Global Impact of a Unilateral Waste Trade Regulation*

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Abstract

China banned imports of several waste categories beginning in 2017. Exploiting variation in the types of materials covered by the ban, I combine a difference-in-differences approach with the gravity model of trade to estimate its impact on global waste flows. My results show that the ban led to an overall decline in international waste flows, primarily through the reduction in imports by China. While some of the low-value waste materials like plastics were diverted to other lower-income countries, overall trade in high-value waste like metals declined. Back-of-the-envelope calculations suggest that low-income countries saved 1.3-3.8 billion USD in external costs by 2020, roughly 14-32% of the savings by China. My results indicate that a unilateral regulation can meaningfully lower environmental costs beyond the regulation-imposing country.

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1 Introduction

International trade in waste, which has surged over the past three decades, imposes substantial environmental costs on importing countries (Li and Takeuchi, 2023; Shi and Zhang, 2023; Unfried and Wang, 2024). These externality costs are particularly high in developing countries, where the recycling operations are largely informal and unregulated (Vidal, 2014*a*). Moreover, unrecyclable waste is often exported under the guise of recyclable waste (Gutierrez, 2016*a*). Imported recyclable waste contaminated with hazardous and nonrecyclable materials hinders reprocessing, leading to negative environmental impacts. Until 2016, China was a leading destination for many environmentally damaging waste materials, with a share of over 45% in global plastic and paper waste imports. While the Basel Convention aims to regulate hazardous waste flows across countries, international environmental agreements often suffer from the free-rider issue unless carefully designed (Farrokhi and Lashkaripour, 2024).

I exploit China's 2017 waste import ban to study the impact of a unilateral waste trade regulation on global waste flows. This regulation, involving a major importer like China and covering a wide array of waste categories, presented a major shock to the international waste trade market. On the one hand, exporting countries' recycling facilities stockpiled materials, landfilled some recyclables, and scaled back their waste collection programs in the aftermath of the ban (Staub, 2017*a*,*b*; Katz, 2019). On the other hand, reports suggest diversion of some plastic waste to other Southeast Asian countries (Resource Recycling, 2022). Ex-ante, therefore, the direction of the impact of the ban on importing countries is ambiguous. By exploiting variation in the types of materials affected by the ban, I combine a difference-in-differences approach with the workhorse gravity model of trade to estimate the impact of the regulation on bilateral flows of banned waste types. Panel data on bilateral flows of various materials also allow me to quantify the heterogeneity in impact by country and by waste type and how these effects evolve over time.

I find that, on average, China's 2017 waste import ban led to a decrease of 8.1-11% in overall bilateral trade flows of targeted waste types. On estimating the dynamic treatment effects, I find that the ban caused bilateral waste flows to decline by 6.9% in the year of the announcement of the ban relative to their pre-ban level, which was followed by even larger declines in the subsequent years 2018-19. This negative impact on global waste flows is largely due to the decline in waste imports by China. China's total waste imports declined by 32-57.7% in 2017, with this reduction growing in size to 77.7-86.5% by 2020.

However, the negative impact on the global waste trade market is not solely driven by China. Even as low-income countries absorbed some of the displaced low-value waste materials like plastics, increasing those imports by 21.9-29.4% over the 2018-20 period, they decreased imports of high-value waste materials like metals by 43.4-45.7% over 2017-18. Thus, as China reduced its waste imports, some of the low-value waste materials were diverted to other countries, especially to those of low-income, while the international high-value waste trade market shrank. Following the ban, developed countries might retain high-value recyclables that require advanced technology to reprocess or have established local industrial demand, while continuing to export low-value waste that requires labor-intensive manual sorting for reprocessing to other countries.

Further, while the ban severely affected international trade of materials directly covered under the ban, it also substantially reduced trade in other waste materials not directly targeted by the ban like glass and organic waste, which create negative externalities in the receiving countries, especially when commingled with environmentally damaging, hazardous material. The overall reduction in global waste flows is also partly explained by changes on the extensive margin, i.e. country pairs ending trade in waste altogether, where this impact is primarily due to end of imports by China.

The estimated decline in overall waste imports by low-income countries cannot be solely attributed to the waste import restrictions implemented by Southeast Asian countries following China's ban, for two reasons. First, my analysis shows a decline despite accounting for these contemporaneous policy interventions. Second, contrary to expectations, the majority of regulation-imposing countries show increased imports of restricted materials even after they implemented their bans, indicating limited effectiveness of these restrictions. A more plausible explanation, therefore, might be the waste-exporting countries rearranging their export patterns by reducing high-value waste exports while redirecting lower-value materials to alternative destinations. My findings are robust to alternative sets of fixed effects and controls and to an alternative control group composed of precious waste materials unaffected by the ban. I further alleviate the concern that the estimated treatment effect may be due to some omitted variation, rather than China's waste import ban, by conducting two placebo tests with fake treatment years and fake treated waste types.

The literature provides a wide range of estimates for the externality costs from both recycling and disposal of waste (Craighill and Powell, 1996; Eshet, Ayalon and Shechter, 2005; Kinnaman, 2009; McKinsey, 2016; Bond et al., 2020). Drawing from the material-specific externality cost estimates for recycling in Craighill and Powell (1996), my back-of-the-envelope calculations show that China's cumulative external costs drop by roughly 9.5-11.9 billion USD by 2020. Even though other low-income countries absorbed some of the displaced low-value waste, they still achieved cumulative savings of approximately 1.3-3.8 billion USD by 2020—about 14-32% of China's savings—due to the initial reduction in their high-value waste imports. These findings suggest that China's unilateral waste trade regulation not only benefits China itself but also helps other lower-income countries reduce their externality costs. This reduction in waste imports is particularly beneficial for low-income countries, which typically have laxer environmental regulations and consequently, suffer more environmental damage per unit of waste.

My paper contributes to the burgeoning literature on the consequences of waste trade regulations. Martin et al. (2021); Balkevicius, Sanctuary and Zvirblyte (2020); Sun (2019) and Brooks, Wang and Jambeck (2018) study the impact of waste trade regulations imposed by China over the years, while Kellenberg and Levinson (2014) study whether the Basel Convention has been effective in deterring global waste flows. At the domestic level, recent work quantifies the impact of the 2017 China ban on air pollution within China (Unfried and Wang, 2024; Shi and Zhang, 2023; Li and Takeuchi, 2023), waste-management within the US (Sigman and Strowe, 2024), and also, air pollution and relocation of pollution within the

US (Zhang, 2023). I use a panel on bilateral waste flows to estimate how the impact of the comprehensive 2017 ban varied across countries and waste types and its evolution over time.

More broadly, my paper is related to the pollution haven hypothesis literature (Antweiler, Copeland and Taylor, 2001; Copeland and Taylor, 2004, 1994), which posits that trade liberalization results in production of pollution-intensive goods shifting to countries with lower levels of environmental regulation. Also, literature studying the determinants of international waste flows (Copeland, 1991; Baggs, 2009; Kellenberg, 2012; Lee, Wei and Xu, 2020; Thakur, 2024) documents evidence supporting a pollution haven effect in the context of waste trade. My results suggest that waste trade *de-liberalization* shifts high-value waste materials away from lower-income countries, which also tend to have laxer environmental regulations, even as they absorb some of the diverted low-value waste.

This paper also speaks to the literature on the environmental consequences of unilateral and multilateral regulations. While a multilateral agreement needs to balance enforceability of commitments with sufficient participation by countries, a unilateral regulation risks having little impact without other countries' cooperation (Clausing and Wolfram, 2023; Deltas and Thakur, 2024; Farrokhi and Lashkaripour, 2024). I show that a unilateral regulation can be effective in reducing the environmental costs in not only the country implementing the policy but also in other countries. This conclusion, however, would depend critically on the size of the regulation-imposing country and also, on how well the waste-exporting countries are able to adapt to the regulation domestically.

2 China's Waste Import Regulation

Since 1980s, to alleviate the shortage of raw materials, China has been importing waste materials that can be used as inputs in manufacturing production. Over the past three decades, China's waste imports have grown substantially, making China the chief importer in many waste categories. In 2016, China imported 48.9 million metric tons of waste, with its share in global waste imports at 17%. Dissecting China's 2016 imports by waste type,

Table 1 shows that China's share stood at over 45% in both plastic and paper waste imports, at over 25% in yarn waste imports, and at over 2% in several other waste types.

While imported waste provides employment to waste reprocessors and inputs for manufacturing production, the reprocessing or disposal of this waste also poses serious health and environmental concerns, especially when it is contaminated with nonrecyclable biohazardous materials. As a result, the Ministry of Ecology and Environment (formerly, Ministry of Environmental Protection) of China has implemented a series of regulations over the years to crack down on imports of illegal waste materials. The first catalog of forbidden and restricted waste categories was released in 2008, followed by "Operation Green Fence" (OGF) in 2013.[1] Several measures were taken by Chinese customs under OGF, which ran from February to November of 2013, to enforce waste import regulations adopted prior to that year, including rejecting those incoming waste shipments in which share of contaminants was larger than 1.5% by weight.

To study the impact of China's waste import regulations on global waste trade, I focus on the recent "Operation National Sword". In July 2017, the Chinese government announced Operation National Sword, which had two key objectives. The first was to ban imports of harmful waste including plastic, unsorted paper, yarn, and vanadium slag by the end of 2017. The second was to ban imports of those waste categories that can be replaced by domestic sources by the end of 2019. Any hazardous, medical, electronic, or municipal waste is also considered illegal under this regulation.[2] Other waste materials like old corrugated boxes that were not directly banned were also impacted by this regulation, particularly due to the new contamination limit of 0.5% proposed in November 2017 (Resource Recycling, 2022).

According to You (2018), the banned categories fall under five wider types: plastic, paper, yarn, metal, and wood, which I consider as treated. The 2017 regulation did not directly cover imports of glass or organic waste. However, in practice, glass waste may be contaminated

[1]The catalogs are available at: https://english.mee.gov.cn/Resources/Policies/policies/Solidwastes/200806/P020080620471882399901.pdf

[2]The official policy document "Implementation Plan for Banning the Entry of Foreign Waste and Promoting the Reform of Management System of the Solid Waste Import (Decree No. 70, 2017)" is available at: https://www.gov.cn/zhengce/content/2017-07/27/content_5213738.htm.

with hazardous substances and organic waste with biocontaminants with a high likelihood (Bebinger, 2023; Hughes, 2023). Therefore, I consider glass and organic waste among the waste types affected by the ban. Figure 1 shows that while China's share in imports of banned waste and regular non-waste goods moved in a parallel manner prior to the ban, its share in imports of banned waste types declined substantially post the announcement of Operation National Sword in 2017. In contrast, China's share in imports of regular goods followed an upward trend post the announcement of the ban. These patterns hold even when considering total quantity of waste imports by China (See Figure A.1).

As China was a major participant in the global waste trade market, even the implementation of a unilateral import ban by China is bound to affect other countries engaging in waste trade. The direction of the impact of the ban on other countries is, however, unclear. On the one hand, I find reports of the US materials recycling facilities stockpiling materials, landfilling some recyclables, and even cutting down or scaling back recycling collection programs in the aftermath of the ban (Staub, 2017*a*,*b*). On the other hand, reports suggest diversion of some plastic waste to other Southeast Asian countries (Resource Recycling, 2022). In response to this diversion of waste following China's ban, developing countries like Vietnam, Indonesia, Malaysia, Thailand, Taiwan, and India announced temporary restrictions on their waste imports (Resource Recycling, 2022). These countries particularly imposed restrictions on plastic and paper waste imports, which tend to be subject to contamination with harmful substances (Hinz, 2024).

With respect to responses of major waste exporters, empirical evidence demonstrates that while paper waste from the US was diverted to other low-income countries, its plastic waste exports, not only to China but also to other low-income countries, decreased (Sigman and Strowe, 2024). The study by Martin et al. (2021) further reveals that while French plastic waste exports initially shifted to other Asian countries following the ban, this diversion was temporary, with exports eventually redirected to other European Union (EU) member states. Their analysis uncovers additional nuance with regard to waste redistribution within the EU, where Germany and Belgium became primary destinations for low-quality plastic waste, while

Spain and Italy specialized in reprocessing of high-quality plastic waste. Katz (2019) provides further evidence that rising operational costs have undermined the financial viability of waste collection and recycling programs across major developed economies, including the United States, the United Kingdom, and Australia.

Assuming that the overall waste generation is unaffected by the ban, if exporting countries divert their waste to other importing countries, the share of these countries in waste imports would increase. In contrast, if exporting countries begin to scale back their collection programs or manage increasing quantities of waste domestically, the share of other importing countries may even decline with the ban. Table 2 shows that different waste materials vary significantly in their unit-values. Among the waste types affected by the ban, materials like metal, glass, and yarn have considerably higher unit-values than other materials. Such high-value materials tend to be cleaner, easier to recycle, and of better quality, which suggests that the impact of the ban may be heterogeneous by waste type. Following the ban, developed countries might retain high-value recyclables like metals that both require advanced technology to reprocess and have established local industrial demand, while continuing to export labor-intensive, low-value waste like plastics for processing to other countries.

3 Econometric Framework

To study the impact of China's 2017 waste import ban on international waste flows, I derive an equation capable of being estimated based on the workhorse gravity model of trade. Producers of material m in country i can either sell their product domestically or at any destination country j, where m can be a waste or a regular commodity. Let the value to producer in country i of shipping material m to country j be:

$$U_{mijt} = \alpha_{mi} + \beta_1 X_{mjt} + \tilde{\mu}_{ij} + \varepsilon_{mij}, \tag{1}$$

where X_{mjt} are time-varying characteristics specific to country j for material m, $\tilde{\mu}_{ij}$ represents the time-invariant component of the attractiveness of destination j to country i, and

ε_{mij} is an extreme value distributed error term with the cumulative distribution function $\exp\{-\exp\{-\varepsilon_{mij}\}\}$. The value to producer in country i of selling material m domestically is:

$$U_{miit} = \beta_2 X_{mit} + \tilde{\mu}_{ii} + \varepsilon_{mii}, \tag{2}$$

where X_{mit} are time-varying characteristics specific to country i for material m, $\tilde{\mu}_{ii}$ represents the attractiveness of selling domestically , and ε_{mii} is extreme-value distributed. Using standard transformation, the share of material m shipped from i to j is:

$$s_{mijt} = \frac{\exp\{\alpha_{mi} + \beta_1 X_{mjt} + \tilde{\mu}_{ij}\}}{\exp\{\beta_2 X_{mit} + \tilde{\mu}_{ii}\} + \sum_{k \neq i} \exp\{\alpha_{mi} + \beta_1 X_{mkt} + \tilde{\mu}_{ik}\}}, \tag{3}$$

while the share of material m sold domestically is:

$$s_{miit} = \frac{\exp\{\beta_2 X_{mit} + \tilde{\mu}_{ii}\}}{\exp\{\beta_2 X_{mit} + \tilde{\mu}_{ii}\} + \sum_{k \neq i} \exp\{\alpha_{mi} + \beta_1 X_{mkt} + \tilde{\mu}_{ik}\}}. \tag{4}$$

After taking logs, subtracting Equation (4) from Equation (3) yields:

$$\ln(s_{mijt}) - \ln(s_{miit}) = \alpha_{mi} + \beta_1 X_{mjt} - \beta_2 X_{mit} + \mu_{ij}, \tag{5}$$

where $\mu_{ij} = \tilde{\mu}_{ij} - \tilde{\mu}_{ii}$.

To take Equation (5) to data, I need information on the share of each destination country and the share of intranational trade in each material for every exporting country. To be able to compute these shares, I need information on overall volume of each material produced in each country. Inclusion of domestic production is crucial for identification and estimation of the impact of any non-discriminatory trade policy like China's 2017 waste import ban (Yotov et al., 2016). However, comprehensive production data, particularly on volume of production of different materials or generation of each waste category separately, are challenging to obtain. Therefore, like in gravity equation estimations, total domestic production can be imputed using a variable that captures the overall market size of each material, $\mathcal{G}_{mit}$.

Bilateral trade shares are then $s_{mijt} = TF_{mijt}/\mathcal{G}_{mit}$ while share of intranational trade is

$s_{miit} = 1 - \sum_j s_{mijt} = 1 - \sum_j (TF_{mijt}/\mathcal{G}_{mit})$, where TF_{mijt} is the volume of exports from i to j in year t. Substituting the expressions for shares into Equation (5) and simplifying, I obtain the following equation:

$$\ln(TF_{mijt}) = \alpha_{mi} + \beta_1 X_{mjt} - \beta_2 X_{mit} + \mu_{ij} + \ln(\mathcal{G}_{mit} - \sum_j TF_{mijt}) \tag{6}$$

As trade data suffer from heteroscedasticity and a large number of zero flows, I estimate this equation using Poisson Pseudo-Maximum Likelihood (PPML) method, which yields consistent and efficient estimates (Silva and Tenreyro, 2006).

One assumption underlying the above equation is that the cost of disposal is so low that waste generation is largely unresponsive to changes in such costs. For example, as households in the US pay for waste collection through property taxes, management fees, or a fee for maximum volume of waste generated, they essentially face zero marginal cost for waste collection (Sigman and Strowe, 2024). Similarly, for industrial establishments, changes in waste generation would probably be negligible in response to changes in cost of waste collection as this cost would account for only a small share in their overall cost of production. Therefore, the changes in cost of disposal as a result of a waste trade regulation would affect the share of waste disposed through a rearrangement in volume of flows to different destinations (the numerator) rather than via changes in overall waste generated (the denominator).

I employ a difference-in-differences approach to identify the effect of China's 2017 waste import ban on bilateral waste flows. Separating out the term quantifying the treatment effect from the rest of the terms, I write the regression equation as follows:

$$\ln(TF_{mijt}) = \beta_1 Treat_m \times Post_t + \beta_2 X_{it} + \beta_3 X_{jt} + \boldsymbol{\beta_4 \mathbf{X_{mjt}}} + \mu_{mij} + \mu_t + \ln(\mathcal{G}_{mit} - \sum_j TF_{mijt}), \tag{7}$$

where the main variable of interest is the product of $Treat_m$, an indicator for materials affected by China's ban, and $Post_t$, an indicator that takes the value one starting in the year of the announcement of the ban, 2017. Ex-ante, the direction of the treatment effect is unclear. The coefficient of interest β_1 will be positive if trade in banned waste is diverted to countries, negative if countries import lower volumes of waste as a result of China's ban, or zero if countries are unaffected by the ban. The variables, X_{it} and X_{jt}, include exporter or importer specific time-varying covariates such as economic output, income per capita, membership status in international environmental agreements on waste trade, and environmental preferences, which affect the willingness of a country to export or import waste. To isolate the impact of China's ban from the following waste import regulations imposed by other countries, I include several material-importer-year level indicators, $\mathbf{X_{mjt}}$, which take a value of one for all years after country j imposes a restriction on its imports of waste material m. I also control for bilateral effects idiosyncratic to each material using μ_{mij} and secular trends in overall trade flows and trade costs using μ_t. I include the term capturing volume of domestic trade, $\ln(\mathcal{G}_{mit} - \sum_j TF_{mijt})$, with its coefficient set to unity.

Given the high dimensionality of my data, I experiment with alternative sets of controls and fixed effects to assess the robustness of my results. In some specifications, I control for time-effects idiosyncratic to each trade partner using exporter-year and importer-year effects along with material-type effects and bilateral effects or controls for distance, contiguity, common language, and colonial relationships. In these cases, I control for membership in multilateral agreements using exporter-importer-year level indicators. Alternatively, I control for time effects idiosyncratic to each country pair like bilateral trade costs, bilateral trade imbalances, and membership status of the pair in multilateral agreements, using exporter-importer-year effects along with material type fixed effects. Regardless of the combination of fixed effects, I am able to control for variation both across materials and across years. Therefore, the treatment effects are identified off of the deviation from the time trend within materials, rather than comparisons across materials or years.

To study the dynamic impact of the ban, I also estimate an event study DID version of

Equation (7), which is written as follows:

$$\ln(TF_{mijt}) = \beta_0 + \sum_{s \neq 2016} \beta_s Treat_m \times \mathbb{1}(t = s) + \beta_2 X_{it} + \beta_3 X_{jt} + \boldsymbol{\beta_4} \mathbf{X_{mjt}} \tag{8}$$
$$+ \mu_{mij} + \mu_t + \ln(\mathcal{G}_{mit} - \sum_j TF_{mijt}),$$

where 2016, the year before the announcement of the ban, serves as the base category. The parameters of interest, however, cannot be interpreted as quantifying precisely the treatment effects unless the parallel trends assumption is satisfied. I test for parallel trends by estimating Equation (8) and focusing on the coefficients for the years prior to the ban, 2014-15. Further, to assess heterogeneity in the treatment effect by waste type, I estimate the following equation:

$$\ln(TF_{mijt}) = \sum_{n \neq Regular} \beta_n \mathbb{1}(m = n) \times Post_t + \beta_2 X_{it} + \beta_3 X_{jt} + \boldsymbol{\beta_4} \mathbf{X_{mjt}} \tag{9}$$
$$+ \mu_{mij} + \mu_t + \ln(\mathcal{G}_{mit} - \sum_j TF_{mijt}),$$

where regular goods, denoted by $Regular$, together serve as the base category.

Since Equation (7) is in log-level form, the overall treatment effect is $100 \times (e^{\beta_1} - 1)\%$. Analogously, I compute treatment effects over time and by waste type by transforming estimates of β_s and β_n from Equation (8) and Equation (9), respectively. To examine heterogeneous treatment effects across importer types, I extend Equations (8) to (9) by allowing the coefficients β_s and β_n to vary by importer type. Specifically, I include interactions of the treatment indicators $\sum_{s \neq 2016} Treat_m \times \mathbb{1}(t = s)$ and $\sum_{n \neq Regular} \mathbb{1}(m = n) \times Post_t$ with dummy variables for each importer category: the regulation-imposing country, China, and other major waste importers, the lower-income countries (or China's neighbors). These interactions enable estimation of the policy's impact on each type of importer separately.

To check whether China's ban impacts trade flows on the extensive margin, i.e., changes the probability of a country pair trading at all, I first construct an indicator variable Y_{mijt} that equals 1 if there is positive bilateral trade of material m between country i and country

j at time t, and 0 otherwise. I then estimate the following probit model:

$$P(Y_{mijt} = 1|X) = \Phi(\beta_1 Treat_m \times Post_t + \beta_2 X_{it} + \beta_3 X_{jt} + \boldsymbol{\beta_4 \mathbf{X_{mjt}}} \\ + \mu_{mij} + \mu_t + \ln(\mathcal{G}_{mit} - \sum_j TF_{mijt})), \tag{10}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. A statistically significant estimate of β_1 would indicate that China's ban affected the probability of bilateral trade occurring, with a positive (negative) coefficient suggesting an increase (decrease) in the likelihood of trade.

4 Data

As described in the previous section, the estimation of Equation (7) relies on data on bilateral material trade flows and production. I obtain data on volume (in metric tons) of bilateral trade flows for six-digit Harmonized System (HS6) products from the BACI-CEPII database for the years 2014-2020 (Gaulier and Zignago, 2010). Among all HS6 categories, waste categories are those for which the commodity description primarily uses the keywords *waste*, *scrap*, *residue*, or *residual*, as in Kellenberg (2012). The waste categories in my sample fall under ten broad types: glass, gold, metal, organic, paper, plastic, platinum, rubber and leather, wood, and yarn (See Table A.2 for the HS6 codes under each type).

The waste categories affected by the ban: glass, metal, organic, paper, plastic, wood, and yarn, form the treatment group. For each of these waste categories, I also include trade flows on those commodities that are essentially the same material but not waste, i.e., I include HS6 categories that belong within the same HS2 categories as the waste categories, to serve as the control group. However, it is possible that regular materials within the same HS2 are also affected by the ban through recategorization of waste as regular goods or spillovers due to enforcement of contamination limits. Therefore, within each HS2, I include only those HS6 categories of regular materials that are of higher average unit-value than all HS6 materials categorized as waste. This procedure allows me to form a control group that is affected by same sources of variation as the waste materials, such as changes in shipping costs and changes in demand for a particular material in a country, while plausibly avoiding spillovers of China's ban, thereby allowing me to isolate the treatment effect. Further, Table 2 shows that waste types not targeted by the ban, rubber, leather, gold, and platinum, are high unit-value materials which tend to be easier-to-recycle, less contaminated, and remain economically worthwhile to collect for recycling. These waste types serve as an alternative control group in my analysis. The balanced bilateral trade flow panel is generated by aggregating the flows across HS6 categories under each waste or regular material and assuming that a missing trade flow between a country pair is a zero trade flow.

I further require data on the potential market size for each material, $\mathcal{G}_{mit}$. While I do not directly observe the total domestic production of all waste materials, I do observe the total generation of municipal waste from Kaza et al. (2018), which I use to create a proxy for the size of the waste market (See Appendix A for details). While I have domestic production data on most treated waste types and one control waste type, rubber and leather, I lack data on volume of production of regular materials.[3] Therefore, while I am able to estimate the treatment effects using a limited sample of observations where domestic production data are available, in my baseline regressions where regular goods serve as the control group, I exclude the domestic disposal term, $\ln(\mathcal{G}_{mit} - \sum_j TF_{mijt})$.

I control for the impact of waste import regulations imposed by other countries following China's ban by combining information on such regulations from Resource Recycling (2022). As described in Section 3, the mjt level indicators take value one for all years after the importing country j imposes a restriction on imports of waste material m, and zero otherwise. Specifically, these indicators encapsulate the regulations listed in Table 3, which are imposed by developing countries on materials like plastic or paper which are particularly prone to contamination (Hinz, 2024). By focusing on these specific countries and materials—representing

[3] Yotov et al. (2016) provides a list of sources for domestic production data by industry. Further, Borchert et al. (2021, 2022) is the latest dataset containing domestic trade data compiled from administrative sources. However, all these datasets report domestic production in terms of value rather than volume, which is required in estimation of Equation (7).

the most likely targets for waste diversion——these indicators capture the most crucial policy and enforcement changes that may have also affected global waste flows post China's ban.

I also control for membership status of countries in an international environmental agreement on waste trade, the Basel Ban Amendment. The Basel Ban Amendment is an agreement among members to the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and Their Disposal, better known as the Basel Convention, to prohibit members of the Organization for Economic Cooperation and Development (OECD), the European Union (EU), and Liechtenstein (Annex VII countries) from exporting hazardous waste defined under the Convention to all other countries (IPEN and Basel Action Network, 2020). Thus, a non-Annex VII country that has ratified the agreement cannot accept hazardous waste from Annex VII countries, regardless of whether they have ratified the agreement or not. Similarly, an Annex VII country that has ratified the agreement cannot export hazardous waste to non-Annex VII countries, regardless of whether they have ratified the agreement or not. While the Basel Ban Amendment entered into force only toward the end of my sample period, in December 2019, the ratification of the amendment by countries might reflect their environmental preferences related to waste reprocessing or disposal.

I construct two types of variables used to control for participation in the Basel Ban Amendment. First, I create exporter (importer)-year level indicators that equal one for all years after an exporter (importer) ratifies the amendment, and zero otherwise. Second, I construct an exporter-importer-year level indicator that equals one in two scenarios: when an OECD/EU exporter that has ratified the amendment trades with a non-OECD/EU importer, or when an OECD/EU exporter trades with a non-OECD/EU importer that has ratified the amendment.[4] For all other country pairs, this indicator equals zero. In all my regressions, I include whichever of these two measures is not absorbed by the fixed effects.

I also control for the size and income per capita of the exporting and importing countries using data on GDP and GDP per capita, both in constant 2015 USD, from World Development Indicators database. To control for the environmental preferences of countries, I use

[4]Liechtenstein is not included in my sample.

data on the Environmental Performance Index (EPI) from Wolf et al. (2022). The EPI quantifies the environmental performance of a country's policies, on a scale of 0-100, by combining 32 different indicators on the protection of human health and ecosystem vitality. While EPI may be an imperfect measure of the environmental preferences of a country, it is the only measure in my knowledge that provides this information on a comprehensive list of countries. The EPI, however, are available only for alternate years of my sample period, starting in 2014. To complete the series, I linearly interpolate the EPI for the remaining years.

I also obtain data on time-invariant and time-varying bilateral trade barriers. I obtain data on great circle distances from Mayer and Zignago (2011), calculated using the latitude and longitude of the most important city or official capital of each country. I also use their indicators on contiguity, common language, and ever having had a colonial link between country pairs as additional bilateral controls. To control for the relationship between trade imbalance and the quality composition of trade (Hummels and Skiba, 2004; Lee, Wei and Xu, 2020), I construct a measure of bilateral trade surplus from the importing country's perspective. To do so, I first gather the bilateral trade volume data on those commodities that can be shipped in the same transport vessels as waste, i.e., I exclude trade data on animal and food products as well as mineral oils and gases (HS codes: 01-24 and 2705-2713), which require special shipping containers. Then, I construct the trade surplus from the importing country's perspective as the ratio of its total export volume to import volume to use as control in all my specifications. All my results in Section 5 are robust to including this trade imbalance measure in regressions and to including time-invariant bilateral controls in place of the bilateral fixed effects.

The complete bilateral trade panel comprises 4,668,482 observations (7 years $\times$ 227 exporters $\times$ 226 importers $\times$ 13 materials).[5] In the alternate sample, where the high-value waste categories serve as the control group, the complete bilateral trade panel comprises 3,591,140 (7 years $\times$ 227 exporters $\times$ 226 importers $\times$ 10 materials).

[5]The materials in my sample comprise the 7 treated waste types and a regular material corresponding to each waste material. For paper, no regular HS6 category exists for which the unit-value is larger than all waste HS6 categories. Therefore, I have 7 waste materials in the treated group and 6 regular materials in the control group.

5 Waste Flow Results

In this section, I present the results on the impact of China's 2017 waste import regulation on overall international waste flows, and then, assess the heterogeneity of the impact by importing country and waste type.

5.1 Global Impact

Column (2) in Table 4 presents the results from estimation of Equation (7). I find that the DID estimate is -0.084 and statistically significant at the 10% level. Specifically, China's 2017 waste import ban led to a decrease of 8.1% in bilateral trade flows of targeted waste categories on average. Since column (2) includes fixed effects at the material-exporter-importer level and year level along with controls for exporter-year and importer-year characteristics, I identify this effect off of the variation within material types specific to each country pair.

My results are robust to including material type and exporter-importer fixed effects separately (in column (1)), to including exporter-year and importer-year fixed effects in place of exporter-year and importer-year controls along with exporter-importer-year controls (in column (3)), and to including exporter-importer-year fixed effects (in column (4)). The estimated effect ranges from 9.8% to 11% decline in bilateral flows of targeted waste types across these specifications. However, I consider column (2), with the highest Adjusted Pseudo-R^2, as my preferred specification.

To account for waste import bans enacted by other countries after China's ban, I include controls at the material-importer-year level encapsulating restrictions listed in Table 3. Column (2) reveals that, contrary to expectations, for most countries imports of restricted materials increased even after they implemented their bans. These increases range from 31.3-156% across banned waste materials and regulation-imposing countries. The sole exception are Indian imports of plastic waste, which experienced a 46.2% decline, following its 2019 plastic waste import restriction. These findings suggest that the decline in the global waste trade market cannot be attributed to the regulations that followed China's ban. In fact, these regulations seemed to have proved ineffective in achieving their intended goal, as demonstrated by the continued banned waste imports into the regulation-imposing countries. These patterns continue to hold in columns (1) and (3)-(4).

The difference in the number of observations across specifications (1)-(4) is explained as follows. Even though I estimate the different specifications on the same number of observations, depending on the specification, observations separated by fixed effects or singletons are dropped from the regression (Correia, Guimarães and Zylkin, 2021).[6] While keeping these observations does not affect the coefficient estimates, statistical significance may be overstated. Therefore, the estimation algorithm now automatically drops these observations (Correia, 2015; Correia, Guimarães and Zylkin, 2021).

Table 5 presents the results from estimation of Equation (8). Firstly, I find only small and statistically insignificant coefficients on the pre-ban interactions in most specifications, which provides evidence in favor of parallel trends. Column (2) shows that the ban caused bilateral flows of banned waste types to decline by 6.9% in the year of the announcement of the ban relative to their level in 2016. This initial decline was followed by larger declines in subsequent years: 9.7% in 2018 and 15.1% in 2019. Even though I estimate a negative impact in 2020 as well, this impact is not statistically significant. These findings are robust to alternative specifications in columns (1) and (3)-(4), where effects are also quantitatively larger. Therefore, China's waste import ban seems to have adversely affected waste flows between the average country pair, with this adverse effect increasing in magnitude over the years. Next, I investigate whether the decline in global waste trade market is solely due to reduced imports by China, or if other countries also experience a shift in their waste imports.

5.2 By Importer

In addition to the direct impact on China, the waste import ban could have affected other countries' waste imports as well. If the displaced waste was simply diverted to other countries,

[6] This occurs when the outcome variable is perfectly predicted by a fixed effect (or a combination of fixed effects). This happens when all observations of the dependent variable are zeros (separated by fixed effects) or when it has only one observation (singleton) for a particular fixed effect category.

their waste imports would increase. If, instead, the exporting countries began to increasingly manage their waste domestically as a result of the ban, then the other countries' waste imports would decrease. Moreover, such a response could vary with time. To quantify these effects, I add interactions between the term capturing dynamic treatment effects, $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$, and importing country group indicators to Equation (8). These triple interaction coefficients show the *additional* effect on imports for that country group, beyond the baseline effect on the rest-of-world (ROW) captured by the coefficients on $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$. The sum of the coefficients on $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and its interaction, therefore, represents the *total* impact on the imports of that country group.

Figure 2 presents the results after including interactions with an indicator for China as the importing country (corresponding to column (2) in Table A.3). These results show that while ROW was on average unaffected by the ban, China's total waste imports declined over the years post the announcement of the ban. Specifically, Table A.3 shows that the coefficients on $\sum_{s=2017}^{2020} Treat \times \mathbb{1}(t = s)$ are statistically insignificant across specifications, suggesting that on average waste imports of countries other than China were unaffected by the ban. Further, the coefficients on the interactions between $\sum_{s=2017}^{2020} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ are negative and statistically significant at the 1% level in all specifications. China's banned waste imports fell by an additional 29.7-57.4% in 2017, beyond the impact on banned waste imports of ROW, with this effect growing to 78.3-87.2% by 2020. Therefore, China's total waste imports declined by 32-57.7% in 2017, with this effect growing to 77.7-86.5% by 2020. These findings suggest that the negative impact on global waste flows is primarily driven by the decline in China's imports.

To determine whether other countries are also impacted by China's ban, I additionally include interactions of the term capturing dynamic treatment effect with indicators for two different importing country groups in turn. First, I add interactions with an indicator for a low-income importing country. The low-income country indicator takes a value of 1 for those countries in my sample that lie in the bottom 30% of the distribution of GDP per capita as of 2014, the first year of my sample period. Figure 3 shows that the total impact on low-income countries is negative and statistically significant at the 10% level in 2017 (the counterpart Table A.4 presents further details). Although I also observe negative coefficients in 2018-2020, these are rather imprecisely estimated, and hence, not statistically significant. The total impact on low-income importers amounts to a decline of 33.2% in 2017. On countries other than China and the low-income group, I find evidence of diversion of banned waste materials. The coefficient on $Treat \times \mathbb{1}(year = 2018)$ is positive and statistically significant at least at the 10% level in all specifications. ROW increased their waste imports by 4.3-10% in 2018, with this effect growing to 6.7-7.9% by 2020. These results are robust to alternative specifications, as shown in columns (1) and (3)-(4) in Table A.4.

Further, not only is the treatment effect on China still persistently negative, but also the size of this effect is larger than that on low-income importers over 2017-20. These results provide suggestive evidence that low-income importers also decreased their waste imports as a result of the ban, albeit to a smaller extent than China. While surprising, my findings align with other evidence, which finds a decrease in US plastic waste exports not only to China but also to other low-income countries (Sigman and Strowe, 2024), redirection of French waste exports to other EU countries (Martin et al., 2021), and deterioration in financial viability of waste collection programs in developed economies (Katz, 2019) following the ban. The decline in waste exports to low-income countries could partly stem from impaired collection programs in waste exporting countries following the ban. This explanation is particularly compelling given that all my specifications control for concurrent waste import restrictions, ruling out the possibility that subsequent bans by other countries drive the reduction in low-income countries' waste imports.

My results, however, differ from Balkevicius, Sanctuary and Zvirblyte (2020) and Sun (2019) who provide some evidence of diversion of waste, especially of low-quality, to other developing countries as a result of the earlier Operation Green Fence. As OGF primarily involved increased screening of waste shipments for contamination at the border, Balkevicius, Sanctuary and Zvirblyte (2020) rank countries based on the average unit-value of their exports within each waste category to study the differentiated impact on low-quality waste imports.

While this analysis identifies variation in impacts across waste types, the use of only waste trade data prevents estimation of the overall treatment effect on waste flows. Sun (2019) also employs a difference-in-differences approach where regular commodities that belong to the same resource group as waste serve as the control group. In contrast, my study involves analysis of global waste flows rather than focusing solely on developing country imports, a broader set of waste categories, and the more sweeping 2017 regulation, which banned entire waste categories outright.

Second, I add interactions with an indicator for a country in China's neighborhood. The Neighbor indicator takes a value of 1 for those countries in my sample that lie in the top 10% of the distribution of geographical proximity to China. I measure geographical proximity using the great circle distances from Mayer and Zignago (2011). Table A.5 shows that, unlike low-income importers, countries neighboring China increased their waste imports as a result of China's ban. These findings suggest that while low-income countries reduced their banned waste imports, other countries, especially China's neighbors, absorbed some of the diverted waste material. Next, I examine whether heterogeneity in impacts by waste types explains the surprising decline in waste imports by low-income countries.

5.3 By Waste Type

To analyze heterogeneous effects across waste types, I first classify materials based on their average unit values (See Table 2). Materials with substantially higher unit-values—metal, glass, and yarn–are classified as *high-value*, while those with markedly lower unit-values are *low-value*. This classification aims to capture key economic differences across materials; high-value materials are potentially more readily recyclable than low-value waste materials. Further, demand by different countries across materials varies with their industrial composition and specialization in different reprocessing activities.

Table A.6 presents the results from estimation of event-study version of Equation (9) after including interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. Left panel in Figure 4 shows that low-income countries decreased their high-value waste imports by 43.4-45.7% over 2017-18, relative to the level in 2016. Although I also find negative point estimates for the subsequent years, 2019-20, these estimates are not statistically significant. Column (2) in Table A.6 further shows that the coefficients on the interaction terms, $\mathbb{1}(m = \text{High-value}) \times \sum_{s=2017}^{2018} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$, are negative and statistically significant at least at the 10% level. These patterns are qualitatively robust to different specifications, as shown in columns (1) and (3)-(4) of Table A.6.

The right panel in Figure 4 shows that low-income countries increased their low-value waste imports by 21.9-29.4% in 2018-2020, relative to the level in 2016. I also find evidence of diversion of low-value waste to ROW, which amounts to an increase of 8.8% in 2020. Column (2) in Table A.6 shows that the coefficients on $\mathbb{1}(m = \text{Low-value}) \times \sum_{s=2017}^{2020}(s = t)$ and $\mathbb{1}(m = \text{Low-value}) \times \sum_{s=2017}^{2020} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$ are positive and statistically significant across most specifications. Therefore, both low-income countries and ROW absorbed some of the diverted low-value waste materials between 2017-2020. Finally, Figure 4 shows that China substantially decreased its imports of banned waste materials over the years regardless of value, although this negative impact is larger for low-value waste materials.

These results taken together reveal that low-value waste materials were diverted to low-income countries, consistent with expectations, while high-value materials saw reduced exports across destinations, including low-income countries. This suggests that for high-value waste materials, the overall international trade declined rather than shifting to new destinations. While I do not disaggregate the underlying mechanisms—differences in industrial composition or specialization in different recycling processes across countries, and material-specific recyclability—the observed heterogeneity in impacts across waste types provides a robust explanation for the counterintuitive reduction in waste imports by low-income countries, largely driven by high-value waste materials.

To ensure that the heterogeneity in impacts is driven by certain high-value waste materials, I also present results from the estimation of Equation (9) where the waste types are now individual categories in my sample. Column (2) in Table 6 shows that China substantially decreased its imports of all targeted waste types, including those not directly covered by the ban, with the largest declines for glass (94.3%), organic (84.1%), plastic (80.2%), and wood (79.1%). Low-income countries experienced a diversion of paper, plastic, organic, and wood waste, amounting to an increase of 36.1%, 6.7%, 10.8%, and 39.5%, respectively. Further, I find that these countries decreased their imports of high-value waste materials, metal and glass, although these effects are not statistically significant. ROW, similarly, experienced diversion of low-value waste materials, organic, plastic, and wood, although to a lower extent than low-income countries. These patterns hold across specifications in Table 6.

Therefore, as China reduced its waste imports, some of the low-value waste materials were absorbed by other countries, especially low-income countries, while the overall international high-value waste trade market shrank. Moreover, while low-income countries absorbed some of the displaced low-value waste, they could only partially make up for the reduction in the size of the international low-value waste trade market. Following the ban, developed countries might retain high-value recyclables like metals that require advanced technology to reprocess or have established local industrial demand, while continuing to export low-value waste like plastics for labor-intensive reprocessing to other countries.[7]

5.4 Extensive Margin

Being a sizeable shock to the international waste trade market, China's waste import ban could have led some country pairs to stop trading in waste altogether. Therefore, the negative treatment effects I estimate may be due to changes on the extensive margin, i.e., due to cessation of bilateral trade, rather than those on the intensive margin. To estimate the extent to which extensive margin drives the reduction in global waste trade market, I estimate Equation (10) after adding the interaction between $Treat \times Post$ and $\mathbb{1}(j = \text{China})$.

Table 7 shows that the coefficients on both $Treat \times Post$ and its interaction with $\mathbb{1}(j = \text{China})$ are negative and statistically significant at the 1% level across specifications. Fur-

[7]Even before the ban, I find a divide in the direction of global waste flows, where higher-income economies typically handle high-value waste materials while lower-income countries process primarily low-value waste. In 2016, for instance, the average GDP per capita of the largest importers of high-value waste (accounting for 50% share in global imports) was 2.5 times that of largest importers of low-value waste.

ther, the coefficient on the triple interaction term is larger in magnitude than on the double interaction term. Upon estimating the average marginal effects, I find that China's 2017 ban decreased the probability of a typical pair trading at all by 0.5-3.9 percentage points (p.p.), with an additional negative impact when China is the importer of 4.4-17.5 p.p.[8] Therefore, while extensive margin seems to be a pertinent driver of the reduction in the size of the global waste trade market, this impact is primarily due to end of exports to China by other countries.

6 Robustness Checks

In this section, I assess the robustness of my results to an alternative control group that includes other waste types not covered under the ban. I further alleviate the concern that the estimated treatment effect is due to some form of omitted variation, rather than China's waste import ban, by conducting two placebo tests.

6.1 Alternative Control Group

In Section 5, I use regular HS6 materials, which were not a part of China's 2017 waste import ban, within the same HS2 categories as banned waste materials as the control group. While international flows of waste directly targeted by the ban and other waste materials contaminated with biohazardous substances are adversely affected, waste composed of easily recyclable, precious materials, would, like regular materials, not be affected by the ban. Such waste includes precious metals, like gold and platinum, and rubber and leather. Table A.2 shows the HS6 codes of these three waste types. Table 1 shows that China accounted for only a small share in global imports of these types while Table 2 shows that these waste materials, on average, have substantially higher value per unit than the targeted waste materials, which provide further reason to include these in the control group.

[8]For a dummy variable D, average marginal effect is computed as $\frac{\sum_i \Phi(X_i\beta|D=1)-\Phi(X_i\beta|D=0)}{n}$, where i denotes the observation and n the sample size.

I replicate the results in Section 5 with the alternative control group—gold, platinum, and rubber and leather. The results from the replication are in Figures A.2 to A.4 and the accompanying Tables A.7 to A.14. Figure A.3 shows that, like China, low-income countries, also decreased their overall banned waste imports as a result of the ban. Figure A.4 further shows that the decline in waste imports by low-income countries is driven by an overall reduction in the size of international high-value waste market while these countries still absorbed some of the diverted low-value waste. Table A.13 shows that the reduction in the international high-value waste market is primarily driven by reduction in trade in materials like metal and glass. Finally, Table A.14 shows that the impact on the extensive margin is driven by countries ending exports to China altogether. Overall, my findings with the alternative control group are qualitatively similar and quantitatively stronger than the baseline results.

Due to lack of data on generation of gold and platinum waste by country, I again exclude the domestic disposal term, $\ln(\mathcal{G}_{mit} - \sum_j TF_{mijt})$, from these regressions. Inclusion of the domestic disposal term, however, is important for identification of the impact of a non-discriminatory trade policy (Yotov et al., 2016). I find that my conclusions in Section 5 are also robust to restricting the control group to rubber and leather, for which generation data that I use in my regressions are available.[9]

6.2 Placebo Tests

To verify that my results are not due to some form of omitted variation, I conduct two placebo tests by assigning fake treated years and fake treated materials in turn. I first drop all data post the announcement of the ban, i.e., 2017 onward, and pick a fake treatment year before estimating Equation (7). Figure 5 shows the distribution of the absolute values of the test statistic on $Treat \times Post$ across two fake treatment years—2015 or 2016—and the 4 specifications.[10] I find no statistically significant effect using any fake treatment year or any specification even at the 10% level. These results lend further support to parallel trends.

[9]Results with only rubber and leather in the control group are available upon request.

[10]Total number of regressions I estimate is 8 (2 fake treatment years $\times$ 4 specifications).

Next, I drop all observations on the treated waste types and pick a fake treated material before estimating Equation (7). Since my control group contains 6 regular materials (glass, metal, organic, plastic, wood, and yarn), I test every possible combination of these materials as fake treated groups, with a total of 41 different combinations to test.[11] Figure 6 displays the distribution of the absolute value of the test statistics across all 41 combinations and 4 specifications. Only 6% of these tests (10 out of 164) show statistical significance at the 10% level, mostly when glass is designated as treated. However, this effect disappears when glass is grouped with other materials in the fake treated group. This suggests that the control materials were largely unaffected by the ban. Figures A.5 to A.6 show that omitted variation is not a concern even with the alternative control group.

7 Conclusion

I quantify the impact of China's Operation National Sword, announced in 2017, on international waste flows by combining a difference-in-differences approach with the gravity model of trade. I find that the waste import ban implemented by China caused bilateral flows of banned waste to decline by 6.9% in the year of the announcement of the ban relative to their pre-ban level, which was followed by even larger declines in 2018-19. The negative impact on the international waste trade market is largely due to the decline in imports by China. China decreased its waste imports by 32-57.7% in 2017, with this reduction growing to 77.7-86.5% by 2020. However, the reduction in China's imports alone does not explain the hit that the global waste trade market took. Low-income countries also substantially decreased their high-value waste imports in the initial years following the implementation of the ban, while absorbing some of the displaced low-value waste. While the ban severely affected international trade of plastic waste, it also substantially reduced trade in other waste materials not directly targeted by the ban like glass and organic waste, which can create negative

[11] This includes 6 combinations with one material treated, 15 with two materials treated, and 20 with three materials treated. Testing four or five materials as treated would give the same results as testing two or one materials respectively, just with opposite signs.

externalities in the receiving countries, especially when commingled with environmentally damaging and hazardous material. Although changes on the extensive margin partly explain the reduction in global waste flows, this impact is primarily due to end of imports by China.

The literature provides a wide range of estimates for the externality costs from recycling and disposal of waste (Craighill and Powell, 1996; Eshet, Ayalon and Shechter, 2005; Kinnaman, 2009; McKinsey, 2016; Bond et al., 2020). By some estimates (Bond et al., 2020), the externality costs of plastic waste can be as high as \$1000/metric ton, which is equal to European Union tax on nonrecycled plastic waste levied on member countries starting on January 1, 2021. To quantify the externality costs imposed on waste importing countries, I rely on the estimates from Craighill and Powell (1996), which provides externality cost estimates from recycling of different materials.[12] Although countries import waste materials for use in local industries after recycling, much of this material ends up being disposed of, especially when difficult to recycle or contaminated with hazardous substances (Vidal, 2014*b*; Gutierrez, 2016*b*; Brooks, Wang and Jambeck, 2018). Therefore, given that landfilling generates higher environmental damages than recycling (Laurent et al., 2014), my estimates likely represent only a fraction of the true environmental burden borne by waste-importing countries.

China's external costs drop by 1.4 billion USD in 2017, with this impact growing to 3.8 billion USD by 2020. The cumulative savings in external costs in China by 2020 are, therefore, roughly 11.9 billion USD. Further, China is not the only country benefiting from the waste import ban. Other low income countries save 2.2 billion USD in 2017, which declines to 1.9 billion USD by 2018. These countries eventually face extra external costs of 161 million

[12] Specifically, the authors estimate £111.41/metric ton for aluminum, £67.20/metric ton for glass, £73.79/metric ton for paper, £31.64/metric ton for steel, £12.07/metric ton for high-density polyethylene, £21.25/metric ton for polyethylene terephthalate, and £11.55/metric ton for polyvinyl chloride, in externality costs from recycling. I convert the average costs for high- and low-value wastes into 2020 USD/metric ton, arriving at estimates of \$160.8/metric ton and \$68.052/metric ton, respectively, before use in my calculations. Further, lower-income countries with lower levels of environmental regulation likely incur higher externality costs from each unit of waste that is reprocessed locally. Therefore, social marginal costs (SMC) of waste are likely strongly negatively correlated with GDP per capita. Assuming that this relationship can be represented by $SMC_i = \beta/ln(\text{GDP per capita}_i)$, I arrive at estimates of \$185.19/metric ton for high-value waste and \$78.37/metric ton for low-value waste for China. The SMCs for low-income countries in my sample is by extension even higher. However, I use China's SMC values throughout my calculations, ensuring that any variations in total externality costs between countries are driven solely by differences in changes in waste volumes rather than by per unit cost differences.

USD by 2020. Nevertheless, the low-income countries see cumulative savings to the tune of 3.8 billion USD by 2020, roughly 32% of the cumulative savings in China. The savings in low-income countries are driven by the decline in their high-value waste imports in the initial years of the ban, even as they absorbed some of the displaced low-value waste.[13]

The conclusion that net environmental benefits arise from shifting waste trade patterns also partially relies on prior evidence that each unit of high-value waste material causes greater environmental damage than low-value waste. While some studies support this conclusion (Craighill and Powell, 1996), the literature seems to lack consensus due to challenges in waste classification, measuring toxicity, and measuring local variation in impacts (Eshet, Ayalon and Shechter, 2005; Laurent et al., 2014; Liboiron, 2016). Therefore, if this evidence proves inaccurate, it would alter my externality cost estimates. Although validating these differential environmental impacts across waste types is beyond the scope of this study, I experiment with setting uniform externality cost per unit for the two types of waste.[14] I find that cumulative savings for low-income countries by 2020 are now 1.3 billion USD, roughly 14% of the savings by China.

Overall, a unilateral environmental regulation implemented by a big participant in the waste trade market such as China can have positive consequences not just for China itself but also for other low-income countries that served as havens for the environmentally damaging waste originating in the developed world. My findings, further, suggest that as low income countries have the potential to serve as alternative destinations for waste, especially that of low-value, a unilateral waste trade regulation may fall short unless waste management and recycling programs for such waste pick up sufficiently in exporting countries. This finding is especially noteworthy because low income countries also tend to have laxer environmental regulations, thereby having the potential for the same quantity of waste to cause more environmental damage in such countries.

[13]All back-of-the-envelope calculations are based on estimates in column (2) in Table A.6.

[14]I now set the SMCs for both waste types at the lower value of $78.37/metric ton.

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8 Figures and Tables

Figure 1: China's Share in Imports of Treated and Control Commodities

This figure shows China's share in imports of commodities in the treated and control groups between 2014-2020. The dashed line represents the year right before the announcement of Operation National Sword in 2017. For both treated and control groups, shares in each year have been normalized by the respective 2016 share.

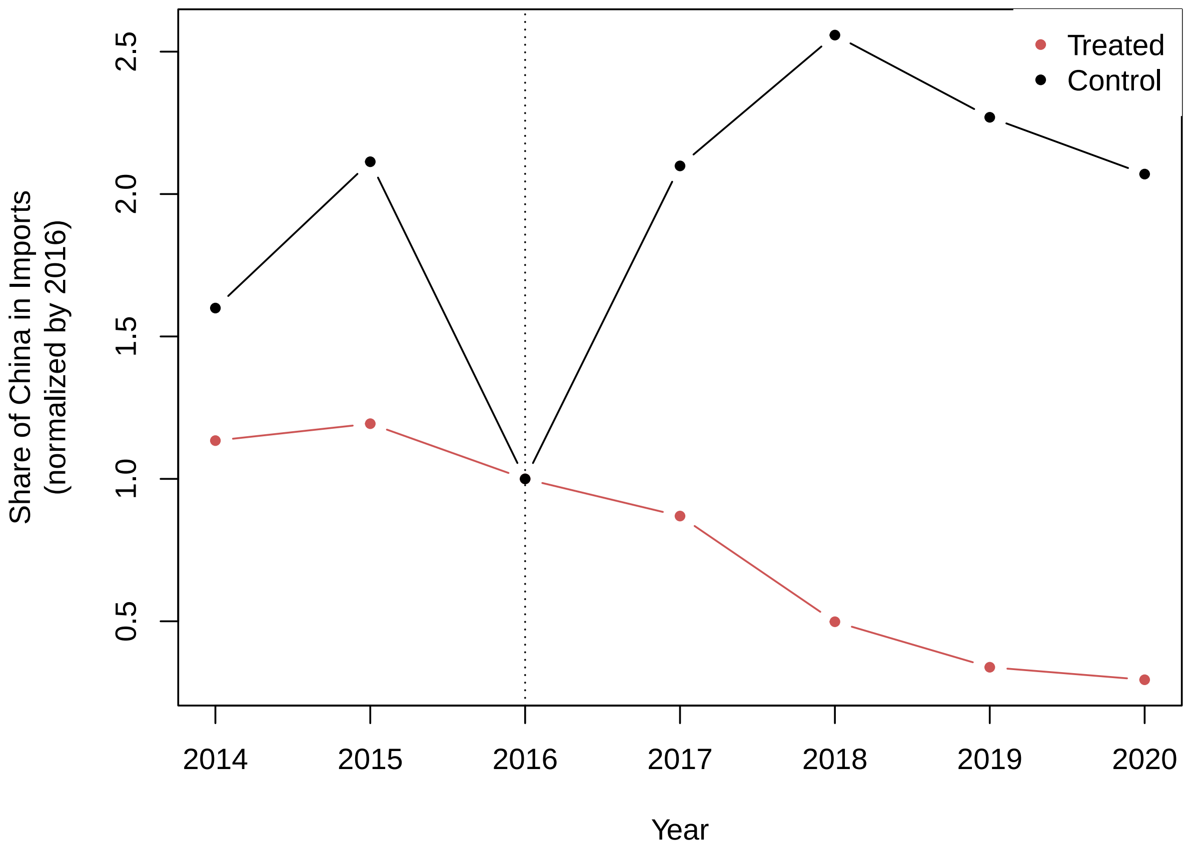


Figure 2: Dynamic Impact on China

This figure presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t=s)$ and $\mathbb{1}(j=\text{China})$. The black bars are the coefficients to $\sum_{s\neq 2016} Treat \times \mathbb{1}(t=s)$, capturing total impact on rest-of the-world (ROW), while the red bars are the coefficients to the sum of $\sum_{s\neq 2016} Treat \times \mathbb{1}(t=s)$ and $\sum_{s\neq 2016} Treat \times \mathbb{1}(t=s) \times \mathbb{1}(j=\text{China})$, capturing total impact on China. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

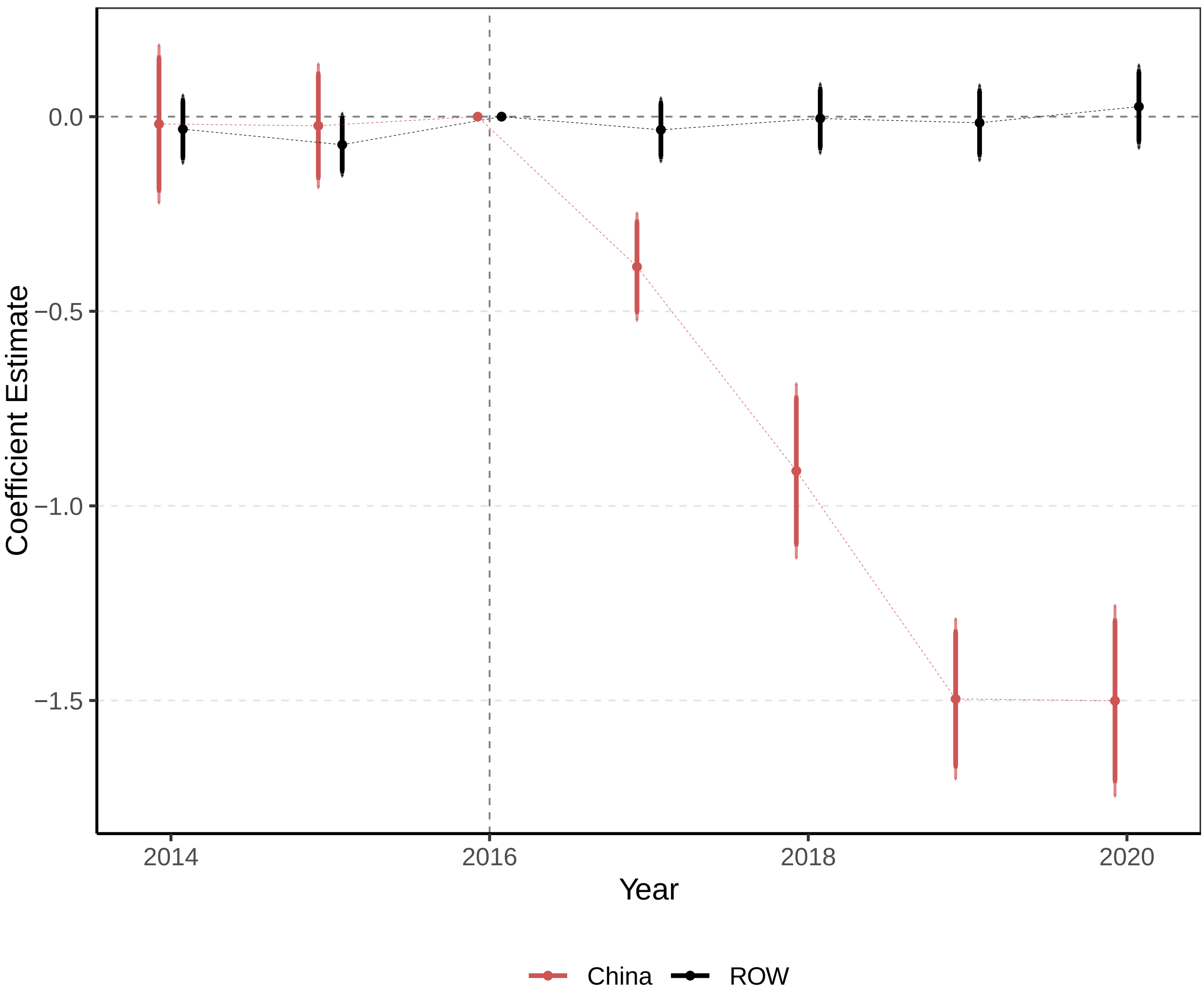


Figure 3: Dynamic Impact by Importer

This figure presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{Low-income})$. The black bars are the coefficients to $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$, capturing total impact on rest-of-the-world (ROW), the red bars are the coefficients to the sum of $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s) \times \mathbb{1}(j = \text{China})$, capturing the total impact on China, and the blue bars are the coefficients to the sum of $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$, capturing the total impact on lower-income countries. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

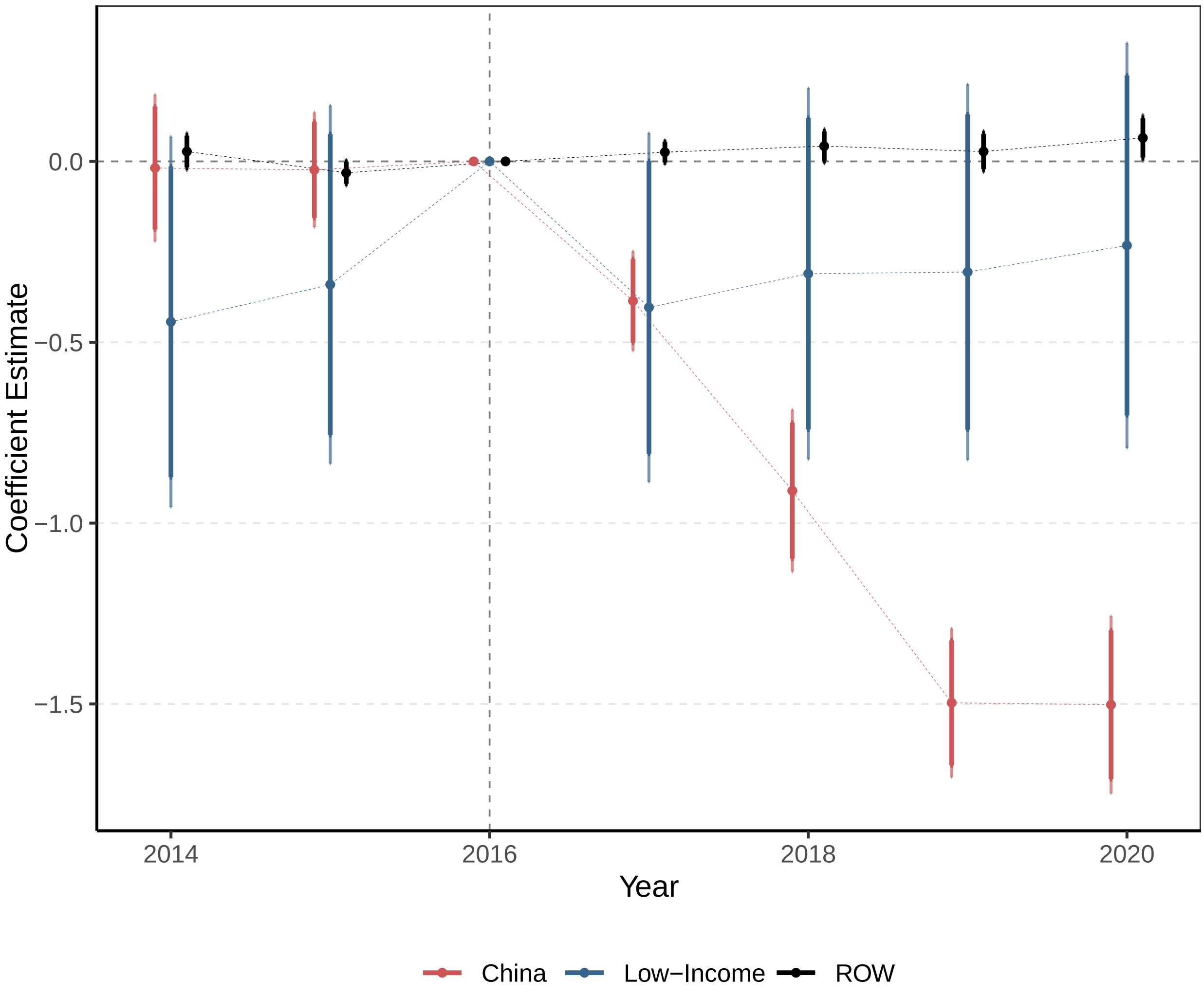
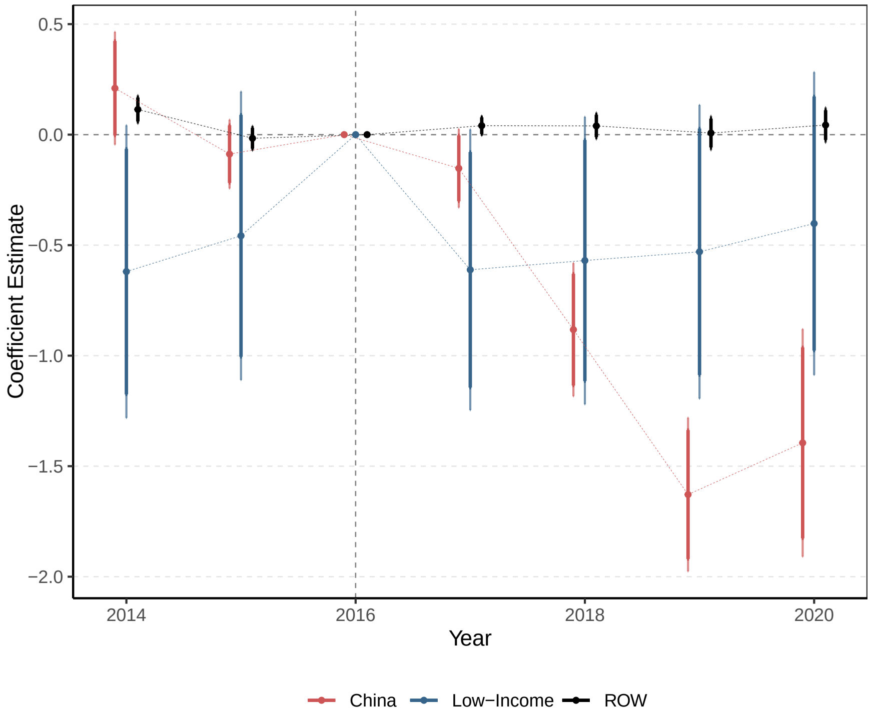


Figure 4: Dynamic Impact by Waste Quality

This figure presents the results from estimation of event-study version of Equation (9) where $n \in \{\text{High-value waste}, \text{Low-value waste}\}$ after including interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. The left panel shows the coefficients for $\sum_{n \neq Regular} \mathbb{1}(m = \text{High-value}) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and its interactions while the right panel shows the coefficients for $\sum_{n \neq Regular} \mathbb{1}(m = \text{Low-value}) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and its interactions. The black bars are the coefficients to $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$, capturing total impact on rest-of-the-world (ROW), the red bars are the coefficients to the sum of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{China})$, capturing total impact on China, and the blue bars are the coefficients to the sum of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$, capturing total impact on lower-income countries. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.



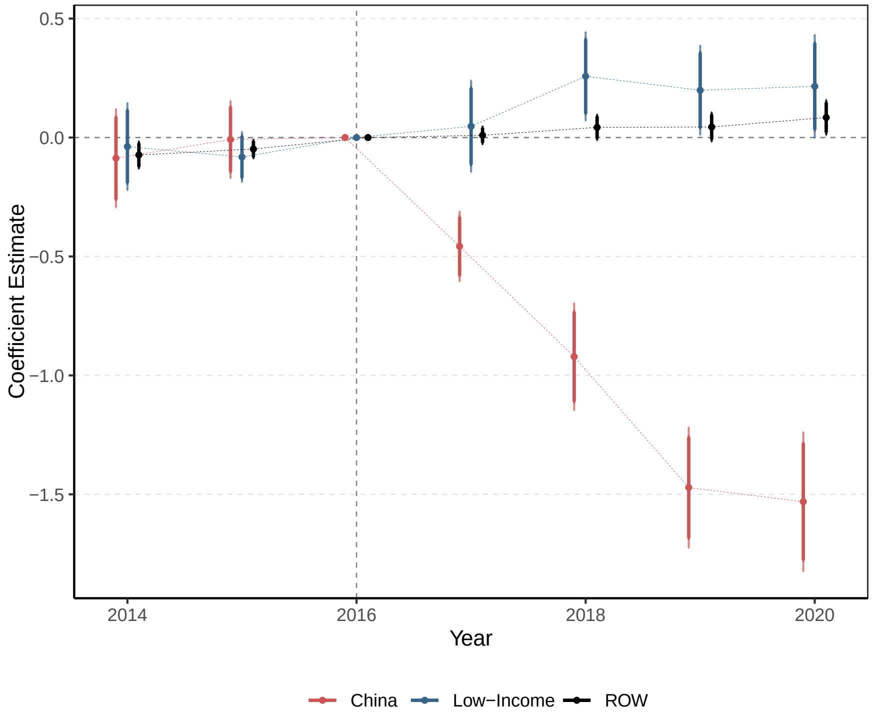


Figure 5: Placebo Test with Fake Treatment Year

This figure shows a histogram of the absolute value of the test statistics on $Treat \times Post$ from estimation of Equation (7) after dropping observations for the years post the announcement of the ban. Each test statistic corresponds to a different year, 2015-16, serving as the fake treatment year and a different set of fixed effects and controls, as in models (1)-(4) in Table 4.

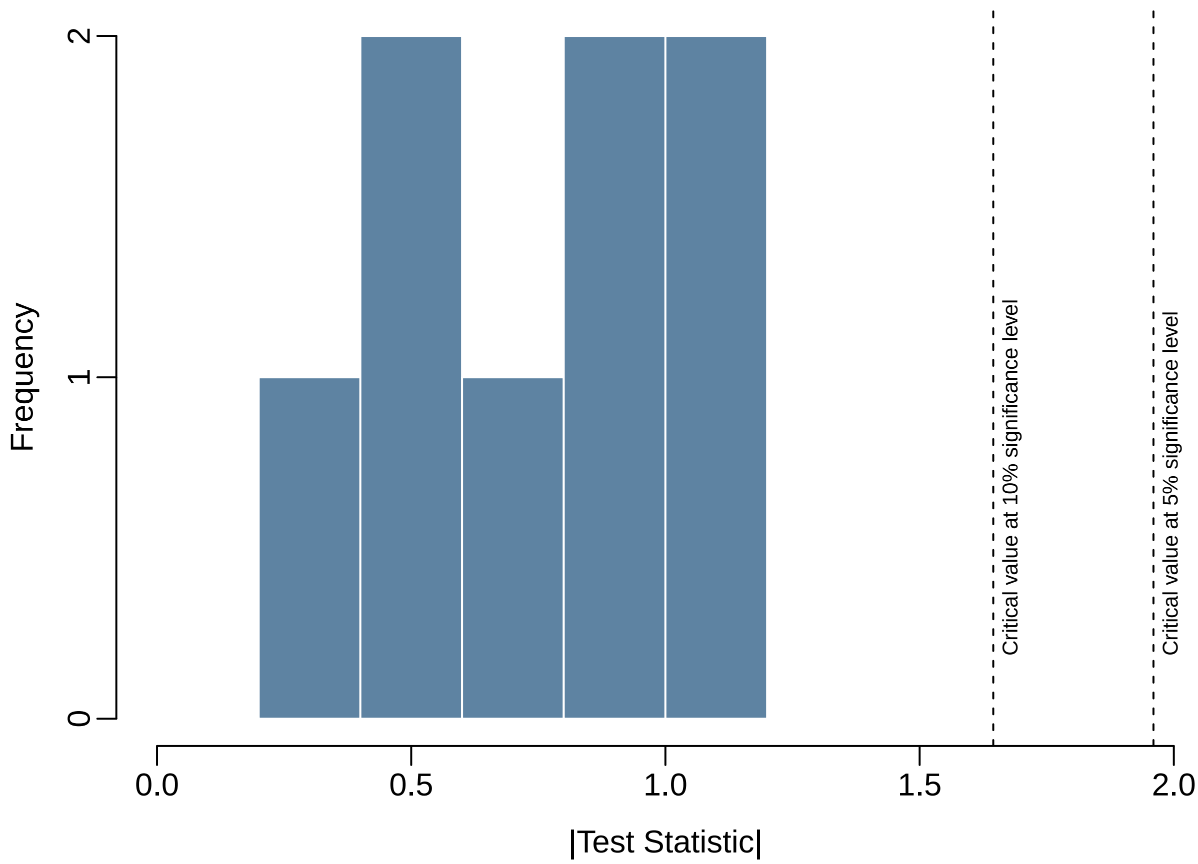


Figure 6: Placebo Test with Fake Treated Waste Type

This figure shows a histogram of the absolute value of the test statistics on $Treat \times Post$ from estimation of Equation (7) after dropping observations for the treated waste types. Each test statistic corresponds to a different set of regular materials serving as the fake treated group and a different set of fixed effects and controls, as in models (1)-(4) in Table 4.

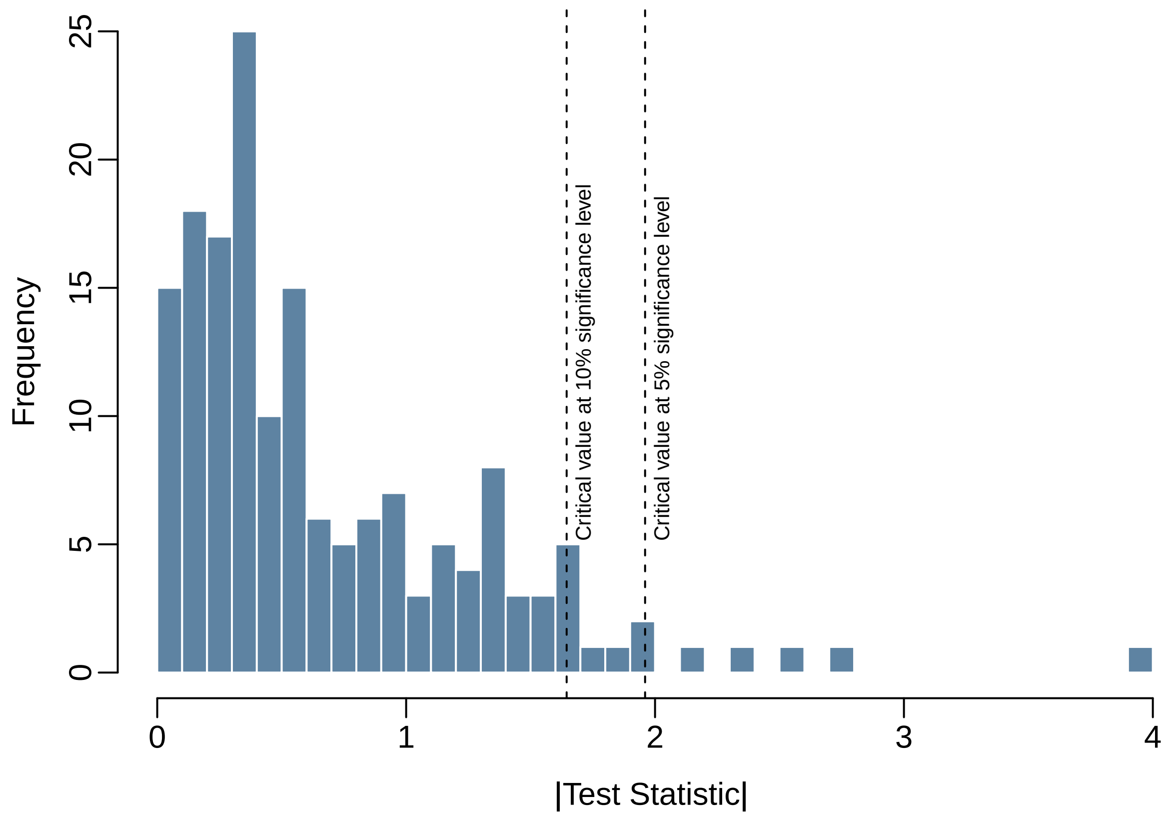


Table 1: China's Waste Imports in 2016

This table presents China's share in imports and total quantity of imports for each waste type in 2016.

Type	China's Share (%)	China's Imports (1000 metric tons)
Plastic	48.11	7,320.45
Paper	47.88	27,753.49
Yarn	25.38	858.71
Organic	8.59	3,505.37
Metal	6.92	9,118.02
Rubber/Leather	2.27	31.77
Glass	1.69	72.19
Wood	0.81	212.72
Gold	0.10	0.02
Platinum	0.001	0.0003

Table 2: Unit-Value by Waste Type

This table presents the average unit value for each waste type based on traded quantities (in metric tons) and values (in USD) from BACI-CEPII database (Gaulier and Zignago, 2010) in 2014.

Type	Unit Value (1000 USD/metric ton)
Organic	5.14
Wood	5.69
Plastic	6.55
Paper	8.39
Metal	21.15
Rubber/Leather	33.75
Glass	34.68
Yarn	133.75
Platinum	10,146.59
Gold	18,976.63

Table 3: Waste Import Regulations imposed by Other Countries

This table presents the regulation imposing country, the regulated waste material, and the year of implementation of the regulation, compiled based on information in Resource Recycling (2022).

Country	Type	Year
Indonesia	Plastic	2018
Malaysia	Plastic	2018
Taiwan	Plastics, Paper	2018
Thailand	Plastic	2018
Vietnam	Plastics, Paper	2018
India	Plastic	2019
Indonesia	Paper	2019
India	Paper	2020

Table 4: Overall Impact

This table presents the results from estimation of Equation (7). Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat × Post	-0.103*	-0.084*	-0.110*	-0.116*
	(0.058)	(0.048)	(0.061)	(0.063)
$\mathbb{1}(m = \text{Plastic/Paper}) \times \mathbb{1}(j = \text{Vietnam})$	0.807***	0.859***	0.768***	0.833***
$\times \mathbb{1}(t \geq 2018)$	(0.138)	(0.116)	(0.168)	(0.195)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Indonesia})$	0.666**	0.700**	0.496	0.500
$\times \mathbb{1}(t \geq 2018)$	(0.329)	(0.334)	(0.356)	(0.361)
$\mathbb{1}(m = \text{Paper}) \times \mathbb{1}(j = \text{Indonesia})$	0.220*	0.282**	0.163	0.159
$\times \mathbb{1}(t \geq 2019)$	(0.130)	(0.128)	(0.140)	(0.142)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Thailand})$	0.907***	0.940***	1.062***	1.075***
$\times \mathbb{1}(t \geq 2018)$	(0.274)	(0.271)	(0.235)	(0.237)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Malaysia})$	0.837***	0.871***	0.623***	0.630***
$\times \mathbb{1}(t \geq 2018)$	(0.214)	(0.209)	(0.235)	(0.236)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{India})$	-0.648***	-0.619***	-0.660***	-0.677***
$\times \mathbb{1}(t \geq 2019)$	(0.179)	(0.179)	(0.170)	(0.170)
$\mathbb{1}(m = \text{Paper}) \times \mathbb{1}(j = \text{India})$	0.235	0.272*	0.375**	0.364**
$\times \mathbb{1}(t \geq 2020)$	(0.147)	(0.151)	(0.148)	(0.149)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.822	0.977	0.830	0.832
Observations	2,066,161	888,625	2,582,824	1,832,188

Table 5: Dynamic Impact

This table presents the results from estimation of Equation (8). Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat$\times\mathbb{1}(t=2014)$	-0.025	-0.027	-0.012	-0.012
	(0.047)	(0.039)	(0.051)	(0.052)
Treat$\times\mathbb{1}(t=2015)$	-0.080*	-0.052	-0.078	-0.091
	(0.049)	(0.040)	(0.054)	(0.058)
Treat$\times\mathbb{1}(t=2017)$	-0.097*	-0.071*	-0.092	-0.108*
	(0.054)	(0.039)	(0.059)	(0.062)
Treat$\times\mathbb{1}(t=2018)$	-0.122*	-0.102**	-0.133*	-0.154**
	(0.065)	(0.049)	(0.074)	(0.078)
Treat$\times\mathbb{1}(t=2019)$	-0.188**	-0.164**	-0.181**	-0.181**
	(0.080)	(0.065)	(0.080)	(0.083)
Treat$\times\mathbb{1}(t=2020)$	-0.147**	-0.108	-0.159**	-0.164**
	(0.073)	(0.068)	(0.076)	(0.080)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.822	0.977	0.830	0.832
Observations	2,066,161	888,625	2,582,824	1,832,188

Table 6: Impact by Waste Type

This table presents the results from estimation of Equation (9) after adding interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times Post$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
$\mathbb{1}(m = \text{Glass}) \times \text{Post}$	-0.049	-0.059	-0.048	-0.046
	(0.070)	(0.069)	(0.069)	(0.070)
$\mathbb{1}(m = \text{Metal}) \times \text{Post}$	0.001	0.010	0.019	0.015
	(0.041)	(0.029)	(0.043)	(0.045)
$\mathbb{1}(m = \text{Paper}) \times \text{Post}$	0.027	0.000	0.040	0.041
	(0.040)	(0.033)	(0.043)	(0.044)
$\mathbb{1}(m = \text{Organic}) \times \text{Post}$	0.066*	0.037	0.070*	0.072*
	(0.040)	(0.032)	(0.040)	(0.041)
$\mathbb{1}(m = \text{Plastic}) \times \text{Post}$	0.171***	0.144***	-0.167	-0.165
	(0.055)	(0.050)	(0.112)	(0.112)
$\mathbb{1}(m = \text{Wood}) \times \text{Post}$	0.224***	0.208***	0.231***	0.232***
	(0.047)	(0.040)	(0.047)	(0.047)
$\mathbb{1}(m = \text{Yarn}) \times \text{Post}$	0.014	-0.018	0.016	0.017
	(0.038)	(0.031)	(0.038)	(0.039)
$\mathbb{1}(m = \text{Glass}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-3.060***	-2.810***	-2.155***	-2.147***
	(0.297)	(0.257)	(0.666)	(0.668)
$\mathbb{1}(m = \text{Metal}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-1.137***	-0.882***	-1.148***	-1.172***
	(0.205)	(0.117)	(0.234)	(0.242)
$\mathbb{1}(m = \text{Paper}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-1.031***	-0.760***	-1.032***	-1.059***
	(0.181)	(0.088)	(0.208)	(0.216)
$\mathbb{1}(m = \text{Organic}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-2.127***	-1.873***	-2.115***	-2.139***
	(0.564)	(0.561)	(0.577)	(0.568)
$\mathbb{1}(m = \text{Plastic}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-2.041***	-1.765***	-1.785***	-1.780***
	(0.180)	(0.122)	(0.224)	(0.230)
$\mathbb{1}(m = \text{Wood}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-2.003***	-1.772***	-2.023***	-2.015***
	(0.669)	(0.667)	(0.658)	(0.653)
$\mathbb{1}(m = \text{Yarn}) \times \text{Post} \times \mathbb{1}(j = \text{China})$	-0.777***	-0.384	-0.780***	-0.750**
	(0.279)	(0.235)	(0.295)	(0.302)
$\mathbb{1}(m = \text{Glass}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	-0.182	-0.182	-0.170	-0.101
	(0.263)	(0.237)	(0.259)	(0.282)
$\mathbb{1}(m = \text{Metal}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	-0.166	-0.198	-0.175	-0.193
	(0.190)	(0.173)	(0.194)	(0.205)
$\mathbb{1}(m = \text{Paper}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	0.321***	0.308***	0.351***	0.339**
	(0.113)	(0.097)	(0.133)	(0.139)
$\mathbb{1}(m = \text{Organic}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	0.093	0.066	0.106	0.181
	(0.111)	(0.118)	(0.108)	(0.120)
$\mathbb{1}(m = \text{Plastic}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	-0.085	-0.079	0.324*	0.391**
	(0.129)	(0.115)	(0.167)	(0.172)
$\mathbb{1}(m = \text{Wood}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	0.164	0.125	0.164	0.237
	(0.321)	(0.317)	(0.321)	(0.339)
$\mathbb{1}(m = \text{Yarn}) \times \text{Post} \times \mathbb{1}(j = \text{Low-income})$	0.243	0.138	0.243	0.323
	(0.159)	(0.084)	(0.164)	(0.198)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.832	0.978	0.839	0.842
Observations	2,066,161	888,625	2,582,824	1,832,188

Table 7: Extensive Margin

This table presents the results from estimation of Equation (10) after adding an interaction of $Treat \times Post$ with $\mathbb{1}(j = \text{China})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat × Post	-0.071***	-0.133***	-0.037***	-0.034***
	(0.006)	(0.011)	(0.007)	(0.008)
Treat × Post × $\mathbb{1}(j = \text{China})$	-0.325***	-0.667***	-0.355***	-0.427***
	(0.048)	(0.098)	(0.046)	(0.056)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Log-likelihood	-515,346.4	-290,267.2	-606,111.8	-516,995.5
Observations	2,043,586	553,272	2,559,161	1,781,888

Appendix to
"Global Impact of a Unilateral Waste Trade Regulation"

Prakrati Thakur

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A Waste Generation Data

I assume that $\mathcal{G}_{mit} = \lambda_{mi}\mathcal{M}_{it}$, where m is a waste material, $\mathcal{M}_{it}$ is total municipal waste generated in country i in year t, and λ_{mi} is a scalar that reflects the fraction of waste generation that is of type m. The municipal waste generation data, however, are available for only a single year, 2016 (Kaza et al., 2018). To obtain a series for each country, I first estimate the cross-section relationship between $\mathcal{M}_{i,2016}$ and a set of country characteristics, such as GDP per capita and GDP via the regression $\ln(\mathcal{M}_{i,2006}) = a_0 + a_{GDP}\ln(GDP_{i,2006}) + a_{GDPpc}\ln(GDPpc_{i,2016}) + e_i$. I then project these elasticities to the time domain to obtain estimates of municipal waste for country i in year t from:

$$\mathcal{M}_{it} = \left(\frac{GDP_{it}}{GDP_{i,2016}}\right)^{a_{GDP}} \left(\frac{GDPpc_{it}}{GDPpc_{i,2016}}\right)^{a_{GDPpc}} W_{i,2016}. \tag{11}$$

The λ_{mi} are calibrated based on the waste composition across countries in the literature. With the exception of yarn, gold, and platinum, Kaza et al. (2018) also provides the share of each waste type in my sample in overall municipal waste generation (See Table A.1). However, the biggest source of waste generation are the industries, not households. I assume that industrial waste generation is proportional to the size of a country's industrial sector, which is strongly correlated with GDP and municipal waste generation. As industries account for 94-97% of waste generation (Liboiron, 2016; Kaza et al., 2018), I scale up λ_{mi} by a factor of 20. My results are robust to an alternative scaling factor of 15.

Table A.1: Waste Composition across Income Groups

This table provides the waste composition, in percentages, from (Kaza et al., 2018) across four income groups of countries. The four income groups are as follows: High Income Countries (HIC), Upper-Middle Income Countries (UMC), Lower-Middle Income Countries (LMC), Low Income Countries (LIC).

Group	**Glass**	**Metal**	**Organic**	**Paper**	**Plastic**	**Rubber/Leather**	**Wood**
HIC	5	6	32	25	13	4	4
UMC	4	2	54	12	11	1	1
LMC	3	2	53	12.5	11	0.5	1
LIC	1	2	56	7	6.4	0.3	0.3

B Additional Figures and Tables

Figure A.1: China's Import Quantity of Treated and Control Commodities

This figure shows China's total import quantity of commodities in the treated and control groups between 2014-2020. The dashed line represents the year right before the announcement of Operation National Sword in 2017. For both treated and control groups, quantities in each year have been normalized by the respective 2016 quantity.

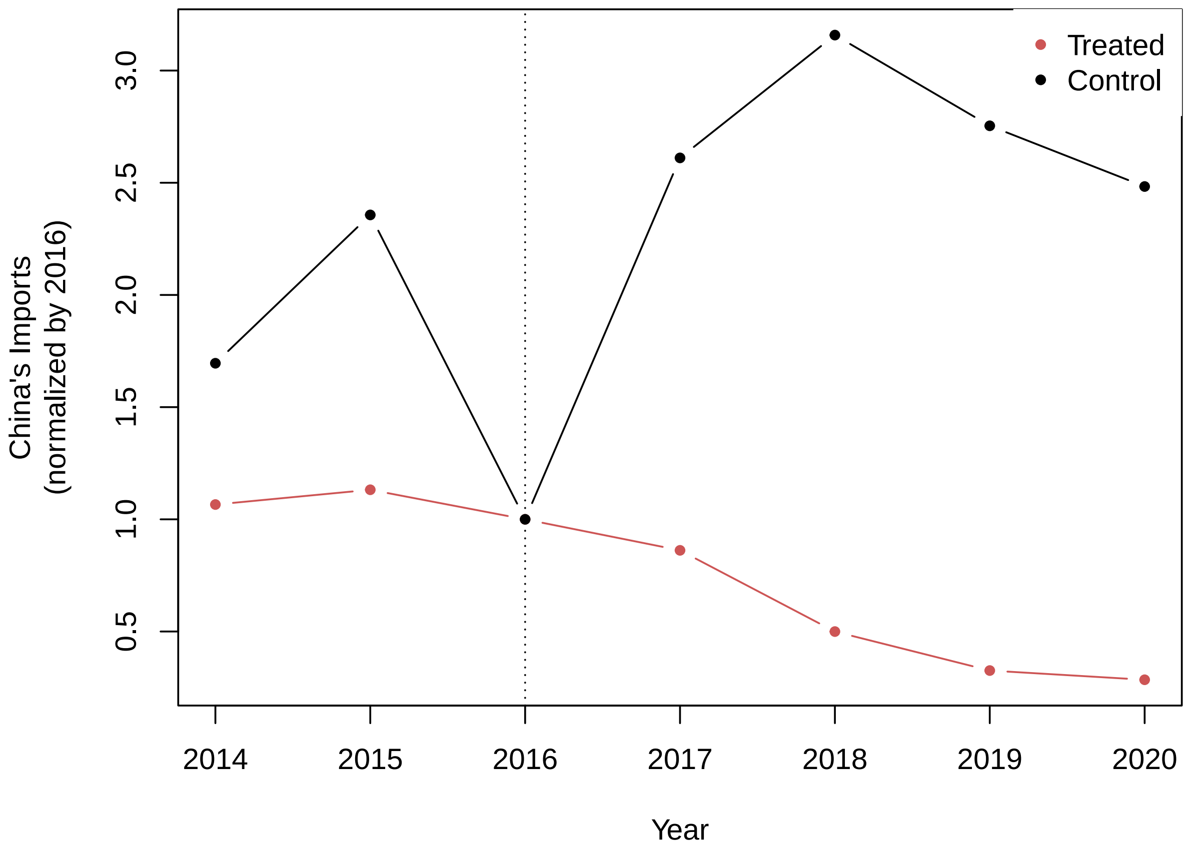

Figure A.2: Dynamic Impact on China - Alternative Control Group

This figure presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq2016} Treat \times \mathbb{1}(t=s)$ and $\mathbb{1}(j=\text{China})$. The black bars are the coefficients to $\sum_{s\neq2016} Treat \times \mathbb{1}(t=s)$, capturing total impact on rest-of the-world (ROW), while the red bars are the coefficients to the sum of $\sum_{s\neq2016} Treat \times \mathbb{1}(t=s)$ and $\sum_{s\neq2016} Treat \times \mathbb{1}(t=s) \times \mathbb{1}(j=\text{China})$, capturing total impact on China. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

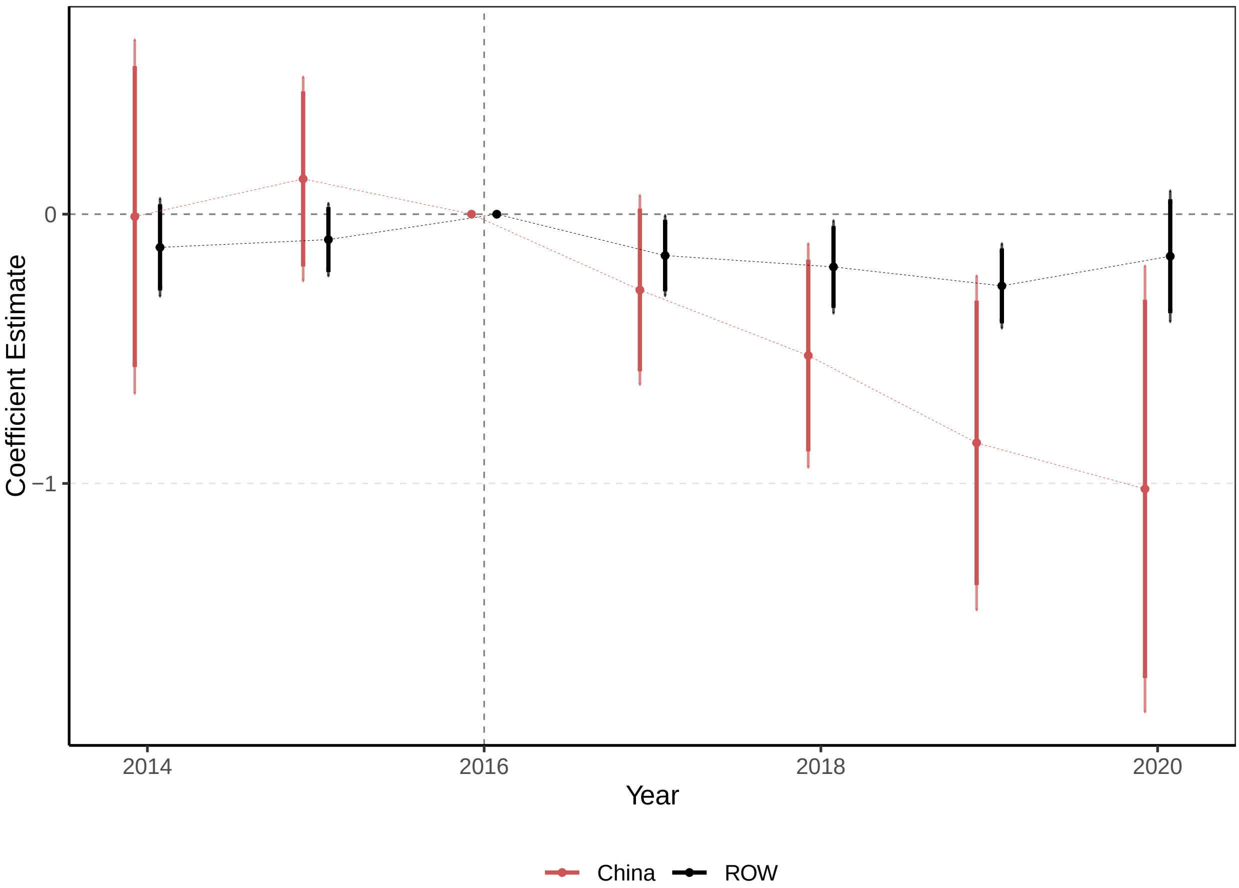

Figure A.3: Dynamic Impact by Importer - Alternative Control Group

This figure presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{Low-income})$. The black bars are the coefficients to $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$, capturing total impact on rest-of-the-world (ROW), the red bars are the coefficients to the sum of $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s) \times \mathbb{1}(j = \text{China})$, capturing the total impact on China, and the blue bars are the coefficients to the sum of $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$, capturing the total impact on lower-income countries. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

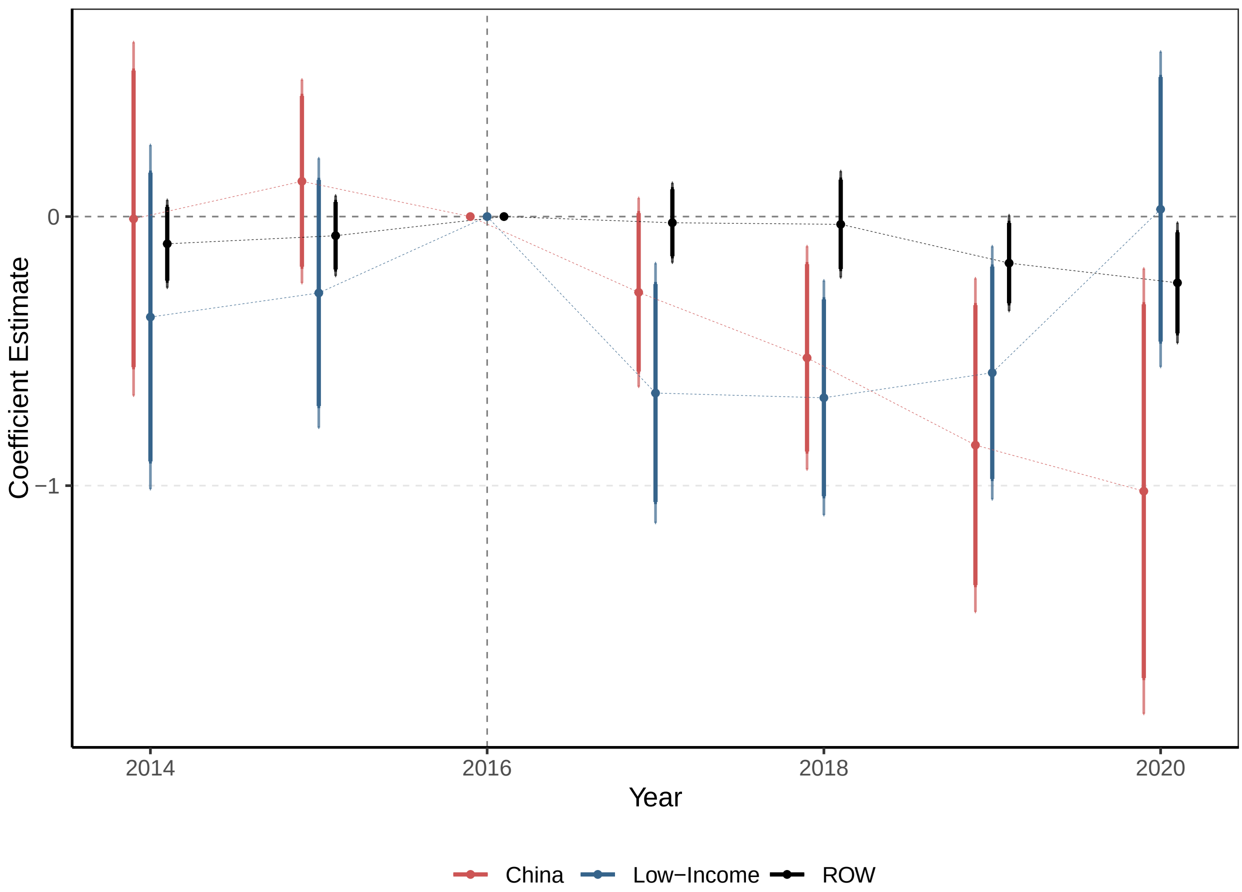

Figure A.4: Dynamic Impact by Waste Value - Alternative Control Group

This figure presents the results from estimation of event-study version of Equation (9) where $n \in \{\text{High-value waste}, \text{Low-value waste}\}$ after including interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. The left panel shows the coefficients for $\sum_{n \neq Regular} \mathbb{1}(m = \text{High-value}) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and its interactions while the right panel shows the coefficients for $\sum_{n \neq Regular} \mathbb{1}(m = \text{Low-value}) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and its interactions. The black bars are the coefficients to $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$, capturing total impact on rest-of-the-world (ROW), the red bars are the coefficients to the sum of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{China})$, capturing total impact on China, and the blue bars are the coefficients to the sum of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ and $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s) \times \mathbb{1}(j = \text{Low-income})$, capturing total impact on lower-income countries. The solid circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

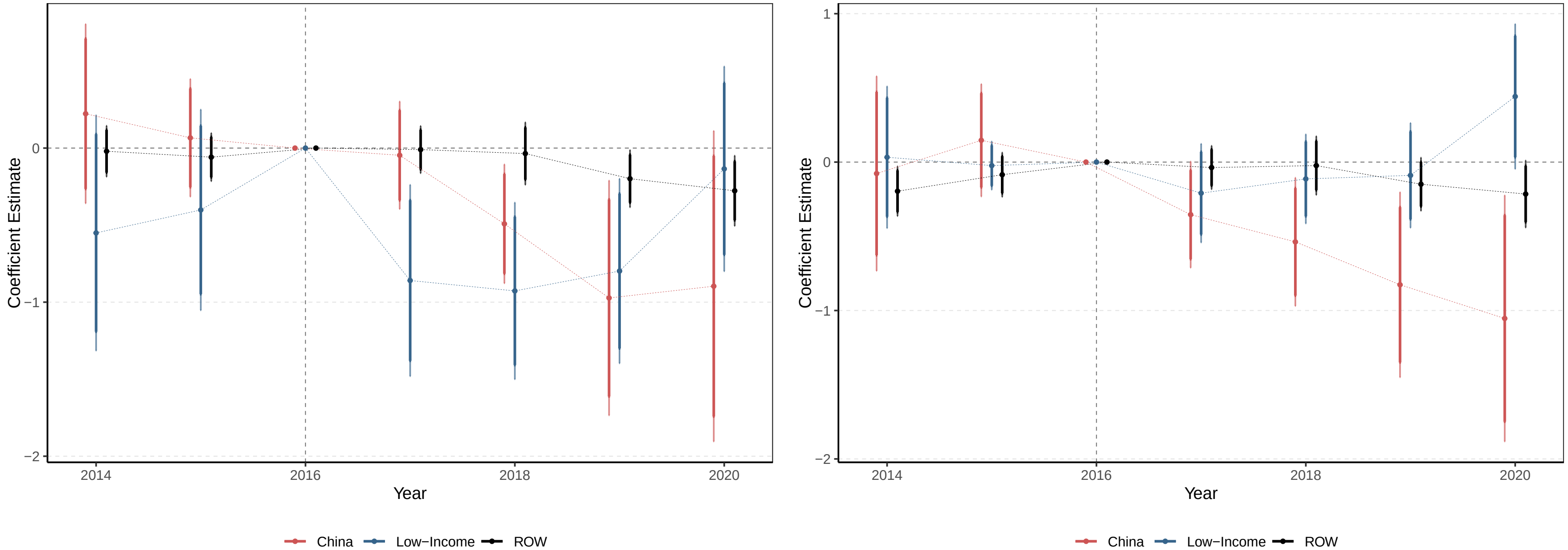

Figure A.5: Placebo Test with Fake Treatment Year - Alternative Control Group

This figure shows a histogram of the absolute value of the test statistics on $Treat \times Post$ from estimation of Equation (7) after dropping observations for the years post the announcement of the ban. Each test statistic corresponds to a different year, 2015-16, serving as the fake treatment year and a different set of fixed effects and controls, as in models (1)-(4) in Table 4.

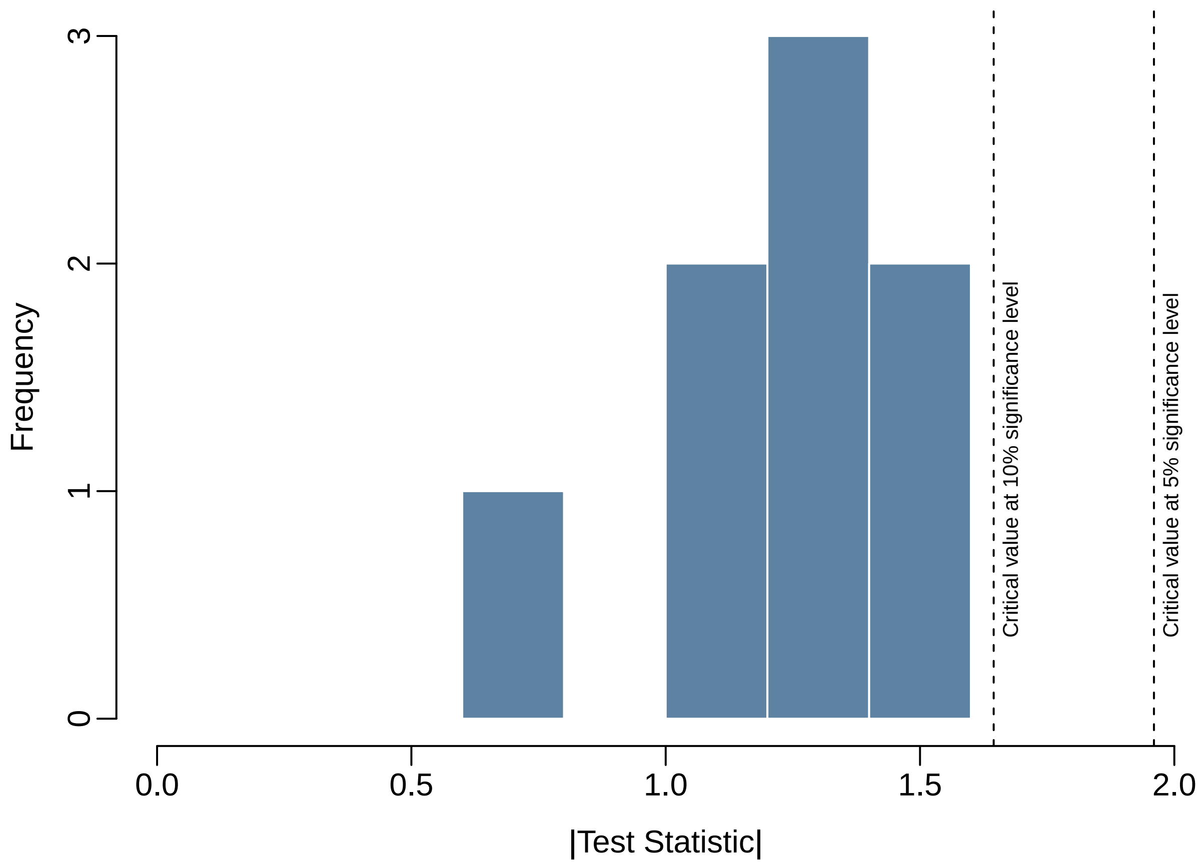

Figure A.6: Placebo Test with Fake Treated Waste Type - Alternative Control Group

This figure shows a histogram of the absolute value of the test statistics on $Treat \times Post$ from estimation of Equation (7) after dropping observations for the treated waste types. Each test statistic corresponds to a different set of control waste materials serving as the fake treated group and a different set of fixed effects and controls, as in models (1)-(4) in Table 4.

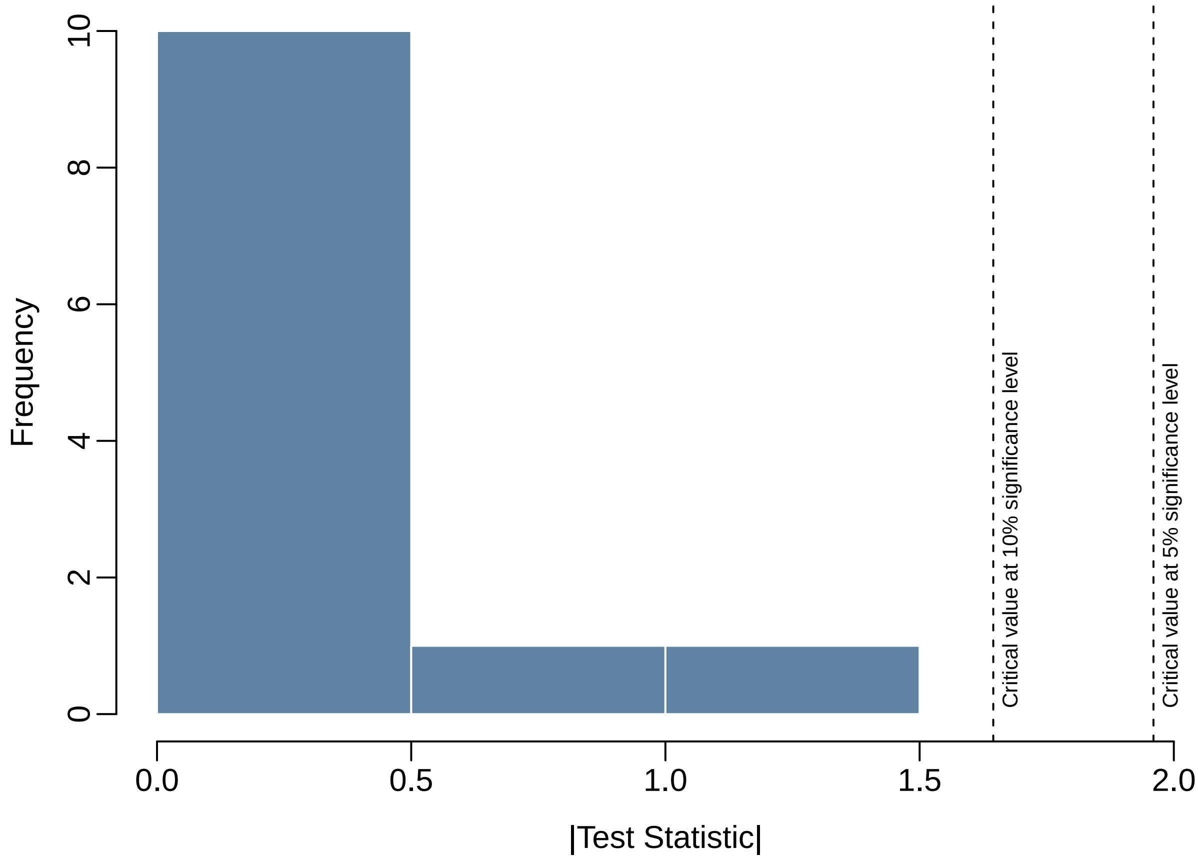

Table A.2: HS6 Categories of Waste

This table lists the HS6 codes under each waste type.

Type	HS6 Codes
Glass	700100
Gold	711291
Metal	261900, 262011, 262019, 262021, 262029, 262030, 262040, 262060, 262091, 262099, 262190, 720410, 720421, 720429, 720430, 720441, 720449, 720450, 740400, 750300, 760200, 780200, 790200, 800200, 810110, 810197, 810210, 810297, 810330, 810420, 810530, 810600, 810730, 810830, 810930, 811020, 811090, 811100, 811213, 811219, 811222, 811229, 811252, 811259, 811292, 811299
Organic	180200, 230210, 230230, 230240, 230250, 230310, 230320, 230330, 230800
Paper	470620, 470691, 470692, 470693, 470710, 470720, 470730, 470790
Plastic	391510, 391520, 391530, 391590
Platinum	711292
Rubber/Leather	400400, 401700, 411520
Wood	440131, 440139, 450190, 680800
Yarn	500300, 500400, 500500, 500600, 500720, 510310, 510320, 510330, 520210, 520291, 520299, 530130, 530290, 530390, 530500, 550510, 550520, 620610, 621410, 621510, 631010, 631090

Table A.3: Dynamic Impact on China

This table presents the results from estimation of Equation (8) after adding the interaction between $\sum_{s \neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat×$\mathbb{1}(t = 2014)$	-0.009	-0.032	-0.009	-0.009
	(0.051)	(0.045)	(0.055)	(0.057)
Treat×$\mathbb{1}(t = 2015)$	-0.050	-0.072*	-0.060	-0.070
	(0.044)	(0.041)	(0.048)	(0.050)
Treat×$\mathbb{1}(t = 2017)$	-0.006	-0.034	-0.003	-0.019
	(0.048)	(0.042)	(0.053)	(0.056)
Treat×$\mathbb{1}(t = 2018)$	0.061	-0.005	0.052	0.050
	(0.052)	(0.046)	(0.056)	(0.058)
Treat×$\mathbb{1}(t = 2019)$	0.022	-0.016	0.030	0.031
	(0.053)	(0.049)	(0.057)	(0.059)
Treat×$\mathbb{1}(t = 2020)$	0.055	0.026	0.048	0.048
	(0.058)	(0.054)	(0.062)	(0.065)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{China})$	-0.328*	0.013	-0.213	-0.234
	(0.195)	(0.112)	(0.184)	(0.194)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{China})$	-0.502**	0.049	-0.387*	-0.419
	(0.223)	(0.091)	(0.220)	(0.265)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{China})$	-0.854***	-0.352***	-0.778***	-0.787***
	(0.253)	(0.081)	(0.271)	(0.285)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{China})$	-1.579***	-0.905***	-1.526***	-1.659***
	(0.292)	(0.122)	(0.306)	(0.355)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{China})$	-2.021***	-1.480***	-1.913***	-1.906***
	(0.283)	(0.114)	(0.295)	(0.321)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{China})$	-2.058***	-1.527***	-1.988***	-2.001***
	(0.217)	(0.132)	(0.212)	(0.256)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.823	0.979	0.831	0.833
Observations	2,066,161	888,625	2,582,824	1,832,188

Table A.4: Dynamic Impact by Importer

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{Low-income})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat$\times\mathbb{1}(t = 2014)$	0.054	0.027	0.061	0.062
	(0.038)	(0.027)	(0.040)	(0.042)
Treat$\times\mathbb{1}(t = 2015)$	-0.012	-0.032*	-0.018	-0.026
	(0.025)	(0.019)	(0.027)	(0.029)
Treat$\times\mathbb{1}(t = 2017)$	0.037	0.026	0.037	0.020
	(0.034)	(0.017)	(0.037)	(0.042)
Treat$\times\mathbb{1}(t = 2018)$	0.095**	0.042*	0.091**	0.090**
	(0.040)	(0.025)	(0.043)	(0.044)
Treat$\times\mathbb{1}(t = 2019)$	0.059	0.027	0.074*	0.078*
	(0.041)	(0.030)	(0.041)	(0.043)
Treat$\times\mathbb{1}(t = 2020)$	0.076*	0.065**	0.073	0.074
	(0.044)	(0.033)	(0.047)	(0.050)
Treat$\times\mathbb{1}(t = 2014)\times\mathbb{1}(j = \text{China})$	-0.392**	-0.045	-0.284	-0.305
	(0.192)	(0.107)	(0.180)	(0.190)
Treat$\times\mathbb{1}(t = 2015)\times\mathbb{1}(j = \text{China})$	-0.540**	0.008	-0.429**	-0.463*
	(0.220)	(0.083)	(0.216)	(0.262)
Treat$\times\mathbb{1}(t = 2017)\times\mathbb{1}(j = \text{China})$	-0.897***	-0.411***	-0.818***	-0.826***
	(0.251)	(0.072)	(0.268)	(0.282)
Treat$\times\mathbb{1}(t = 2018)\times\mathbb{1}(j = \text{China})$	-1.614***	-0.952***	-1.565***	-1.699***
	(0.290)	(0.117)	(0.304)	(0.353)
Treat$\times\mathbb{1}(t = 2019)\times\mathbb{1}(j = \text{China})$	-2.058***	-1.524***	-1.957***	-1.954***
	(0.281)	(0.109)	(0.293)	(0.319)
Treat$\times\mathbb{1}(t = 2020)\times\mathbb{1}(j = \text{China})$	-2.079***	-1.567***	-2.013***	-2.028***
	(0.214)	(0.129)	(0.208)	(0.253)
Treat$\times\mathbb{1}(t = 2014)\times\mathbb{1}(j = \text{Low-income})$	-0.508*	-0.471*	-0.571**	-0.576**
	(0.269)	(0.263)	(0.286)	(0.294)
Treat$\times\mathbb{1}(t = 2015)\times\mathbb{1}(j = \text{Low-income})$	-0.281	-0.309	-0.307	-0.322
	(0.254)	(0.253)	(0.280)	(0.290)
Treat$\times\mathbb{1}(t = 2017)\times\mathbb{1}(j = \text{Low-income})$	-0.327	-0.429*	-0.307	-0.293
	(0.254)	(0.246)	(0.277)	(0.288)
Treat$\times\mathbb{1}(t = 2018)\times\mathbb{1}(j = \text{Low-income})$	-0.293	-0.353	-0.318	-0.325
	(0.270)	(0.261)	(0.288)	(0.299)
Treat$\times\mathbb{1}(t = 2019)\times\mathbb{1}(j = \text{Low-income})$	-0.326	-0.333	-0.375	-0.397
	(0.275)	(0.264)	(0.293)	(0.304)
Treat$\times\mathbb{1}(t = 2020)\times\mathbb{1}(j = \text{Low-income})$	-0.223	-0.297	-0.251	-0.265
	(0.302)	(0.283)	(0.311)	(0.323)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.824	0.979	0.832	0.834
Observations	2,066,161	888,625	2,582,824	1,832,188

Table A.5: Dynamic Impact by Neighborhood

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{Neighbor})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat×$\mathbb{1}(t = 2014)$	-0.037	-0.045	-0.039	-0.037
	(0.059)	(0.053)	(0.064)	(0.067)
Treat×$\mathbb{1}(t = 2015)$	-0.083	-0.078	-0.101*	-0.109*
	(0.052)	(0.050)	(0.058)	(0.060)
Treat×$\mathbb{1}(t = 2017)$	-0.003	-0.023	-0.004	-0.015
	(0.054)	(0.049)	(0.059)	(0.061)
Treat×$\mathbb{1}(t = 2018)$	-0.009	-0.041	-0.006	-0.006
	(0.059)	(0.053)	(0.065)	(0.067)
Treat×$\mathbb{1}(t = 2019)$	-0.009	-0.043	0.005	0.007
	(0.060)	(0.058)	(0.065)	(0.067)
Treat×$\mathbb{1}(t = 2020)$	0.020	-0.003	0.021	0.022
	(0.062)	(0.062)	(0.067)	(0.070)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{China})$	-0.301	0.026	-0.183	-0.205
	(0.197)	(0.116)	(0.186)	(0.197)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{China})$	-0.469**	0.054	-0.346	-0.381
	(0.225)	(0.095)	(0.222)	(0.267)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{China})$	-0.857***	-0.362***	-0.777***	-0.791***
	(0.254)	(0.085)	(0.273)	(0.286)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{China})$	-1.509***	-0.869***	-1.467***	-1.603***
	(0.294)	(0.125)	(0.309)	(0.356)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{China})$	-1.989***	-1.452***	-1.888***	-1.882***
	(0.285)	(0.118)	(0.297)	(0.322)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{China})$	-2.023***	-1.496***	-1.960***	-1.976***
	(0.218)	(0.135)	(0.214)	(0.258)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{Neighbor})$	0.137	0.060	0.153	0.147
	(0.114)	(0.081)	(0.115)	(0.118)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{Neighbor})$	0.177**	0.026	0.205**	0.195**
	(0.084)	(0.065)	(0.087)	(0.090)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{Neighbor})$	-0.013	-0.058	0.004	-0.019
	(0.123)	(0.068)	(0.129)	(0.150)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{Neighbor})$	0.358***	0.193**	0.285**	0.281**
	(0.112)	(0.081)	(0.115)	(0.122)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{Neighbor})$	0.144	0.141*	0.113	0.110
	(0.119)	(0.075)	(0.119)	(0.131)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{Neighbor})$	0.164	0.156	0.130	0.118
	(0.159)	(0.103)	(0.158)	(0.169)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.824	0.979	0.831	0.833
Observations	2,066,161	888,625	2,582,824	1,832,188

Table A.6: Dynamic Impact by Waste Value

This table presents the results from estimation of event-study version of Equation (9) where $n \in \{\text{High-value waste}, \text{Low-value waste}\}$ after including interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014)$	0.142***	0.114***	0.142***	0.143***
	(0.046)	(0.033)	(0.049)	(0.051)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015)$	-0.012	-0.016	-0.023	-0.031
	(0.032)	(0.029)	(0.036)	(0.037)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017)$	0.012	0.041*	0.018	-0.004
	(0.049)	(0.023)	(0.053)	(0.059)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018)$	0.079*	0.039	0.089*	0.086*
	(0.046)	(0.031)	(0.049)	(0.051)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019)$	0.025	0.007	0.051	0.053
	(0.052)	(0.040)	(0.051)	(0.053)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020)$	0.060	0.043	0.069	0.070
	(0.055)	(0.041)	(0.059)	(0.064)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{China})$	-0.267	0.096	-0.093	-0.133
	(0.203)	(0.134)	(0.193)	(0.203)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{China})$	-0.596***	-0.071	-0.421*	-0.477*
	(0.227)	(0.084)	(0.233)	(0.277)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{China})$	-0.650***	-0.193**	-0.514*	-0.525*
	(0.247)	(0.093)	(0.273)	(0.290)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{China})$	-1.659***	-0.922***	-1.522***	-1.692***
	(0.326)	(0.157)	(0.350)	(0.397)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{China})$	-2.190***	-1.636***	-1.987***	-1.990***
	(0.297)	(0.182)	(0.346)	(0.371)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{China})$	-2.044***	-1.438***	-1.946***	-1.990***
	(0.287)	(0.266)	(0.292)	(0.325)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{Low-income})$	-0.759**	-0.734**	-0.759**	-0.782**
	(0.344)	(0.338)	(0.344)	(0.355)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{Low-income})$	-0.383	-0.441	-0.373	-0.398
	(0.332)	(0.333)	(0.337)	(0.350)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{Low-income})$	-0.512	-0.652**	-0.473	-0.471
	(0.328)	(0.324)	(0.332)	(0.345)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{Low-income})$	-0.560*	-0.609*	-0.560*	-0.580*
	(0.336)	(0.330)	(0.338)	(0.352)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{Low-income})$	-0.560	-0.537	-0.599*	-0.643*
	(0.346)	(0.336)	(0.347)	(0.362)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{Low-income})$	-0.395	-0.446	-0.391	-0.423
	(0.362)	(0.344)	(0.361)	(0.376)

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$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2014)$	-0.048	-0.073**	-0.031	-0.028
	(0.040)	(0.030)	(0.042)	(0.043)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2015)$	-0.011	-0.048**	-0.011	-0.019
	(0.028)	(0.020)	(0.029)	(0.032)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2017)$	0.063**	0.009	0.057*	0.045
	(0.030)	(0.019)	(0.033)	(0.036)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2018)$	0.114***	0.043	0.094**	0.096**
	(0.042)	(0.028)	(0.044)	(0.045)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2019)$	0.097**	0.044	0.100**	0.107**
	(0.042)	(0.032)	(0.045)	(0.047)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2020)$	0.096**	0.084**	0.082*	0.083
	(0.048)	(0.038)	(0.049)	(0.052)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2014)\times\mathbb{1}(j = \text{China})$	-0.370*	-0.014	-0.300*	-0.325*
	(0.193)	(0.110)	(0.175)	(0.185)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2015)\times\mathbb{1}(j = \text{China})$	-0.555**	0.040	-0.459**	-0.486*
	(0.222)	(0.085)	(0.211)	(0.257)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2017)\times\mathbb{1}(j = \text{China})$	-0.998***	-0.467***	-0.926***	-0.942***
	(0.252)	(0.077)	(0.267)	(0.281)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2018)\times\mathbb{1}(j = \text{China})$	-1.695***	-0.964***	-1.635***	-1.755***
	(0.270)	(0.118)	(0.289)	(0.334)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2019)\times\mathbb{1}(j = \text{China})$	-2.121***	-1.516***	-2.011***	-2.018***
	(0.287)	(0.133)	(0.294)	(0.313)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2020)\times\mathbb{1}(j = \text{China})$	-2.207***	-1.615***	-2.123***	-2.130***
	(0.207)	(0.154)	(0.210)	(0.250)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2014)\times\mathbb{1}(j = \text{Low-income})$	-0.029	0.035	-0.253*	-0.240*
	(0.119)	(0.098)	(0.140)	(0.140)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2015)\times\mathbb{1}(j = \text{Low-income})$	-0.092	-0.033	-0.184*	-0.173
	(0.072)	(0.058)	(0.109)	(0.113)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2017)\times\mathbb{1}(j = \text{Low-income})$	0.013	0.038	0.013	0.069
	(0.089)	(0.100)	(0.124)	(0.121)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2018)\times\mathbb{1}(j = \text{Low-income})$	0.197*	0.215**	0.127	0.145
	(0.113)	(0.099)	(0.139)	(0.151)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2019)\times\mathbb{1}(j = \text{Low-income})$	0.144	0.154	0.067	0.076
	(0.106)	(0.101)	(0.135)	(0.152)
$\mathbb{1}(m = \text{Low-value})\times\mathbb{1}(t = 2020)\times\mathbb{1}(j = \text{Low-income})$	0.145	0.131	0.069	0.095
	(0.136)	(0.117)	(0.152)	(0.185)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.827	0.979	0.834	0.837
Observations	2,066,161	888,625	2,582,824	1,832,188

Table A.7: Overall Impact - Alternative Control Group

This table presents the results from estimation of Equation (7). Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat × Post	-0.243***	-0.269***	-0.233***	-0.241***
	(0.081)	(0.084)	(0.079)	(0.079)
$\mathbb{1}(m = \text{Plastic/Paper}) \times \mathbb{1}(j = \text{Vietnam})$	0.966***	1.031***	0.552***	0.552***
$\times\mathbb{1}(t \geq 2018)$	(0.132)	(0.151)	(0.185)	(0.197)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Indonesia})$	0.740**	0.733**	0.467	0.485
$\times\mathbb{1}(t \geq 2018)$	(0.334)	(0.342)	(0.400)	(0.400)
$\mathbb{1}(m = \text{Paper}) \times \mathbb{1}(j = \text{Indonesia})$	0.328**	0.369***	0.219	0.230*
$\times\mathbb{1}(t \geq 2019)$	(0.132)	(0.137)	(0.134)	(0.136)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Thailand})$	0.958***	0.982***	0.941***	0.918***
$\times\mathbb{1}(t \geq 2018)$	(0.260)	(0.267)	(0.268)	(0.270)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{Malaysia})$	0.838***	0.870***	0.241	0.284
$\times\mathbb{1}(t \geq 2018)$	(0.206)	(0.205)	(0.292)	(0.295)
$\mathbb{1}(m = \text{Plastic}) \times \mathbb{1}(j = \text{India})$	-0.545***	-0.532***	-0.650***	-0.650***
$\times\mathbb{1}(t \geq 2019)$	(0.189)	(0.192)	(0.186)	(0.186)
$\mathbb{1}(m = \text{Paper}) \times \mathbb{1}(j = \text{India})$	0.274*	0.301*	0.419**	0.410**
$\times\mathbb{1}(t \geq 2020)$	(0.158)	(0.165)	(0.173)	(0.173)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.849	0.968	0.857	0.857
Observations	940,841	337,201	1,084,993	695,412

Table A.8: Dynamic Impact - Alternative Control Group

This table presents the results from estimation of Equation (8). Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat$\times\mathbb{1}(t=2014)$	-0.106	-0.095	-0.143	-0.153
	(0.097)	(0.100)	(0.099)	(0.101)
Treat$\times\mathbb{1}(t=2015)$	-0.011	-0.054	-0.034	-0.052
	(0.074)	(0.071)	(0.076)	(0.079)
Treat$\times\mathbb{1}(t=2017)$	-0.197**	-0.209***	-0.204**	-0.232***
	(0.080)	(0.078)	(0.080)	(0.082)
Treat$\times\mathbb{1}(t=2018)$	-0.272***	-0.329***	-0.285***	-0.302***
	(0.094)	(0.100)	(0.095)	(0.096)
Treat$\times\mathbb{1}(t=2019)$	-0.397***	-0.433***	-0.396***	-0.415***
	(0.101)	(0.093)	(0.100)	(0.102)
Treat$\times\mathbb{1}(t=2020)$	-0.255*	-0.297**	-0.280**	-0.286**
	(0.133)	(0.124)	(0.132)	(0.133)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.849	0.968	0.857	0.857
Observations	940,841	337,201	1,084,993	695,412

Table A.9: Dynamic Impact on China - Alternative Control Group

This table presents the results from estimation of Equation (8) after adding the interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat×$\mathbb{1}(t = 2014)$	-0.123	-0.123	-0.138	-0.139
	(0.102)	(0.092)	(0.099)	(0.099)
Treat×$\mathbb{1}(t = 2015)$	-0.042	-0.094	-0.050	-0.060
	(0.075)	(0.069)	(0.073)	(0.074)
Treat×$\mathbb{1}(t = 2017)$	-0.157*	-0.154**	-0.154*	-0.173**
	(0.082)	(0.076)	(0.081)	(0.083)
Treat×$\mathbb{1}(t = 2018)$	-0.193**	-0.196**	-0.194**	-0.206**
	(0.095)	(0.088)	(0.094)	(0.094)
Treat×$\mathbb{1}(t = 2019)$	-0.261***	-0.266***	-0.256***	-0.267***
	(0.087)	(0.080)	(0.086)	(0.086)
Treat×$\mathbb{1}(t = 2020)$	-0.135	-0.156	-0.142	-0.144
	(0.129)	(0.124)	(0.125)	(0.125)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{China})$	0.161	0.114	-0.417	-0.468
	(0.377)	(0.347)	(0.482)	(0.503)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{China})$	0.198	0.225	-0.203	-0.246
	(0.202)	(0.205)	(0.367)	(0.391)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{China})$	-0.127	-0.128	-0.172	-0.210
	(0.198)	(0.194)	(0.162)	(0.168)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{China})$	-0.136	-0.329	0.004	-0.014
	(0.210)	(0.228)	(0.196)	(0.200)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{China})$	-0.580*	-0.583*	-0.305	-0.334
	(0.329)	(0.325)	(0.388)	(0.383)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{China})$	-0.671	-0.864**	-0.472	-0.424
	(0.467)	(0.439)	(0.439)	(0.429)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.852	0.971	0.857	0.858
Observations	940,841	337,201	1,084,993	695,412

Table A.10: Dynamic Impact by Importer - Alternative Control Group

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j =$ China$)$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j =$ Low-income$)$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat×$\mathbb{1}(t = 2014)$	-0.132	-0.101	-0.145*	-0.151*
	(0.083)	(0.083)	(0.079)	(0.080)
Treat×$\mathbb{1}(t = 2015)$	-0.026	-0.071	-0.031	-0.045
	(0.086)	(0.076)	(0.083)	(0.083)
Treat×$\mathbb{1}(t = 2017)$	-0.033	-0.023	-0.037	-0.061
	(0.079)	(0.076)	(0.079)	(0.080)
Treat×$\mathbb{1}(t = 2018)$	-0.020	-0.029	-0.023	-0.036
	(0.103)	(0.101)	(0.100)	(0.100)
Treat×$\mathbb{1}(t = 2019)$	-0.153	-0.173*	-0.143	-0.153*
	(0.093)	(0.091)	(0.092)	(0.092)
Treat×$\mathbb{1}(t = 2020)$	-0.234*	-0.246**	-0.229*	-0.233*
	(0.121)	(0.114)	(0.119)	(0.120)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j =$ China$)$	0.169	0.093	-0.411	-0.456
	(0.373)	(0.346)	(0.478)	(0.500)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j =$ China$)$	0.181	0.202	-0.222	-0.260
	(0.206)	(0.208)	(0.369)	(0.393)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j =$ China$)$	-0.250	-0.259	-0.288*	-0.322*
	(0.197)	(0.194)	(0.160)	(0.168)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j =$ China$)$	-0.310	-0.496**	-0.168	-0.184
	(0.213)	(0.235)	(0.199)	(0.203)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j =$ China$)$	-0.687**	-0.676**	-0.419	-0.448
	(0.331)	(0.329)	(0.389)	(0.384)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j =$ China$)$	-0.572	-0.774*	-0.384	-0.335
	(0.466)	(0.438)	(0.437)	(0.427)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j =$ Low-income$)$	-0.282	-0.272	-0.267	-0.221
	(0.351)	(0.343)	(0.336)	(0.333)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j =$ Low-income$)$	-0.208	-0.213	-0.195	-0.169
	(0.274)	(0.271)	(0.266)	(0.268)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j =$ Low-income$)$	-0.582**	-0.633**	-0.527*	-0.497*
	(0.279)	(0.260)	(0.273)	(0.279)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j =$ Low-income$)$	-0.662**	-0.645***	-0.645**	-0.634**
	(0.281)	(0.249)	(0.272)	(0.277)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j =$ Low-income$)$	-0.446	-0.408	-0.453	-0.457
	(0.298)	(0.264)	(0.293)	(0.296)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j =$ Low-income$)$	0.334	0.273	0.324	0.335
	(0.365)	(0.328)	(0.353)	(0.357)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.852	0.971	0.858	0.858
Observations	940,841	337,201	1,084,993	695,412

Table A.11: Dynamic Impact by Neighborhood - Alternative Control Group

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{China})$ and an interaction between $\sum_{s\neq 2016} Treat \times \mathbb{1}(t = s)$ and $\mathbb{1}(j = \text{Neighbor})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat×$\mathbb{1}(t = 2014)$	-0.115	-0.092	-0.122	-0.133
	(0.102)	(0.099)	(0.101)	(0.102)
Treat×$\mathbb{1}(t = 2015)$	-0.015	-0.074	-0.032	-0.047
	(0.102)	(0.089)	(0.101)	(0.101)
Treat×$\mathbb{1}(t = 2017)$	-0.042	-0.032	-0.048	-0.069
	(0.081)	(0.076)	(0.080)	(0.081)
Treat×$\mathbb{1}(t = 2018)$	-0.030	-0.028	-0.034	-0.046
	(0.107)	(0.103)	(0.105)	(0.105)
Treat×$\mathbb{1}(t = 2019)$	-0.147	-0.170	-0.139	-0.151
	(0.109)	(0.105)	(0.108)	(0.109)
Treat×$\mathbb{1}(t = 2020)$	-0.275*	-0.290**	-0.270*	-0.274*
	(0.141)	(0.135)	(0.140)	(0.140)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{China})$	0.152	0.083	-0.434	-0.475
	(0.378)	(0.348)	(0.482)	(0.504)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{China})$	0.171	0.205	-0.221	-0.258
	(0.213)	(0.212)	(0.373)	(0.397)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{China})$	-0.241	-0.250	-0.278*	-0.315*
	(0.198)	(0.194)	(0.161)	(0.168)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{China})$	-0.299	-0.497**	-0.157	-0.174
	(0.216)	(0.234)	(0.201)	(0.206)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{China})$	-0.694**	-0.680**	-0.422	-0.449
	(0.336)	(0.332)	(0.393)	(0.389)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{China})$	-0.531	-0.732*	-0.343	-0.294
	(0.471)	(0.442)	(0.443)	(0.433)
Treat×$\mathbb{1}(t = 2014)$×$\mathbb{1}(j = \text{Neighbor})$	-0.017	-0.043	-0.031	0.013
	(0.234)	(0.218)	(0.225)	(0.224)
Treat×$\mathbb{1}(t = 2015)$×$\mathbb{1}(j = \text{Neighbor})$	-0.055	-0.033	-0.025	-0.003
	(0.148)	(0.136)	(0.143)	(0.145)
Treat×$\mathbb{1}(t = 2017)$×$\mathbb{1}(j = \text{Neighbor})$	-0.293*	-0.314**	-0.270	-0.266
	(0.166)	(0.150)	(0.170)	(0.179)
Treat×$\mathbb{1}(t = 2018)$×$\mathbb{1}(j = \text{Neighbor})$	-0.295*	-0.343**	-0.299*	-0.295*
	(0.166)	(0.163)	(0.168)	(0.168)
Treat×$\mathbb{1}(t = 2019)$×$\mathbb{1}(j = \text{Neighbor})$	-0.198	-0.187	-0.234	-0.225
	(0.174)	(0.169)	(0.168)	(0.171)
Treat×$\mathbb{1}(t = 2020)$×$\mathbb{1}(j = \text{Neighbor})$	0.488*	0.414*	0.404*	0.412*
	(0.254)	(0.244)	(0.243)	(0.247)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.852	0.971	0.858	0.858
Observations	940,841	337,201	1,084,993	695,412

Table A.12: Dynamic Impact by Waste Value - Alternative Control Group

This table presents the results from estimation of event-study version of Equation (9) where $n \in \{\text{High-value waste}, \text{Low-value waste}\}$ after including interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times \sum_{s \neq 2016} \mathbb{1}(t = s)$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014)$	-0.052	-0.020	-0.066	-0.076
	(0.086)	(0.084)	(0.084)	(0.088)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015)$	-0.025	-0.059	-0.038	-0.060
	(0.089)	(0.080)	(0.087)	(0.088)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017)$	-0.038	-0.010	-0.042	-0.086
	(0.085)	(0.078)	(0.087)	(0.093)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018)$	-0.028	-0.035	-0.020	-0.040
	(0.106)	(0.103)	(0.104)	(0.105)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019)$	-0.182*	-0.199**	-0.158	-0.177*
	(0.100)	(0.095)	(0.100)	(0.103)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020)$	-0.242*	-0.277**	-0.229*	-0.231*
	(0.127)	(0.116)	(0.126)	(0.128)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{China})$	0.303	0.244	-0.220	-0.247
	(0.336)	(0.309)	(0.418)	(0.429)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{China})$	0.111	0.125	-0.218	-0.233
	(0.211)	(0.211)	(0.293)	(0.306)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{China})$	-0.030	-0.037	0.012	0.022
	(0.199)	(0.194)	(0.176)	(0.179)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{China})$	-0.193	-0.456**	0.056	0.012
	(0.259)	(0.222)	(0.268)	(0.269)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{China})$	-0.868**	-0.774*	-0.469	-0.482
	(0.392)	(0.400)	(0.479)	(0.472)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{China})$	-0.378	-0.619	-0.198	-0.088
	(0.582)	(0.527)	(0.535)	(0.539)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{Low-income})$	-0.536	-0.530	-0.423	-0.363
	(0.414)	(0.403)	(0.367)	(0.369)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{Low-income})$	-0.324	-0.343	-0.246	-0.176
	(0.348)	(0.344)	(0.303)	(0.310)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{Low-income})$	-0.820**	-0.850***	-0.723**	-0.720**
	(0.355)	(0.328)	(0.322)	(0.361)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{Low-income})$	-0.948***	-0.892***	-0.894***	-0.932***
	(0.355)	(0.313)	(0.319)	(0.350)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{Low-income})$	-0.683*	-0.599*	-0.682**	-0.747**
	(0.363)	(0.322)	(0.330)	(0.353)
$\mathbb{1}(m = \text{High-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{Low-income})$	0.133	0.142	0.173	0.130
	(0.413)	(0.361)	(0.388)	(0.414)

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$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2014)$	-0.225***	-0.196**	-0.232***	-0.229***
	(0.083)	(0.085)	(0.080)	(0.080)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2015)$	-0.026	-0.085	-0.022	-0.030
	(0.087)	(0.076)	(0.083)	(0.083)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2017)$	-0.026	-0.037	-0.030	-0.036
	(0.078)	(0.075)	(0.076)	(0.076)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2018)$	-0.009	-0.024	-0.025	-0.029
	(0.102)	(0.101)	(0.099)	(0.099)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2019)$	-0.120	-0.149	-0.124	-0.126
	(0.091)	(0.091)	(0.090)	(0.090)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2020)$	-0.221*	-0.215*	-0.226*	-0.228*
	(0.121)	(0.115)	(0.118)	(0.118)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{China})$	0.176	0.119	-0.395	-0.420
	(0.364)	(0.346)	(0.445)	(0.452)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{China})$	0.179	0.232	-0.217	-0.233
	(0.210)	(0.208)	(0.342)	(0.351)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{China})$	-0.328*	-0.317	-0.355**	-0.370**
	(0.199)	(0.197)	(0.158)	(0.159)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{China})$	-0.527**	-0.514**	-0.377	-0.397*
	(0.245)	(0.243)	(0.238)	(0.234)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{China})$	-0.706**	-0.677**	-0.411	-0.434
	(0.332)	(0.332)	(0.393)	(0.389)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{China})$	-0.826*	-0.838*	-0.574	-0.595
	(0.438)	(0.440)	(0.430)	(0.428)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2014) \times \mathbb{1}(j = \text{Low-income})$	0.189	0.229	-0.034	0.046
	(0.269)	(0.257)	(0.267)	(0.251)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2015) \times \mathbb{1}(j = \text{Low-income})$	-0.011	0.061	-0.165	-0.095
	(0.121)	(0.112)	(0.147)	(0.146)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2017) \times \mathbb{1}(j = \text{Low-income})$	-0.202	-0.173	-0.244	-0.239
	(0.186)	(0.185)	(0.204)	(0.208)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2018) \times \mathbb{1}(j = \text{Low-income})$	-0.165	-0.090	-0.273	-0.285
	(0.176)	(0.182)	(0.195)	(0.200)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2019) \times \mathbb{1}(j = \text{Low-income})$	0.014	0.060	-0.064	-0.082
	(0.197)	(0.200)	(0.217)	(0.219)
$\mathbb{1}(m = \text{Low-value}) \times \mathbb{1}(t = 2020) \times \mathbb{1}(j = \text{Low-income})$	0.714***	0.657**	0.596**	0.593**
	(0.276)	(0.273)	(0.278)	(0.277)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.860	0.972	0.865	0.866
Observations	940,841	337,201	1,084,993	695,412

Table A.13: Impact by Waste Type - Alternative Control Group

This table presents the results from estimation of Equation (9) after adding interactions of $\sum_{n \neq Regular} \mathbb{1}(m = n) \times Post$ with $\mathbb{1}(j = \text{China})$ and with $\mathbb{1}(j = \text{Low-income})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
$\mathbb{1}(m = \text{Glass})\times$Post	-0.182*	-0.175*	-0.170	-0.171
	(0.108)	(0.105)	(0.105)	(0.105)
$\mathbb{1}(m = \text{Metal})\times$Post	-0.097	-0.102	-0.077	-0.088
	(0.086)	(0.081)	(0.085)	(0.086)
$\mathbb{1}(m = \text{Paper})\times$Post	-0.102	-0.115	-0.079	-0.080
	(0.083)	(0.080)	(0.082)	(0.081)
$\mathbb{1}(m = \text{Organic})\times$Post	-0.057	-0.078	-0.040	-0.042
	(0.085)	(0.082)	(0.082)	(0.082)
$\mathbb{1}(m = \text{Plastic})\times$Post	0.036	0.031	-0.290**	-0.290**
	(0.088)	(0.085)	(0.128)	(0.128)
$\mathbb{1}(m = \text{Wood})\times$Post	0.096	0.091	0.113	0.113
	(0.091)	(0.086)	(0.089)	(0.088)
$\mathbb{1}(m = \text{Yarn})\times$Post	-0.114	-0.134	-0.100	-0.097
	(0.086)	(0.083)	(0.084)	(0.084)
$\mathbb{1}(m = \text{Glass})\times$Post$\times\mathbb{1}(j = \text{China})$	-2.384***	-2.389***	-0.995	-0.996
	(0.385)	(0.381)	(0.787)	(0.786)
$\mathbb{1}(m = \text{Metal})\times$Post$\times\mathbb{1}(j = \text{China})$	-0.391	-0.457*	0.045	0.032
	(0.302)	(0.270)	(0.386)	(0.375)
$\mathbb{1}(m = \text{Paper})\times$Post$\times\mathbb{1}(j = \text{China})$	-0.363	-0.336	0.098	0.066
	(0.253)	(0.249)	(0.356)	(0.345)
$\mathbb{1}(m = \text{Organic})\times$Post$\times\mathbb{1}(j = \text{China})$	-1.477***	-1.450**	-1.007	-1.038
	(0.564)	(0.567)	(0.726)	(0.723)
$\mathbb{1}(m = \text{Plastic})\times$Post$\times\mathbb{1}(j = \text{China})$	-1.358***	-1.344***	-0.627*	-0.632*
	(0.257)	(0.256)	(0.362)	(0.362)
$\mathbb{1}(m = \text{Wood})\times$Post$\times\mathbb{1}(j = \text{China})$	-1.331*	-1.337*	-0.866	-0.864
	(0.690)	(0.697)	(0.729)	(0.728)
$\mathbb{1}(m = \text{Yarn})\times$Post$\times\mathbb{1}(j = \text{China})$	-0.049	0.035	0.395	0.377
	(0.273)	(0.331)	(0.399)	(0.398)
$\mathbb{1}(m = \text{Glass})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	-0.323	-0.349	-0.336	-0.358
	(0.288)	(0.263)	(0.281)	(0.275)
$\mathbb{1}(m = \text{Metal})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	-0.369*	-0.378*	-0.378*	-0.488*
	(0.213)	(0.197)	(0.205)	(0.261)
$\mathbb{1}(m = \text{Paper})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	0.179	0.147	0.189	0.092
	(0.155)	(0.155)	(0.174)	(0.192)
$\mathbb{1}(m = \text{Organic})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	-0.050	-0.116	-0.060	-0.080
	(0.165)	(0.159)	(0.164)	(0.162)
$\mathbb{1}(m = \text{Plastic})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	-0.247	-0.269*	0.157	0.140
	(0.171)	(0.160)	(0.199)	(0.196)
$\mathbb{1}(m = \text{Wood})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	0.009	-0.074	-0.016	-0.041
	(0.338)	(0.336)	(0.335)	(0.334)
$\mathbb{1}(m = \text{Yarn})\times$Post$\times\mathbb{1}(j = \text{Low-income})$	0.106	-0.050	0.079	0.051
	(0.193)	(0.138)	(0.190)	(0.189)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Adj. Pseudo R^2	0.872	0.971	0.878	0.880
Observations	940,841	337,201	1,084,993	695,412

Table A.14: Extensive Margin - Alternative Control Group

This table presents the results from estimation of Equation (10) after adding an interaction of $Treat \times Post$ with $\mathbb{1}(j = \text{China})$. Each column corresponds to a different set of fixed effects and controls. Standard errors clustered by exporter-importer pair in parentheses. Significance codes: *** p<0.01, ** p<0.05, * p<0.1

	Quantity			
	(1)	(2)	(3)	(4)
Treat × Post	0.026**	0.054***	0.022**	0.021*
	(0.010)	(0.019)	(0.010)	(0.011)
Treat × Post × $\mathbb{1}(j = \text{China})$	-0.212***	-0.428**	-0.170**	-0.098
	(0.066)	(0.166)	(0.070)	(0.076)
Controls				
Country-Year	✓	✓		
Bilateral-Year			✓	
Concurrent waste import bans	✓	✓	✓	✓
Fixed Effects				
Type	✓		✓	✓
Year	✓	✓		
Bilateral	✓		✓	
Type-Bilateral		✓		
Country-Year			✓	
Bilateral-Year				✓
Log-likelihood	-241,382.4	-125,544.8	-268,734.9	-232,619.0
Observations	936,842	239,742	1,080,856	684,042