-income countries as importers. Similarly, Column (2) includes the sample with all 88 countries as exporters but only upper-middle-income countries as importers. The other two columns follow this pattern. My results show that the 2018 Chinese policy increases the probability of exporting PPTV waste, relative to other waste, to high-income countries by 1.7%, upper-middle-income countries by 2.6%, and lower-middle-income countries by 1.5%. The findings 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.

For the intensive margin (see Table 5), I find evidence of statistically significant increases in PPTV waste exports, relative to other waste, to high-income countries by 23.6%, upper-middle-income countries by 35.8%, and lower-middle-income countries by 16.8% in response to the 2018 Chinese policy change. More volumes of PPTV waste arrived in

TABLE 5: **Intensive margin of waste exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)				
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 policy. *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.

upper-middle-income countries compared to those arriving in high-income and lower-middle-income countries.

These results indicate that more waste is exported to upper-middle-income, high-income, and lower-middle-income countries than to low-income countries. This suggests that low-income countries may lack proper waste infrastructure to manage and dispose of imported waste effectively. They might face challenges in allocating financial resources to invest in the necessary infrastructure and regulations for effective waste management.

Tables 6 and 7 present the extensive and intensive margins of waste re-exports, respectively. For each country group, there are two sets of regression results. Odd-numbered columns include the same country-pairs analyzed in waste exports, while even-numbered columns use subsamples that reported waste re-exports. This defines a subset of my sample to include countries that reported re-exporting any waste in 2005-2020. The results in even-numbered columns serve as part of robustness checks in case of the presence of measurement errors.

TABLE 6: **Extensive margin of waste re-exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)								
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 re-exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste re-exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low-income countries, respectively. As robustness checks, even-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese policy. *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.

In contrast to changes in waste export patterns, the 2018 Chinese policy did not alter re-export patterns. The probability of exporting PPTV waste to upper-middle-income and lower-middle-income countries increased similarly by about 0.2-0.7% but remained small (Table 6). However, estimates for intensive margin change are larger in magnitude than the estimates for extensive margin change. The 2018 Chinese policy led to an increase of 2.8-8.8% in waste exports to upper-middle-income countries and 2.3-7.0% to lower-middle-income countries (Table 7). Although lower-middle-income countries lack recycling or waste-to-energy facilities compared to high-income countries, they become destinations for waste re-exports, likely allowing non-recyclable items to be melted, dumped, or burned.

5.2 Waste export and re-export by importing country's region

Table 8 shows the quantity change of PPTV waste in comparison to other waste exported to seven different regions from 88 countries. After the 2018 Chinese policy was implemented, the probability of exporting PPTV waste to the East Asian & Pacific and Europe & Central

TABLE 7: **Intensive margin of waste re-exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)								
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 re-exports from 88 countries (excluding China and Hong Kong) to high-income countries. Similarly, Columns (3), (5), and (7) represent waste re-exports from 88 countries (excluding China and Hong Kong) to upper-middle, lower-middle, and low-income countries, respectively. As robustness checks, even-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese policy. *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

Asian regions increased by 4.5% and 2.5%, respectively. However, the coefficients of other regions are not statistically different from zero. This result suggests that exporters search for new trading partners, especially in the East Asian & Pacific and Europe & Central Asian regions. The Chinese policy may reflect some shipments that were redirected from China to other East Asian countries that had not been importing waste previously.

The volume of waste exports is also notably concentrated in the aforementioned two regions (see Table 9). The Chinese policy resulted in a 90.9% and 36.1% increase in the flow of waste to the East Asian & Pacific and Europe & Central Asian regions, respectively. Appendix Table B.6 shows that within the East Asian and & Pacific region, Malaysia, Thailand, and Indonesia experienced significant increases in waste imports in 2018. While these regions could be considered ideal alternative destinations due to their proximity to China, the import shares of these regions before the ban were much lower than those of China. This suggests that the East Asian and & Pacific region could lack sufficient recycling ca-

TABLE 8: **Extensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: I(waste export in kg > 0)							
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 policy. *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.

pacity to absorb the diverted waste flow from China, especially given the sudden spike in import volume. In the Europe & Central Asian region, Norway and Turkey also substantially increased waste imports in 2018 (Appendix Table B.6). Turkey imported only 140 tonnes of PPTV waste exported by European countries in 2017, but the figure surged to 42,842 tonnes in 2018, marking a massive increase within a year. Indeed, Turkey has emerged as a significant waste destination for European countries.

Regarding the extensive and intensive margins of waste re-exports, my results show statistically insignificant coefficients across all regions, except for the positive but small coefficient of the extensive margin in Sub-Saharan Africa (0.2-0.8%) and the intensive margin in Europe & Central Asia (2.4-7.4%). Detailed result tables are available in Appendix Section B.1.

5.3 Do pollution haven effects exist?

To investigate whether more waste is relocated to countries with weak environmental regulations, I categorize countries into two groups: those with relatively stringent regulations (high EPI) and those with weak regulations (low EPI). Table 10 presents the results for

TABLE 9: **Intensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: IHS(waste export in kg)							
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 policy. *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 extensive margin of waste export and re-export. The probability of exporting PPTV waste (relative to other waste) to countries with high EPI scores after the ban increased by 1.7%, slightly higher than that of exporting PPTV waste to countries with low EPI scores. The extensive margin for waste re-export to countries with low EPI scores is statistically significant, rising by 0.2-0.7%. Overall, the extensive margin effects of waste export and re-export are small.

The estimated results of the intensive margin of waste export and re-export are presented in Table 11. The volume of PPTV waste exports (relative to other waste exports) to countries with low EPI scores increased by 26.4%, while it increased by 20.8% to countries with high EPI scores. In terms of re-export, I find that more waste is re-exported to countries with low EPI scores, rising by 2.3-7.3%. These results suggest that countries tend to export waste to their trading partners with less stringent environmental standards, aligning with the findings of Kellenberg (2012).

TABLE 10: **Extensive margin of waste exports/re-exports by importing 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)
Dependent Variable: I(waste export in kg > 0)						
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 The results presented in the column labeled "high" (or "low") EPI show that waste is exported or re-exported to countries with EPI scores higher (or lower) than the median. Columns (1) and (3) represent waste exports and re-exports from 88 countries (excluding China and Hong Kong) to 44 countries with high EPI scores, respectively. Similarly, Columns (2) and (5) represent waste exports and re-exports from 88 countries to 44 countries with low EPI scores, respectively. Columns (4) and (6) serve as robustness checks for columns (3) and (5), respectively, using subsamples that reported any waste re-exported for the period 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese policy. *Post* indicates the post-treatment 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 11: **Intensive margin of waste exports/re-exports by importing 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)
Dependent Variable: IHS(waste export in kg)						
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 The results presented in the column labeled "high" (or "low") EPI show that waste is exported or re-exported to countries with EPI scores higher (or lower) than the median. Columns (1) and (3) represent waste exports and re-exports from 88 countries (excluding China and Hong Kong) to 44 countries with high EPI scores, respectively. Similarly, Columns (2) and (5) represent waste exports and re-exports from 88 countries to 44 countries with low EPI scores, respectively. Columns (4) and (6) serve as robustness checks for columns (3) and (5), respectively, using subsamples that reported any waste re-exported for the period 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 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.

6 Robustness Checks

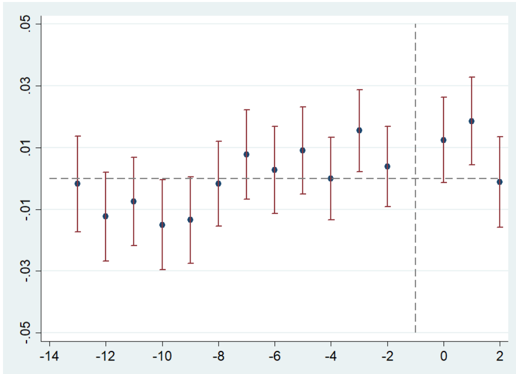
6.1 Pre-trend testing

Figures 6 and 7 present the results of the event study analysis through the estimation of Equation 4. The coefficients in these figures represent the probability or quantity changes in exporting PPTV waste to countries based on income levels. These figures also show the coefficients of pre- and post-treatment periods along with their corresponding confidence intervals for each year.

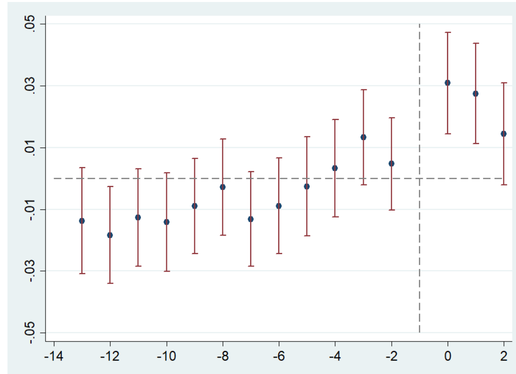
Figure 6 shows that, in the pre-treatment periods, waste exports to high-income (Panel A), upper-middle-income (Panel B), and low-income countries (Panel D) displayed a similar trend across both treatment and control groups. However, the coefficients in Panel C demonstrated a gradual increase over time, attaining statistical significance in the five years leading up to the ban. It's worth noting that if this increasing trend extends beyond the pre-treatment period, the DiD estimator might be upward biased, suggesting that the true effect could be smaller than the estimated coefficient.

The issue of pre-trends also appears in lower-middle-income countries in the event study of an intensive margin, as illustrated in Figure 7. Panel C reveals positive and ascending coefficients during the pre-treatment periods, indicating that PPTV waste exports to lower-middle-income countries were growing at a faster rate than the average of other waste exports even before the ban. This finding implies that the true effect for lower-middle-income countries might be less than the reported 16.8%, considering the upward bias suggested by the pre-trend analysis. However, it is important to note that this interpretation does not alter the overall conclusion that countries primarily export PPTV waste to upper-middle-income countries, followed by high-income countries and lower-middle-income countries.

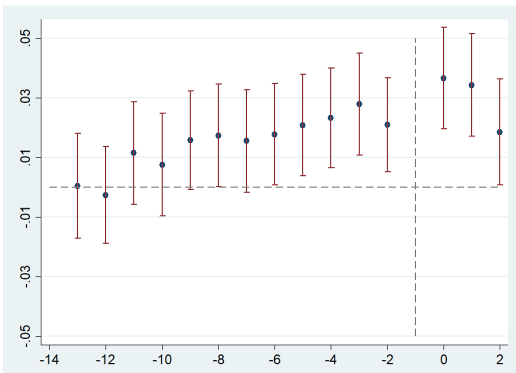
The results of the pre-trend testing regarding waste re-export are reported in Appendix A.1. The overall estimates consistently show insignificance during the pre-treatment periods with the exception of negative and statistically significant coefficients observed in the



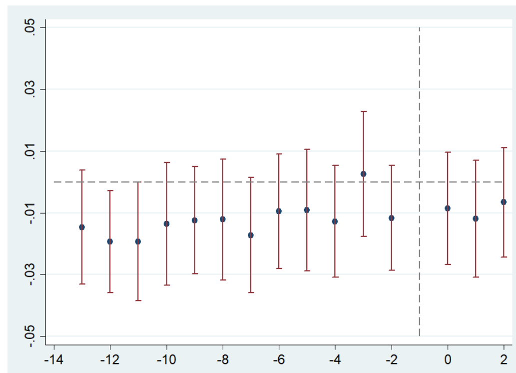
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle-income countries



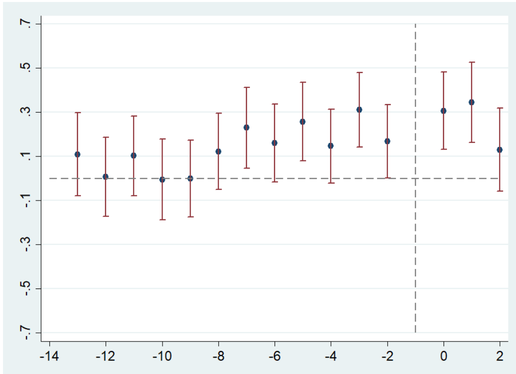
Panel D: Low-income countries

FIGURE 6: **Extensive margin of waste exports - event study analysis**

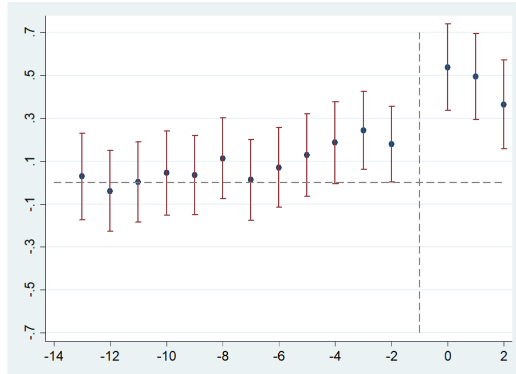
Note: These figures present the coefficients derived from the estimation of Equation 4, which measures the probability of exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1.

5th- and 6th-year lags for lower-middle-income countries (Panel C). However, as mentioned earlier, this result does not change the interpretation that countries re-export more waste to upper-middle-income countries.

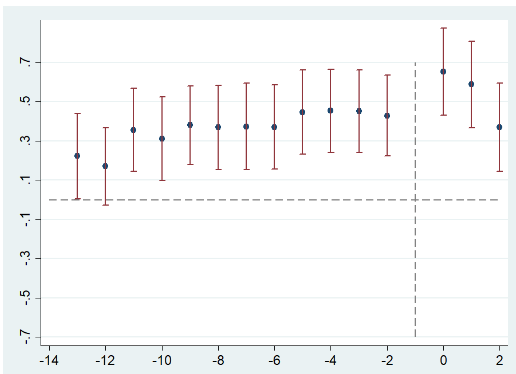
The pre-trend tests of extensive and intensive margins of waste exports to East Asian & Pacific and Europe & Central Asian regions are presented in Appendix Figures A.5 and A.6, respectively. The results indicate that more PPTV waste was exported to these regions than other types of waste a few years before the ban. However, the point estimates exhibit



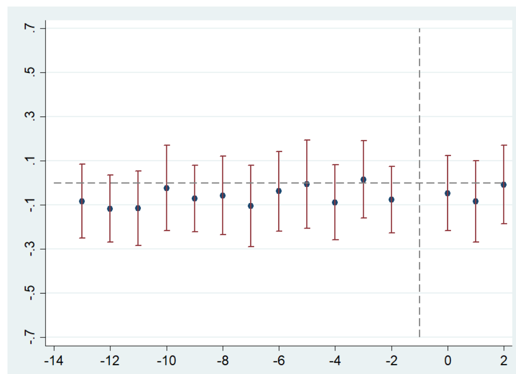
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle-income countries



Panel D: Low-income countries

FIGURE 7: **Intensive margin of waste exports - event study analysis**

Note: These figures present the coefficients derived from the estimation of Equation 4, wherein $I(Export_{ijt,k} > 0)$ is replaced with $IHS(Export_{ijt,k})$. This measures the quantity change in exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1.

a substantial increase in magnitude from the onset of the treatment, particularly for the East Asian & Pacific region. Although the coefficients from regressing Equations 1 and 2 may be overestimated due to the pre-trends, it appears that the ban led to an increase in PPTV waste exports, particularly to the East Asian & Pacific regions.

6.2 Robustness checks

To account for unobserved characteristics within country-pair constants over time, I conducted alternative estimations by incorporating country-pair fixed effects. Additionally, I present the results obtained from a regression without the control variables listed in 1 serving as an additional robustness check. Overall, the estimators derived from regressions without control variables or with time-invariant country-pair fixed effects demonstrate robustness, exhibiting only variations in R-squared values across different specifications. The results of both extensive and intensive margins of waste exports, categorized by the importing country's income level, are presented in Appendix Tables B.12-B.15. Results concerning waste re-exports are available in Appendix Tables B.16-B.19, while the extensive and intensive margins of waste exports by the importing country's region are provided in B.16-B.19.

As discussed in Section 4.3, only one type of paper waste (unsorted waste paper) was banned from import by the 2018 Chinese policy. To address potential spillover effects that the ban might have on three other types of paper waste, I adopt two different approaches: 1) excluding three types of paper waste from my data (omitting them from the control group), and 2) including them in the treatment group, assuming they were also banned. The results for extensive and intensive margins testing SUTVA violations are presented in Appendix Tables C.1 and C.2, respectively.

The result tables show that the probability of exporting PPTV waste to high-, upper-middle-, and lower-middle-income countries increased by 2-2.1%, 3.4-3.5%, and 1.8-1.9%, respectively. The quantity changes in PPTV waste exports to each group of countries increased by 34-35%, 57-59%, and 22-23%, respectively. I find that the coefficients obtained from both approaches are overall larger than those obtained from the main analysis shown in Section 5.1. However, the results of the pre-trend analysis suggest that these estimates may be overestimated given that the values of the coefficients increased over time during pre-treatment periods (see Appendix Figures C.1, C.2, C.3, and C.4). Therefore, there is little concern regarding the outcomes with higher coefficients obtained from controlling for violations of the SUTVA.

To measure the intensive margin, I apply the IHS transformation to the outcome variable. Given recent concerns in research about the sensitivity of results to the units of measurement in outcome variables, I conduct additional regressions using different scale factors. Specifically, I divide the outcome variable by 100 and 10,000 and run regressions. The estimated results are presented in Appendix Table D.1. As expected, using different scale factors yields different coefficients. When employing a smaller unit of measurement (e.g., transitioning from a weight in 100 kg to a weight in 10,000 kg), coefficients become smaller (14.7% to 9.3% for upper-middle-income countries). However, the trend of exporting more PPTV waste to upper-middle-income countries persists across the different units of measurement. One accurate interpretation of the results is that there is an impact of the 2018 Chinese policy on the inverse hyperbolic sine of waste exports to upper-middle-income countries.

7 Concluding Remarks

Since 2018, China no longer imports plastic waste from living sources, paper waste, textile waste, and vanadium slag. I examine the impact of this 2018 Chinese policy change on exports and re-exports to countries by their income level and region. Using UNComtrade data on bilateral trade, the difference-in-difference estimates suggest that the ban positively affected both the extensive and intensive margins of waste exports to upper-middle-income countries and the East Asian Pacific regions. Additionally, I find that the ban had a positive impact on both the extensive and intensive margins 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 is exported to countries with relatively weak environmental regulations compared to other types of waste, lending support to the pollution haven hypothesis.

China has implemented waste import bans to avoid low-quality waste and protect Chinese health and ecosystems. This policy has also altered global waste trade patterns. Given that most countries cannot significantly reduce waste discharges in a short period, they often export waste to other countries if they lack domestic recycling capabilities or sufficient land for waste disposal. Businesses in upper-middle-income countries often import more waste for recycling, utilizing recycled materials in new product production. In situations where countries have lax environmental regulations, unrecycled materials may be disposed of through burning, burial, or ocean discharge. Residents in proximity to these sites bear the immediate impact of harmful gases, contaminated water, and polluted soil.

Improving waste management infrastructure in upper-middle-income countries experiencing a substantial increase in waste imports is crucial, requiring substantial resources and time. During the development of such infrastructure, high-income countries that export over half of their PPTV waste can take immediate action by reducing waste generation and adopting more recyclable products.

Future research could build upon this discovery by incorporating waste prices into the analysis. A higher unit price of waste may suggest higher quality or greater ease of recycling and processing into new products. Examining waste prices could provide insights into the diverse effects of the ban on waste exports across different types of waste and contribute to understanding why upper-middle-income countries emerge as destinations for waste. Moreover, future research has the potential to explore spillover effects of the ban on various aspects. In line with Shi and Zhang (2023)'s investigation into the impact of the waste import ban on air pollution, examining the ban's effects on water quality, human health, or job creation would be intriguing areas for further exploration.

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Appendix

A Figures

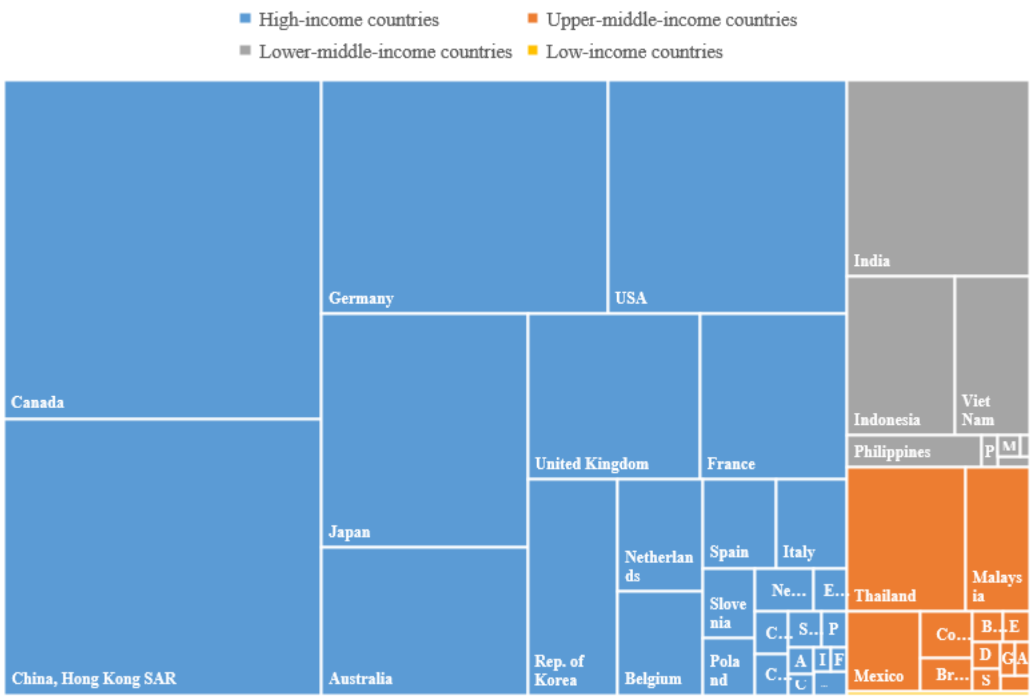


FIGURE A.1: Exports of plastic, paper, textile, and vanadium slag waste to China in 2017

Note: The size of each square corresponds to the cumulative weight of plastic, paper, textile, and vanadium slag waste exported to China from each country, with larger squares indicating higher total weights. Source: UNComtrade (2022).

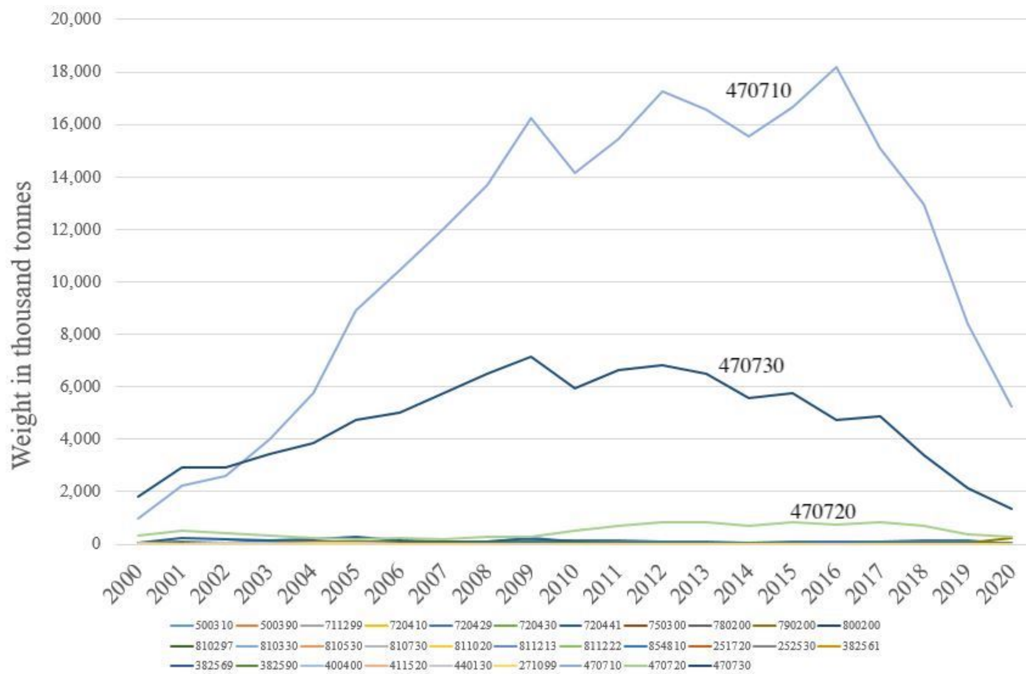
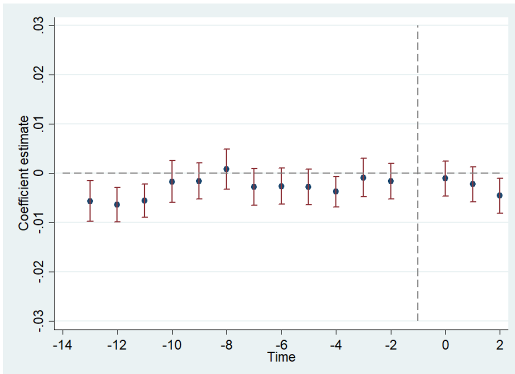


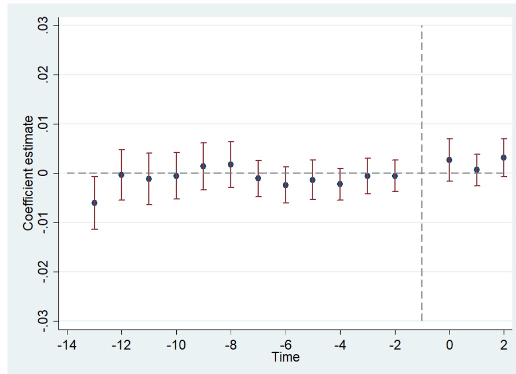
FIGURE A.2: The trend of China's waste imports that have never been banned by the 2018 Chinese policy

Note: Each line represents a specific type of waste that is part of the control group. Source: UNComtrade (2022).

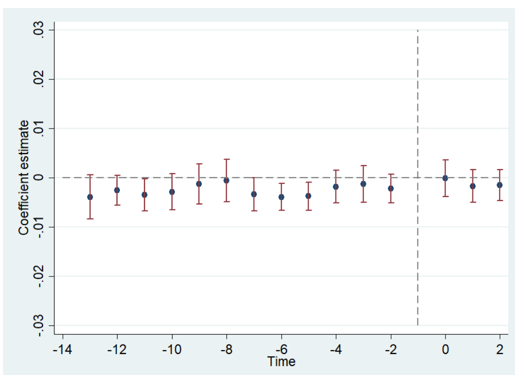
A.1 Pre-trend testing – waste re-exports



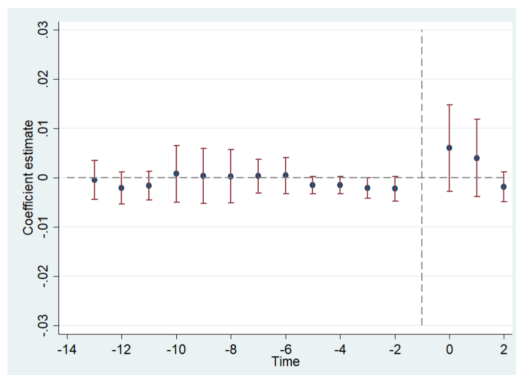
Panel A: High-income countries



Panel B: Upper-middle-income countries



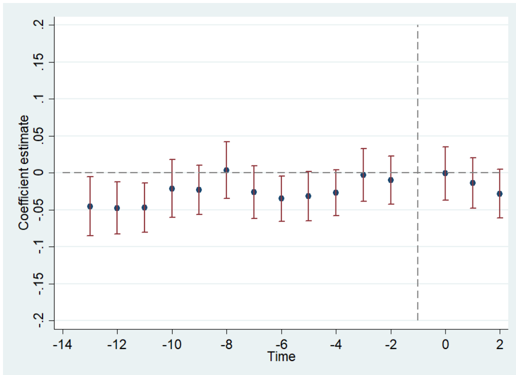
Panel C: Lower-middle-income countries



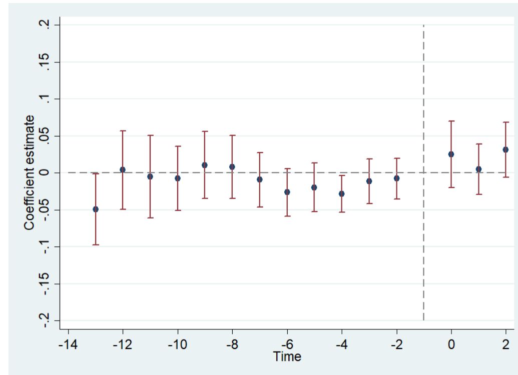
Panel D: Low-income countries

FIGURE A.3: Extensive margin of waste re-exports - event study analysis by importing country's income level

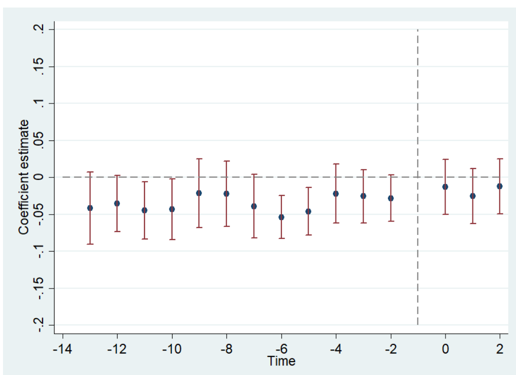
Note: These figures present the coefficients derived from the estimation of Equation 4, which measures the probability of re-exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste re-exports compared to other waste re-exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1



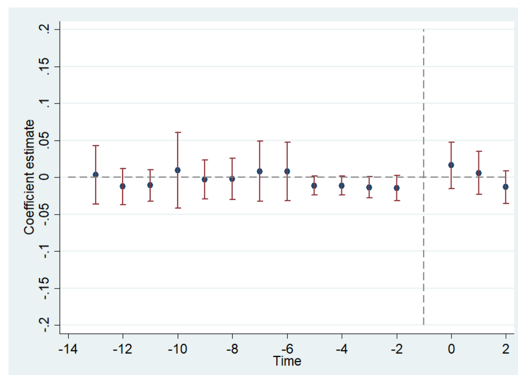
Panel A: High-income countries



Panel B: Upper-middle-income countries



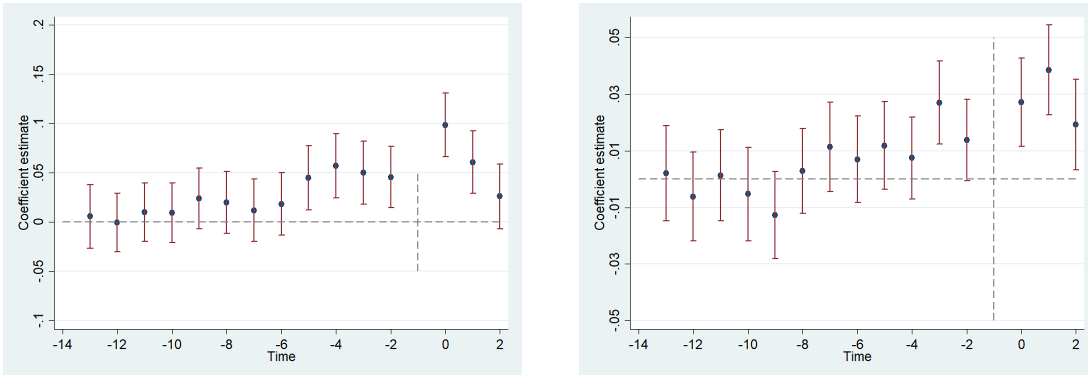
Panel C: Lower-middle income countries



Panel D: Low-income countries

FIGURE A.4: Intensive margin of waste re-exports - event study analysis by importing country's income level

Note: These figures present the coefficients derived from the estimation of Equation 4, wherein $I(Export_{ijt,k} > 0)$ is replaced with $IHS(Export_{ijt,k})$. This measures the quantity change in re-exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste re-exports compared to other waste re-exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1

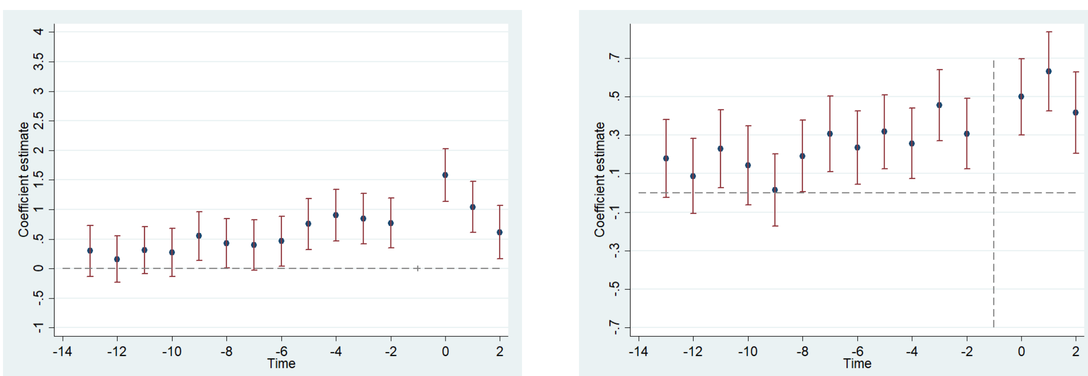


Panel A: East Asia & Pacific

Panel B: Europe & Central Asia

FIGURE A.5: Extensive margin of waste exports - event study analysis by importing country's region

Note: These figures present the coefficients derived from the estimation of Equation 4, which measures the probability of exporting PPTV waste to countries by region. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1



Panel A: East Asia & Pacific

Panel B: Europe & Central Asia

FIGURE A.6: Intensive margin of waste exports - event study analysis by importing country's region

Note: These figures present the coefficients derived from the estimation of Equation 4, wherein $I(Export_{ijt,k} > 0)$ is replaced with $IHS(Export_{ijt,k})$. This measures the quantity change in exporting PPTV waste to countries by region. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available 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)

Continued on next page

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 88 countries

High-income countries (39)				
Australia	Estonia	Israel	Netherlands	Spain
Austria	Finland	Italy	New Zealand	Sweden
Belgium	France	Japan	Norway	Switzerland
Canada	Germany	Korea, Rep.	Poland	Trinidad and Tobago
Chile	Greece	Latvia	Portugal	United Kingdom
Croatia	Hungary	Lithuania	Singapore	United States
Czech Republic	Iceland	Luxembourg	Slovak Republic	Uruguay
Denmark	Ireland	Malta	Slovenia	
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

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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
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 importing country's region

TABLE B.8: Extensive margin of waste re-exports by importing country's 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 (6)	Sub-Saharan (7)
Dependent Variable: I(waste export in kg > 0)							
Treat ° *Post*	0.003	0.002	0.002	-0.008	0.001	0.003	0.002**
	(0.003)	(0.004)	(0.001)	(0.006)	(0.001)	(0.002)	(0.001)
R^2	0.152	0.408	0.4117	0.523	0.146	0.131	0.046
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 re-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 policy. *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 of waste re-exports by importing country's region (excl. China and Hong Kong), 2005-2020, as a robustness check

	East Asia & Pacific (1)	South Asia (2)	Europe & Central Asia (3)	North Amer. (4)	Latin Amer. & Carib. (5)	Middle East & North (6)	Sub-Saharan (7)
Dependent Variable: I(waste export in kg > 0)							
Treat ° *Post*	0.008	0.007	0.005	-0.024	0.002	0.009	0.008**
	(0.010)	(0.011)	(0.004)	(0.017)	(0.004)	(0.007)	(0.003)
R^2	0.146	0.124	0.095	0.517	0.152	0.187	0.059
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,216	3,648	29,536	1,792	18,368	5,504	12,672

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 As a robustness check, this table represents estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese policy. *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 of waste re-exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: IHS(waste export in kg)							
Treat ˚ *Post*	0.043	0.040	0.024*	-0.023	0.006	0.022	0.009
	(0.137)	(0.046)	(0.012)	(0.061)	(0.012)	(0.023)	(0.007)
R^2	0.125	0.120	0.063	0.697	0.139	0.131	0.048
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:							
$\tilde{P}(\cdot)/100$	0.044	0.040	0.024*	-0.023	0.006	0.022	0.009
	(0.037)	(0.048)	(0.013)	(0.060)	(0.012)	(0.024)	(0.007)

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 policy. *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 of waste re-exports by importing country's region (excl. China and Hong Kong), 2005-2020, as a robustness check

	East Asia & Pacific	South Asia	Europe & Central Asia	North Amer.	Latin Amer. & Carib.	Middle East & North Afr.	Sub-Saharan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: IHS(waste export in kg)							
Treat ˚ *Post*	0.130	0.121	0.072*	-0.071	0.019	0.067	0.027
	(0.106)	(0.142)	(0.037)	(0.192)	(0.038)	(0.070)	(0.022)
R^2	0.118	0.128	0.081	0.697	0.155	0.195	0.065
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,216	3,648	29,536	1,792	18,368	5,504	12,672
Calculated (semi-)elasticities:							
$\tilde{P}(\cdot)/100$	0.138	0.129	0.074*	-0.069	0.019	0.069	0.027
	(0.120)	(0.160)	(0.040)	(0.179)	(0.038)	(0.075)	(0.022)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 As a robustness check, this table represents estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy equal to one for the commodity group restricted to import by the 2018 Chinese policy. *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.

B.2 Results from using different specifications

TABLE B.12: Extensive margin of waste exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)				
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 policy. *Post* indicates the post-treatment 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 of waste exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)				
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 policy. *Post* indicates the post-treatment 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 of waste exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)				
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 policy. *Post* indicates the post-treatment 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 of waste exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)				
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 policy. *Post* indicates the post-treatment 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 of waste re-exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)								
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-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy, equal to one for the commodity group restricted to import by the 2018 Chinese policy. *Post* indicates the post-treatment 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 of waste re-exports by importing country's 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)
Dependent Variable: I(waste export in kg > 0)								
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-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy, equal to one for the commodity group restricted to import by the 2018 Chinese policy. *Post* indicates the post-treatment 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 of waste re-exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)								
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-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy, equal to one for the commodity group restricted to import by the 2018 Chinese policy. *Post* indicates the post-treatment 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 of waste re-exports by importing country's 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)
Dependent Variable: IHS(waste export in kg)								
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-numbered columns represent estimated results from using subsamples that reported re-exporting any waste in 2005-2020. *Treat* denotes the treatment dummy, equal to one for the commodity group restricted to import by the 2018 Chinese policy. *Post* indicates the post-treatment 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.20: Extensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: I(waste export in kg > 0)							
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 policy. *Post* indicates the post-treatment 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.21: Extensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: I(waste export in kg > 0)							
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 policy. *Post* indicates the post-treatment 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.22: Intensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: IHS(waste export in kg)							
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 policy. *Post* indicates the post-treatment 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.23: Intensive margin of waste exports by importing country's 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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: IHS(waste export in kg)							
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 policy. *Post* indicates the post-treatment 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.

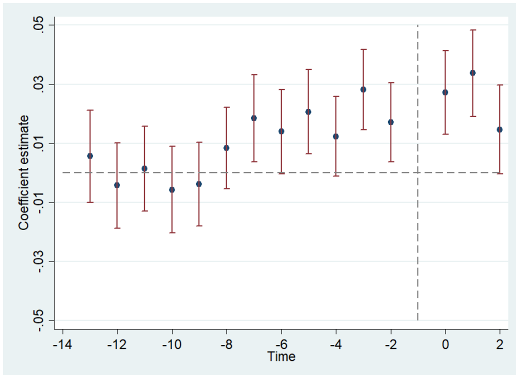
C Testing for SUTVA violations

C.1 Extensive margins

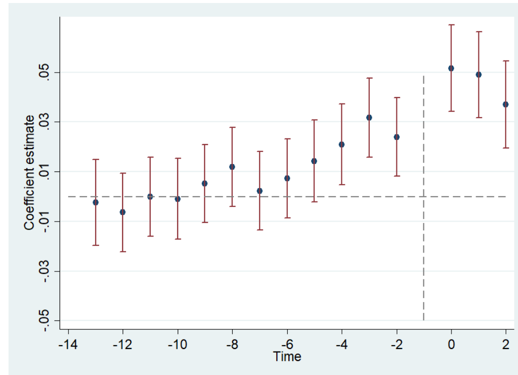
TABLE C.1: Extensive margin of waste exports by importing country's income level (excl. China and Hong Kong), 2005-2020 – testing for SUTVA violations

	High Income Countries		Upper Middle Income Countries		Lower Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: I(waste export in kg > 0)								
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

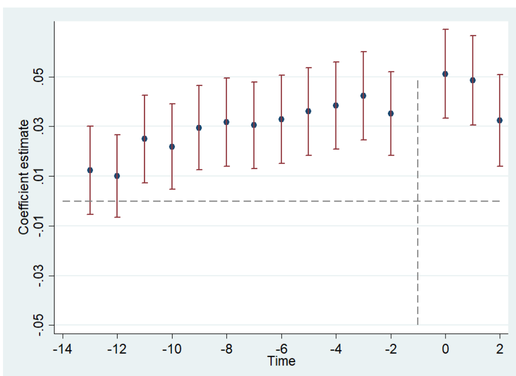
Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The odd-numbered columns present results obtained by excluding three types of paper waste that were not banned by the 2018 Chinese policy from the dataset. In contrast, the even-numbered columns present results obtained by including three types of paper waste in 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 policy. *Post* indicates the post-treatment 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.



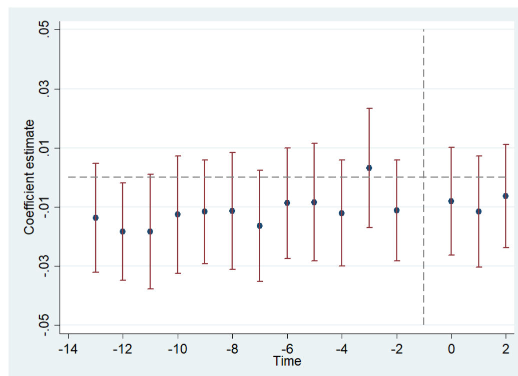
Panel A: High-income countries



Panel B: Upper-middle-income countries



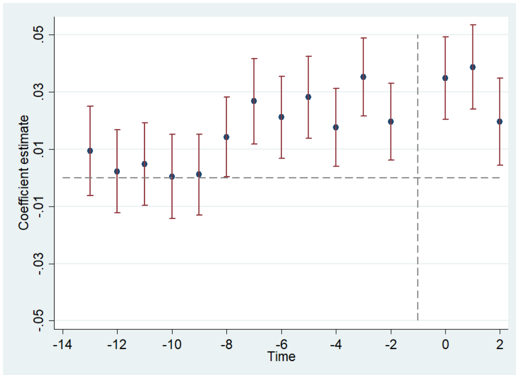
Panel C: Lower-middle-income countries



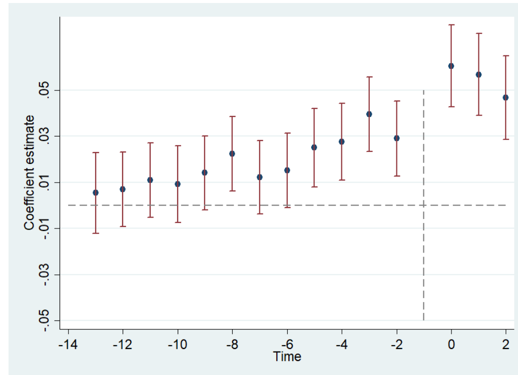
Panel D: Low-income countries

FIGURE C.1: Extensive margin of waste exports - event study analysis, testing for SUTVA violations by excluding three types of paper waste that were not banned by the 2018 Chinese policy

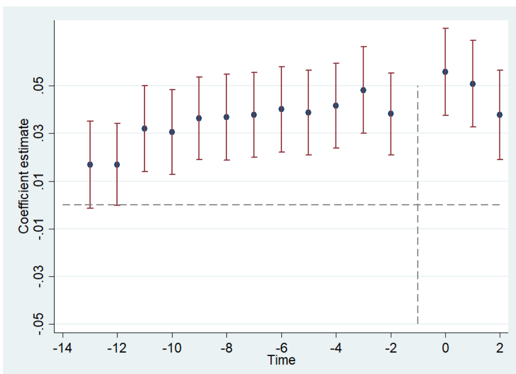
Note: These figures present the coefficients derived from the estimation of Equation 4, which measures the probability of exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1.



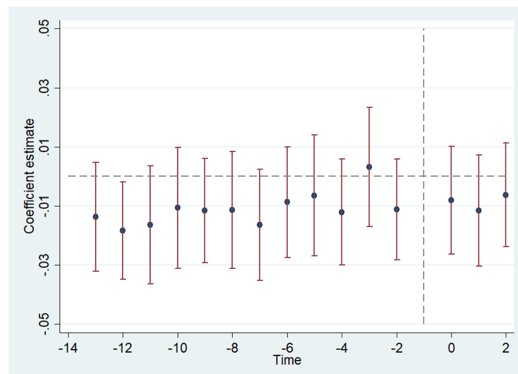
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle-income countries



Panel D: Low-income countries

FIGURE C.2: Extensive margin of waste exports - event study analysis, testing for SUTVA violations by including three types of paper waste in the treatment group

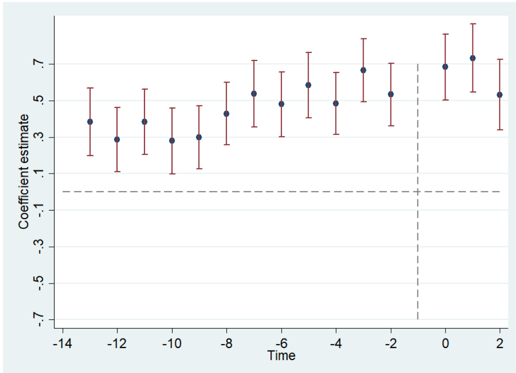
Note: These figures present the coefficients derived from the estimation of Equation 4, which measures the probability of exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1.

C.2 Intensive margins

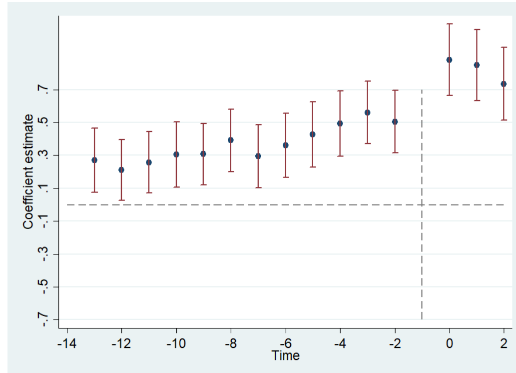
TABLE C.2: Intensive margin of waste exports by importing country's income level (excl. China and Hong Kong), 2005-2020 – testing for SUTVA violations

	High Income Countries		Upper Middle Income Countries		Lower Middle Income Countries		Low Income Countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: IHS(waste export in kg)								
Treat ˚ Post	0.293***	0.300***	0.451***	0.462***	0.209**	0.199***	0.030	0.030
	(0.062)	(0.063)	(0.067)	(0.068)	(0.072)	(0.072)	(0.049)	(0.049)
R^2	0.496	0.500	0.334	0.345	0.337	0.341	0.279	0.270
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
Calculated (semi-)elasticities:								
$\tilde{P}(\cdot)/100$	0.340***	0.350***	0.571***	0.587***	0.233***	0.220**	0.031	0.031
	(0.083)	(0.084)	(0.106)	(0.108)	(0.089)	(0.088)	0.050)	(0.051)

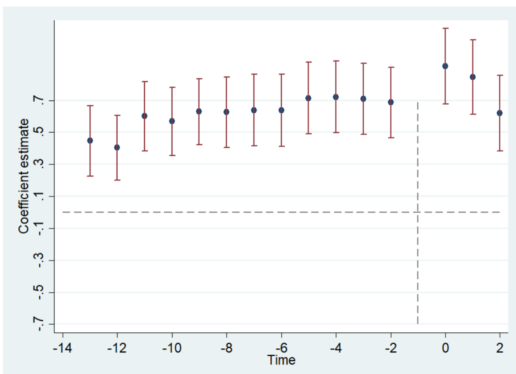
Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The odd-numbered columns present results obtained by excluding three types of paper waste that were not banned by the 2018 Chinese policy from the dataset. In contrast, the even-numbered columns present results obtained by including three types of paper waste in 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 policy. *Post* indicates the post-treatment 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.



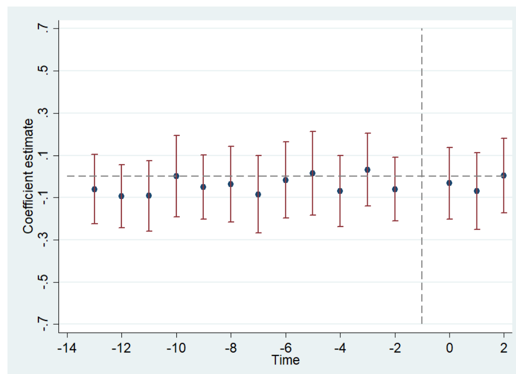
Panel A: High-income countries



Panel B: Upper-middle-income countries



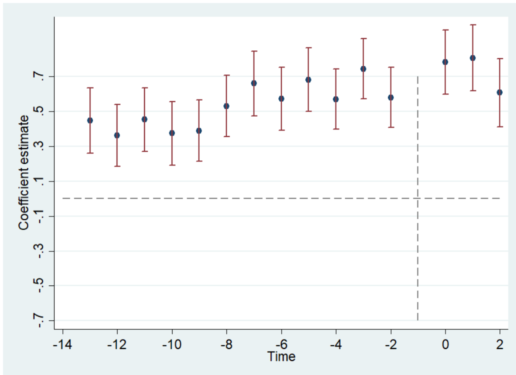
Panel C: Lower-middle-income countries



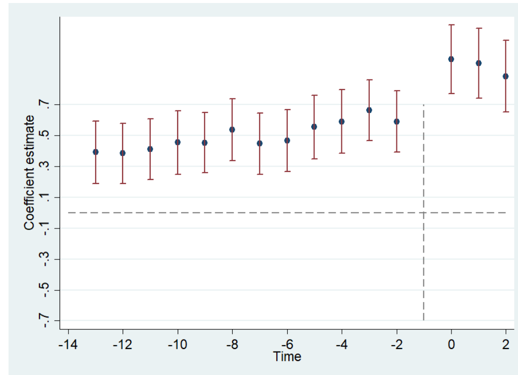
Panel D: Low-income countries

FIGURE C.3: Intensive margin of waste exports - event study analysis, testing for SUTVA violations by excluding three types of paper waste that were not banned by the 2018 Chinese policy

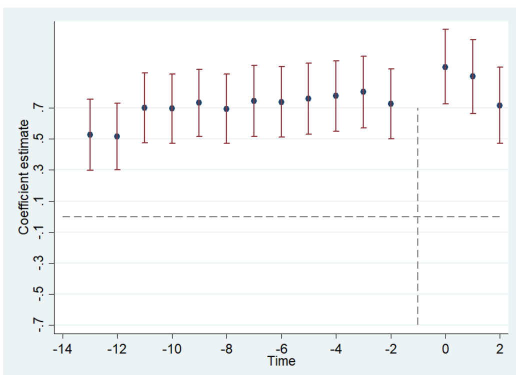
Note: These figures present the coefficients derived from the estimation of Equation 4, wherein $I(Export_{ijt,k} > 0)$ is replaced with $IHS(Export_{ijt,k})$. This measures the quantity change in exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1



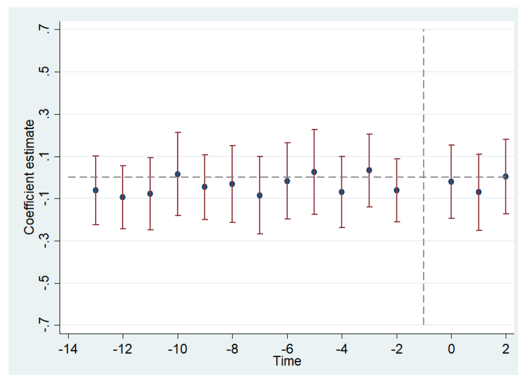
Panel A: High-income countries



Panel B: Upper-middle-income countries



Panel C: Lower-middle-income countries



Panel D: Low-income countries

FIGURE C.4: Intensive margin of waste exports - event study analysis, testing for SUTVA violations by including three types of paper waste in the treatment group

Note: These figures present the coefficients derived from the estimation of Equation 4, wherein $I(Export_{ijt,k} > 0)$ is replaced with $IHS(Export_{ijt,k})$. This measures the quantity change in exporting PPTV waste to countries based on income levels. The coefficients represent the change in outcomes for PPTV waste exports compared to other waste exports. The analysis spans 13 years before and 3 years after the 2018 Chinese policy change, relative to the year immediately preceding the ban. The red bars on the graphs denote 99% confidence intervals. Control variables, based on the gravity model, are employed, and the complete list of these variables is available in Table 1

D IHS with different units of measurement

TABLE D.1: **Intensive margin of waste exports by importing country's income level (excl. China and Hong Kong) using different units of measurement, 2005-2020**

	High Income Countries (1)	Upper Middle Income Countries (2)	Lower Middle Income Countries (3)	Low Income Countries (4)
Dependent Variable: IHS(waste export in 100 kg)				
Treat ˚ *Post*	0.140***	0.138***	0.088*	0.011
	(0.043)	(0.035)	(0.049)	(0.027)
Calculated (semi-)elasticities:				
$\tilde{P}(\cdot)/100$	0.151***	0.147***	0.092*	0.011
	(0.049)	(0.040)	(0.054)	(0.027)
Dependent Variable: IHS(waste export in 10,000 kg)				
Treat ˚ *Post*	0.069***	0.089***	0.034	0.005
	(0.024)	(0.025)	(0.028)	(0.011)
Calculated (semi-)elasticities:				
$\tilde{P}(\cdot)/100$	0.071***	0.093***	0.035	0.005
	(0.026)	(0.028)	(0.029)	(0.011)
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 policy. *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 of waste exports by importing country's income level and EPI (excl. China and Hong Kong), 2005-2020

	High Income Countries		Upper Middle Income Countries		Lower Middle Income Countries		Low Income Countries	
	High EPI	Low EPI	High EPI	Low EPI	High EPI	Low EPI	High EPI	Low EPI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: IHS(waste export in kg)								
Treat ° Post	0.165*	0.258***	0.259***	0.348***	0.134	0.173	0.059	0.009
	(0.089)	(0.089)	(0.098)	(0.094)	(0.095)	(0.108)	(0.078)	(0.059)
R^2	0.558	0.470	0.367	0.386	0.332	0.390	0.247	0.368
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,896	55,680	30,624	33,408	25,056	30,624	8,352	8,352
Calculated (semi-)elasticities:								
$\tilde{P}(\cdot)/100$	0.179*	0.294**	0.296**	0.417***	0.144	0.188	0.061	0.009
	(0.105)	(0.115)	(0.127)	(0.133)	(0.109)	(0.128)	(0.083)	(0.060)

Notes: Standard errors are clustered by country pairs in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The odd-numbered (even-numbered) columns present results from including countries that have relatively higher (lower) EPI scores in 2020. 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 policy. *Post* indicates the post-treatment 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.