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 waste 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. Although this negative impact is largely due to the decline in waste imports by China, other low-income countries also substantially decreased their waste imports. While waste types covered by the ban experienced the greatest impact, trade in other potentially harmful waste categories also declined. Back-of-the-envelope calculations suggest that low-income countries saved 83-375 million USD in external costs by 2020, roughly one-fifth the savings in 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 (Unfried and Wang, 2022; Li and Takeuchi, 2023; Shi and Zhang, 2023). These externality costs are particularly high in developing countries, where the recycling operations are largely informal and unregulated (Vidal, 2014). Moreover, unrecyclable waste is often exported under the guise of recyclable waste (Gutierrez, 2016). Imported recyclable waste contaminated with hazardous and nonrecyclable materials presents challenges in 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 use 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 scaled back their waste collection programs in the aftermath of the ban. 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 waste 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 waste categories also allows me to quantify how these effects evolve over time and which countries and waste types are more severely affected.

I find that, on average, China's 2017 waste import ban led to a decrease of 19.8-21.5% 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 16.1% 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 25-32% in 2017, with this reduction growing in size to 54-64% by 2020.

However, the negative impact on the global waste trade market is not solely driven by China. Low-income countries also decreased their waste imports by 24-29% in the initial year of the ban. Even though this decline was followed by reductions in subsequent years as well, these countries eventually increased their waste imports by 39-56% by 2020. Similar to the impact on low-income countries, countries neighboring China experienced an initial decline followed by an increase in waste imports. I also find that while waste types covered by the ban such as plastic, paper, and metals, experienced the greatest impact, waste materials not directly covered by the ban like glass and organic, which can potentially create large negative externalities in destination countries when contaminated with harmful materials, also experienced reductions in trade.

My findings are robust to alternative sets of fixed effects and controls and to adding other waste types unaffected by the ban to the control group. 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. I also show that my results are driven by changes on the intensive margin, i.e., through reduction in waste trade between countries, rather than those on the extensive margin, i.e., by country pairs ending trade in waste altogether.

The literature provides a wide range of estimates for the social marginal costs of waste (Eshet, Ayalon and Shechter, 2005; Kinnaman, 2009; McKinsey, 2016; Bond et al., 2020). By some estimates (Bond et al., 2020), the social marginal costs of plastic waste can be as high as \$1000/metric ton. Even if I rely on the most conservative estimate of \$4-18/ton suggested by Kinnaman (2009), China's cumulative external costs by 2020 drop by 479 million to 2 billion USD. Even after accounting for the surge in waste imports in later years, the low-income countries see cumulative savings to the tune of 83-375 million USD by 2020, roughly one-fifth the cumulative savings in China.

My results suggest that China's unilateral waste trade regulation not only benefits China itself but also helps other lower-income countries reduce their externality costs. Further, this impact is driven by some of the most environmentally harmful materials like plastics that are difficult to recycle (Brooks, Wang and Jambeck, 2018). Such a reduction in waste imports is particularly crucial for low-income countries, which tend to have laxer environmental regulations and thus, undergo more environmental damage per unit of waste.

My paper contributes to the burgeoning literature on the consequences of waste trade regulations. 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, 2022; Sigman and Strowe, 2024; 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 global impact of the comprehensive 2017 ban evolved over time and which countries and waste types experienced the greatest impact.

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 some evidence supporting a pollution haven effect in the context of waste trade. My results suggest that waste trade *de-liberalization* shifts polluting waste residues away from lower-income countries, which also tend to have laxer environmental regulations.

This paper also speaks to the literature on the environmental consequences of unilateral and multilateral regulations (Clausing and Wolfram, 2023; Deltas and Thakur, 2024; Farrokhi and Lashkaripour, 2024) by showing 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 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 catalogue of forbidden and restricted waste categories was released in 2008, followed by "Operation Green Fence" in 2013. Several measures were taken by Chinese customs under Operation Green Fence, 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. First, by end of 2017, ban imports of harmful waste including plastic, unsorted paper, yarn, and vanadium slag. Second, by end of 2019, ban imports of those waste categories that can be replaced by domestic sources. Any hazardous, medical, electronic, or municipal waste is also considered illegal under this regulation.[1] Other waste materials like old corrugated boxes that were not directly banned were also impacted by this regulation, especially 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 with hazardous substances and organic waste with bio-contaminants with a high likelihood (Bebinger, 2023; Hughes, 2023). Therefore, I consider glass and organic among the waste types affected by the ban. Figure 1 shows that China's share in imports of banned waste types has fallen substantially post the announcement of Operation National Sword in 2017. Further, China's share in imports of waste types not targeted by the ban remains relatively flat throughout my sample period. 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, land filling some recyclables, and even cutting down or scaling back recycling collection programs in the aftermath of the ban. On the other hand, reports suggest diversion of some plastic waste to other Southeast Asian countries (Resource Recycling, 2022). Countries like Vietnam, Indonesia, Malaysia, Thailand, and India also announced temporary restrictions on their waste imports after China's ban.

[1] 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.

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 manage increasing quantities of waste domestically, the share of other importing countries may even decline with the ban.

3 Econometric Framework

To study the impact of China's 2018 waste import ban on international waste flows, I derive an estimable equation using the workhorse gravity model of trade. The waste generators in country i can dispose the waste domestically or buy disposal services at any destination country j. Let the value to waste generator in country i of shipping waste type w to country j be:

$$U_{wijt} = \alpha_{wi} + \beta_1 X_{wjt} + \tilde{\mu}_{ij} + \varepsilon_{wij}, \tag{1}$$

where X_{wjt} are time-varying characteristics specific to country j for waste type w, $\tilde{\mu}_{ij}$ represents the time-invariant component of the attractiveness of destination j to country i, and ε_{wij} is an extreme value distributed error term with the cumulative distribution function $\exp\{-\exp\{-\varepsilon_{wij}\}\}$. The value to generator in country i of disposing waste w domestically is:

$$U_{wiit} = \beta_2 X_{wit} + \tilde{\mu}_{ii} + \varepsilon_{wii}, \tag{2}$$

where X_{wit} are time-varying characteristics specific to country i for waste type w, $\tilde{\mu}_{ii}$ represents the attractiveness of domestic disposal, and ε_{wii} is extreme-value distributed. Using standard transformation, the share of waste w shipped from i to j is:

$$s_{wijt} = \frac{\exp\{\alpha_{wi} + \beta_1 X_{wjt} + \tilde{\mu}_{ij}\}}{\exp\{\beta_2 X_{wit} + \tilde{\mu}_{ii}\} + \sum_{k \neq i} \exp\{\alpha_{wi} + \beta_1 X_{wkt} + \tilde{\mu}_{ik}\}}, \tag{3}$$

while the share of waste w disposed domestically is:

$$s_{wiit} = \frac{\exp\{\beta_2 X_{wjt} + \tilde{\mu}_{ij}\}}{\exp\{\beta_2 X_{wit} + \tilde{\mu}_{ii}\} + \sum_{k \neq i} \exp\{\alpha_{wi} + \beta_1 X_{wkt} + \tilde{\mu}_{ik}\}}. \tag{4}$$

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

$$\ln(s_{wijt}) - \ln(s_{wiit}) = \alpha_{wi} + \beta_1 X_{wjt} - \beta_2 X_{wit} + \mu_{ij} \tag{5}$$

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 waste type for every exporting country. To be able to compute these shares, I need information on overall volume of each waste type generated 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 2018 waste import ban (Yotov et al., 2016). However, comprehensive production data, particularly on volume of generation in each waste category separately, are challenging to obtain. Therefore, like in most gravity equation estimations, I impute total domestic generation using a variable that captures the overall market size of each waste type, $\mathcal{G}_{wit}$.

Bilateral trade shares are then $s_{wijt} = TF_{wijt}/\mathcal{G}_{wit}$ while domestic disposal share is $s_{wiit} = 1 - \sum_j s_{wijt} = 1 - \sum_j (TF_{wijt}/\mathcal{G}_{wit})$, where TF_{wijt} is the volume of exports from i to j in year t. Substituting the expressions for shares into Equation (5) and simplifying, I obtain an estimable equation as follows:

$$\ln(TF_{wijt}) = \alpha_{wi} + \beta_1 X_{wjt} - \beta_2 X_{wit} + \mu_{ij} + \ln(\mathcal{G}_{wit} - \sum_j TF_{wijt}) \tag{6}$$

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 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 2018 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:

$$\ln(TF_{wijt}) = \beta_1 Treat_w \times Post_t + \beta_2 X_{it} + \beta_2 X_{jt} + \mu_{wij} + \mu_t + \ln(\mathcal{G}_{wit} - \sum_j TF_{wijt}), \quad (7)$$

where the main variable of interest is the product of $Treat_w$, an indicator for waste types banned by China, 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 banned waste is diverted to other countries, negative if other countries also import lower volumes of waste as a result of China's ban, or zero if other countries are unaffected by the ban. The variables, X_{it} and X_{jt}, include exporter or importer specific time-varying covariates such as income, income per capita, and environmental preferences, which affect the willingness of a country to export or import waste. I also control for bilateral effects idiosyncratic to each waste type using μ_{wij} and secular trends in overall trade flows and trade costs using μ_t.

To study the dynamic impact of the ban, I also estimate an event study DID version of Equation (7), which is written as follows:

$$\ln(TF_{wijt}) = \beta_0 + \sum_{t \neq 2016} \beta_t Treat_w \times \mathbb{1}(year = t) + \beta_2 X_{it} + \beta_2 X_{jt} + \mu_{wij} + \mu_t + \ln(\mathcal{G}_{wit} - \sum_j TF_{wijt}). \quad (8)$$

Further, to assess heterogeneity in the treatment effect by waste type, I estimate the following equation:

$$\ln(TF_{wijt}) = \sum_{w \neq R/L} \beta_w \mathbb{1}(type = w) \times Post_t + \beta_2 X_{it} + \beta_2 X_{jt} + \mu_{wij} + \mu_t + \ln(\mathcal{G}_{wit} - \sum_j TF_{wijt}), \tag{9}$$

where control waste type, Rubber/Leather, serves as the base category. Since Equation (7) is a log-level regression, the treatment effect is computed as $100 \times (e^{\beta_1} - 1)\%$. Analogously, I am able to compute the heterogeneous treatment effects using estimates of β_t from Equation (8) and β_w from Equation (9).

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 waste type effects and bilateral effects or controls for distance, contiguity, common language, and colonial relationships. Alternatively, I control for time effects idiosyncratic to each country pair like bilateral trade costs and bilateral trade imbalances using exporter-importer-year effects along with waste type fixed effects.

The parameters of interest, however, cannot be interpreted as quantifying precisely the treatment effects unless the parallel trends assumption is satisfied. I test the parallel trends assumption by estimating the following equation:

$$\ln(TF_{wijt}) = \beta_0 + \sum_{t \neq 2016} \beta_t Treat_w \times \mathbb{1}(year = t) + \ln(\mathcal{G}_{wit} - \sum_j TF_{wijt}), \tag{10}$$

where the year before the announcement of the ban, 2016, serves as the base year, and I include the term capturing volume of domestic disposal, $\ln(\mathcal{G}_{wit} - \sum_j TF_{wijt})$, with its coefficient set to unity.

4 Data

As described in the previous section, the estimation of Equation (7) relies on data on bilateral waste trade flows and waste generation. 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 eight broad types: glass, metal, organic, paper, plastic, rubber and leather, wood, and yarn (See Table A.1 for the HS6 codes under each type). Rubber and leather waste, the only waste type in my sample plausibly unaffected by the ban, forms the control group. The balanced bilateral trade flow panel is generated by aggregating the flows across HS6 categories under each waste type 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 waste type, $\mathcal{G}_{wit}$. While I do not directly observe the total domestic waste generation, I do observe the total generation of municipal waste from Kaza et al. (2018), which I use as a proxy for the size of the waste market. I assume that $\mathcal{G}_{wit} = \lambda_{wi}\mathcal{M}_{it}$, where $\mathcal{M}_{it}$ is total municipal waste generated in country i in year t, and λ_{wi} is a scalar that reflects the fraction of waste generation that is of type w.

The municipal waste generation data, however, are available for only a single year, 2016. 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_{wi} are calibrated based on the waste composition across countries in the literature. With the exception of yarn, Kaza et al. (2018) also provides the share of each waste type in my sample in overall municipal waste generation (See Table A.2). 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_{wi} by a factor of 20. My results in Section 5 are robust to an alternative scaling factor of 15.

I control for the size 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 trade partners, I use 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 the results in Section 5 are robust to including this trade imbalance measure in regressions. The complete bilateral trade panel comprises 2,513,798 observations (7 years $\times$ 227 exporters $\times$ 226 importers $\times$ 7 waste types).

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. I first test the parallel trends assumption by estimating Equation (10). Figure 2 shows that, relative to 2016, the difference between treated and control waste flows is not statistically significant in the years prior to the ban, 2014-15, thereby providing evidence of parallel trends. In the years post the announcement, however, I find a negative and statistically significant impact on treated waste flows that increases in magnitude until 2019, after which it diminishes in size.

5.1 Global Impact

Column (2) in Table 2 presents the results from estimation of Equation (7). I find that the DID estimate is -0.232 and statistically significant at the 1% level. Specifically, China's 2017 waste import ban led to a decrease of 20.7% in bilateral trade flows of targeted waste categories on average. Since column (2) includes fixed effects at the waste type-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 waste types specific to each country pair.

My results are robust to including waste 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 (in column (3)), to including exporter-importer fixed effects in place of exporter-importer controls (in column (4)), and to including exporter-importer-year fixed effects (in column (5)). The estimated effect ranges from 19.8% to 21.5% decline in bilateral trade flows across these specifications. However, I consider column (2), with the highest Pseudo-R^2, as my preferred specification.

The different number of observations across specifications (1)-(5) are 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). While keeping these observations does not affect the coefficient estimates, statistical significance may be overstated. Therefore, the algorithm now automatically drops these observations (Correia, 2015; Correia, Guimarães and Zylkin, 2021).

Table 3 presents the results from estimation of Equation (8). Firstly, I find only small and statistically insignificant coefficients on the pre-ban interactions in all specifications, which further provides evidence in favor of parallel trends. Column (2) shows that the ban caused bilateral flows of banned waste types to decline by 16.1% 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: 23.3% in 2018 and 32% 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)-(5). 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, 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 over time. To quantify these effects, I add interactions between the term capturing dynamic treatment effects, $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$, and an indicator for importing country group of interest to Equation (8). The coefficient on these triple interaction terms would represent the differentiated impact on the imports of that particular country group.

Figure 3 presents the results after including interaction terms with an indicator for China as the importing country (See the counterpart Table A.3 for further details). I find that the coefficients on $\sum_{t=2017}^{2019} Treat \times \mathbb{1}(year = t)$ are negative and significant atleast at the 10% level in most specifications. Specifically, the imports of countries other than China decline by 10-15% on average in 2017, with the effect growing to 20-23% by 2019. Further, even though the coefficients on the interactions between $\sum_{t=2017}^{2020} Treat \times \mathbb{1}(year = t)$ and the China as importer indicator are negative in all specifications, they are imprecisely estimated. Even so, the differentiated impact on China's imports in 2019 is negative and statistically significant at the 10% level across all specifications. The differentiated decline in China's imports amounts to 14-19% in 2017, with the effect growing to 50-62% by 2020. Therefore, China's total waste imports declined by 25-32% in 2017, with this effect growing to 54-64% by 2020. Therefore, even though the negative impact on global waste flows is largely driven by decline in China's imports, I do find evidence of a negative impact on imports of other countries as well.

To determine which other countries drive this negative impact, I additionally include interactions of the term capturing dynamic treatment effect with two different types of indicators for importing countries. 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 30% of the countries in my sample that had the lowest GDP per capita as of 2014, the first year of my sample period. Figure 4 shows that the coefficient on interaction between $Treat \times \mathbb{1}(year = 2018)$ and low-income importer is negative and statistically significant atleast at the 10% level across all specifications (See the counterpart Table A.4 for further details). I also observe negative coefficients in 2017 and 2019, which are rather imprecisely estimated and hence, not statistically significant in most specifications. Finally, I observe a positive and statistically significant differentiated impact on low income importer in 2020. The differentiated impact on low-income importers amounts to a decline of 26-31% in 2018 and an increase of 71-92% in 2020.

Further, the finding that China's waste imports are strongly negatively affected over the years continues to hold as per these estimates. Not only is the treatment effect on China persistently negative, but also the size of this treatment effect is larger than that on low-income importers over 2017-19. Therefore, these results suggest that low-income importers also decreased their waste imports initially as result of the ban, albeit to a smaller extent than China. However, this effect was short-lived, and the low-income countries eventually turned into destinations for the waste displaced as a result of the ban.

Second, I add interactions with an indicator for a country in China's neighborhood. The Neighbor indicator takes a value of 1 for those 10% of the countries in my sample that are geographically the closest to China. I measure geographical proximity using the great circle distances from Mayer and Zignago (2011). Table A.5 shows that, similar to low-income importers, countries neighboring China initially decreased their waste imports, albeit to a smaller extent than China, after which they increase their waste imports by 2020. Sigman and Strowe (2024) also find a decrease in plastic waste exports by the US not only to China, but also to other low-income countries. My findings suggest that waste collection programs in exporting countries may have taken a hit in the initial years of the ban, thereby benefiting other low-income countries as well. The other low-income countries, however, made up for at least some of the lost demand for waste by taking in imports a few years after the ban.

5.3 By Waste Type

Table 4 presents the results from estimation of Equation (9). Table 4 shows a negative and statistically significant treatment effect on all waste types, except wood, in all specifications. Global plastic waste trade experienced the largest decline ranging between 38-53%, followed by paper waste ranging between 28-32%, followed by the other waste types, including glass waste and organic waste, which are not directly targeted by the ban, ranging between 14-25%. Plastic waste is arguably the least easily recyclable and most environmentally damaging of all waste categories (Brooks, Wang and Jambeck, 2018). Further, the ban targeted several other categories that are environmentally damaging or hazardous, which includes unsorted paper waste. Therefore, a substantial hit to the global market of banned waste types as a result of the ban is unsurprising. Moreover, my results reveal that the global market of several other waste categories not directly covered under the ban also faced a considerable negative impact as China tightened its restrictions.

6 Robustness Checks

In this section, I assess the robustness of my results to adding other waste types that are plausibly unaffected by the ban to the control group. I further alleviate the concern that the estimated treatment effect is due to some omitted variation, rather than China's waste import ban, by conducting two placebo tests. Finally, I show that my results are driven by changes on the intensive margin rather than on the extensive margin.

6.1 Alternative Control Group

In Section 5, I use rubber/leather waste, which was not part of China's waste import ban in 2017, as the control group. While international trade flows of waste types directly targeted by the ban and other waste types that are likely contaminated with hazardous material are adversely affected, waste types that are easily recyclable and are of high-value would not be affected by the ban. Precious metals like gold and platinum are two such waste types in addition to rubber/leather waste. Table A.1 shows the HS6 codes of these two waste types while Table 1 shows that China accounted for only a small share in global imports of these two types, which provides further reason to include these in the control group.

Therefore, I replicate the results in Section 5 after including gold and platinum waste in the control waste types. However, due to lack of data on generation of gold and platinum waste by country, I exclude the domestic disposal term, $\ln(\mathcal{G}_{wit} - \sum_j TF_{wijt})$, from these regressions. Thus, while I now include several waste types in the control group, I have to forego controlling for intra-national flows, which are important for identification of the impact of a non-discriminatory trade policy (Yotov et al., 2016). Since I omit the domestic disposal term, I now include yarn waste, for which too I lack waste generation data, as part of the treated group.

The replicated results in Figure A.2 and Tables A.6 to A.11 are qualitatively similar but quantitatively larger in magnitude. The downward bias in the treatment effect is expected since volume of domestic disposal in a waste type is positively associated with its export volumes and negatively associated with its likelihood of being treated by the ban.[2] Therefore, these findings suggest that my results are robust to inclusion of other relevant waste types as part of the control group. As expected, Table A.11 further shows that gold and platinum waste trade was unaffected by the ban while yarn waste trade saw a statistically significant negative impact.

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 waste types 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 the DID effect. The DID estimates using either 2015 or 2016 as the fake treatment years across all 5 of my specifications are in Figure 5. Not only are these DID estimates positive, I also 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.

Next, I drop all the observations on the treated waste types, and pick a fake treated waste type before estimating the DID effect. Since my control group originally contains 3 waste types — rubber/leather, gold, and platinum—I can form 6 possible fake treated groups.[3] The DID estimates with the 6 possible fake treated groups are in Figure 6. Again, I find no statistically significant effect using any fake treated group or any specification even at the 10% level.[4] Therefore, the waste types part of the control group, which largely contains

[2]One way to check this is indeed the case is by only excluding the domestic disposal term while replicating the results in Section 5. On doing so, I find that the treatment effect estimates are similarly downward biased.

[3]If I pick only one waste type as treated, I have a total of three possibilities for the fake treated group. If I pick two waste types as treated, I again have a total of 3 possibilities for the fake treated groups. Therefore, I have 6 possible fake treated groups in all.

[4]When I swap the set of treated and control waste types, as in moving from the top row to the bottom row of Figure 6, only the sign of the DID estimate should change. Therefore, the estimates in the bottom row are simply mirror images of the estimates in the top row, verifying that the placebo test was correctly implemented.

high-value waste materials, are unaffected by the ban.

6.3 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 check that this is not the case, I drop all zero bilateral trade flow observations from my panel dataset before estimating Equation (8) again. If changes on the extensive margin indeed drive my findings, then the estimated treatment effects should become smaller in magnitude. However, Table 5 shows that the dynamic DID estimates are both qualitatively and quantitatively similar to those in Table 3, thereby providing evidence in favor of changes on the intensive margin driving my results.

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 16.1% 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 waste imports by China. China decreased its waste imports by 25-32% in 2017, with this reduction growing to 54-64% by 2020. However, reduction in China's imports alone does not explain the hit that the global waste trade market took. Low-income countries and countries neighboring China also substantially decreased their waste imports in the initial years following the implementation of the ban, with these countries eventually turning into destinations for atleast some of the displaced waste. While the ban mostly affected international trade of plastic and paper 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 externalities in the receiving countries, especially when commingled with environmentally damaging and hazardous material.

The literature provides a wide range of estimates for the externality costs of waste (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 the European Union tax on nonrecycled plastic waste levied on member countries starting on January 1, 2021. Even if I rely on the most conservative estimate of $4-18/ton suggested by Kinnaman (2009), China's external costs drop by 64-288 million USD in 2017, with this impact growing to 164-740 million USD by 2020. The cumulative savings in external costs in China by 2020 are, therefore, between 479 million and 2 billion USD. Further, China is not the only country benefiting from the waste import ban. Other low income countries save 54-242 million USD in 2017, which declines to 45-203 million USD by 2019. These countries eventually face extra external costs of 71-322 million USD by 2020. Nevertheless, the low-income countries see cumulative savings to the tune of 83-375 million USD by 2020, roughly one-fifth the cumulative savings in China.[5]

Therefore, 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, a unilateral waste trade regulation may fall short unless waste management and recycling programs 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.

[5]All back-of-the-envelope calculations are based on estimates in column (2) in Tables A.3 to A.4. In computing the externality costs, I also convert the 2009 estimate of $4-18/ton into 2020 USD per metric ton.

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8 Figures and Tables

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

This figure shows China's share in imports of waste types 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.

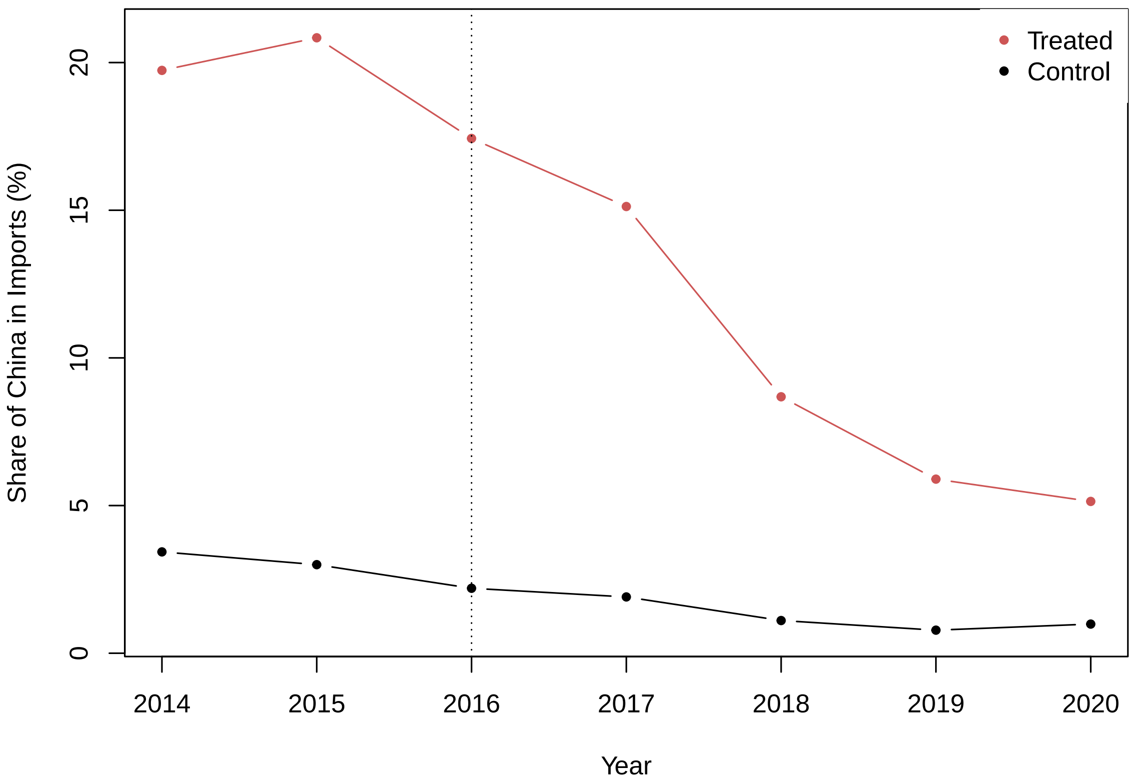

Figure 2: Testing Parallel Trends Assumption

This figure presents the results from estimating Equation (10). The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

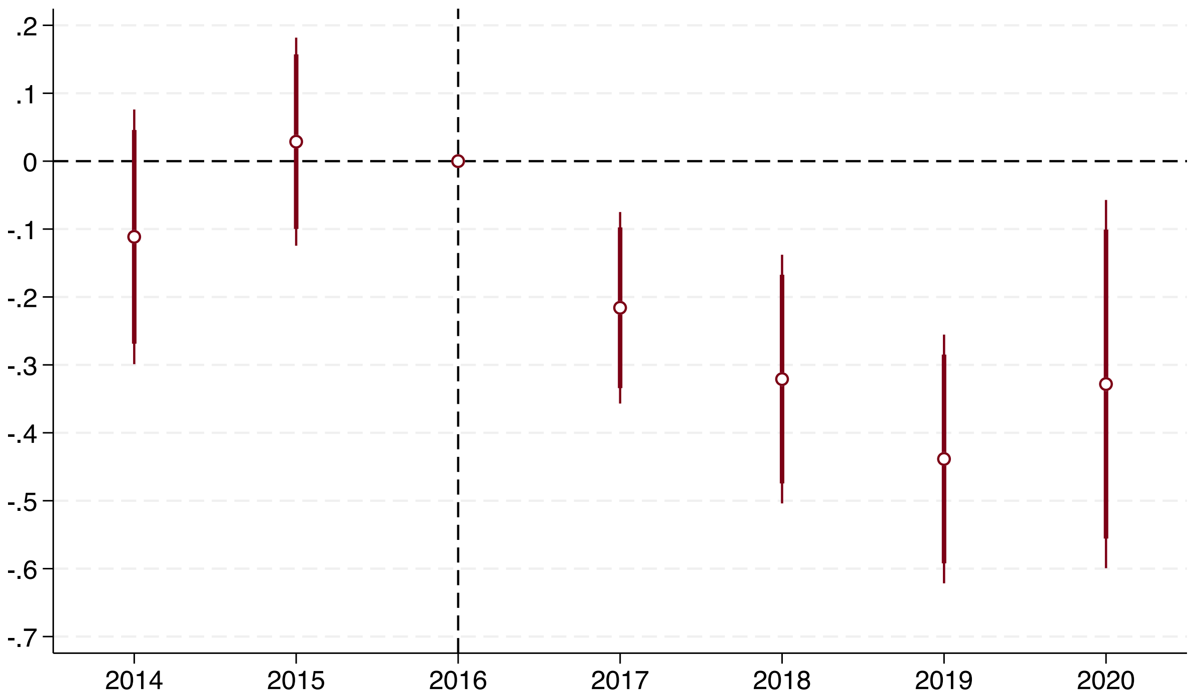

Figure 3: Dynamic Impact on China

This figure presents the results from estimation of Equation (8) after adding the interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer. The top panel shows the coefficients to $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$, while the bottom panel shows the coefficients to the interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and China as Importer indicator. Each model corresponds to a different set of fixed effects and controls, as in Tables 2 to 4. The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

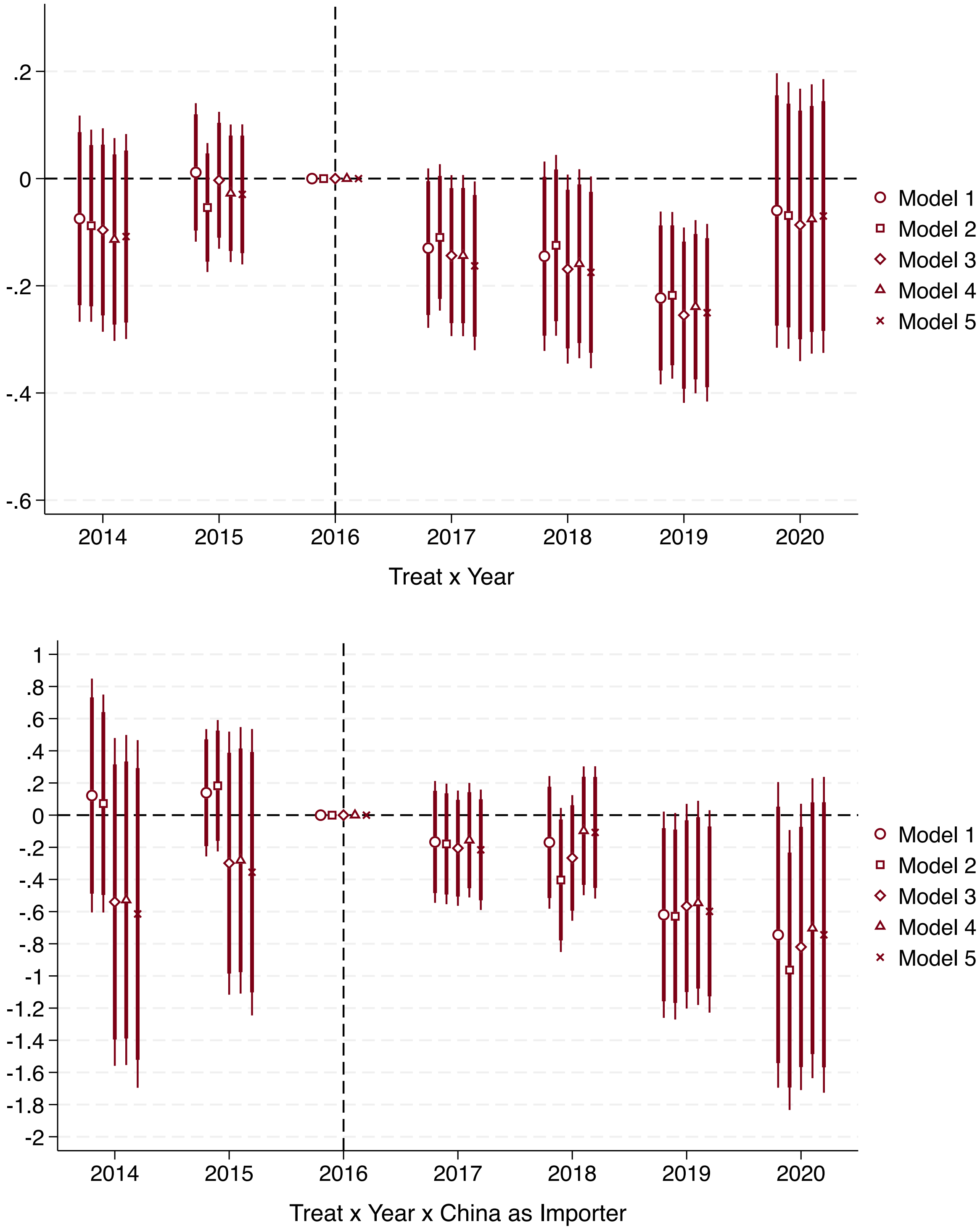

Figure 4: Dynamic Impact by Importer

This figure presents the results from estimation of Equation (8) after adding an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer and an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for low-income importer. The top panel shows the coefficients to $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$, the middle panel shows the coefficients to the interaction with China as Importer indicator, while the bottom panel shows the coefficients to the interaction with low-income importer indicator. Each model corresponds to a different set of fixed effects and controls, as in Tables 2 to 4. The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

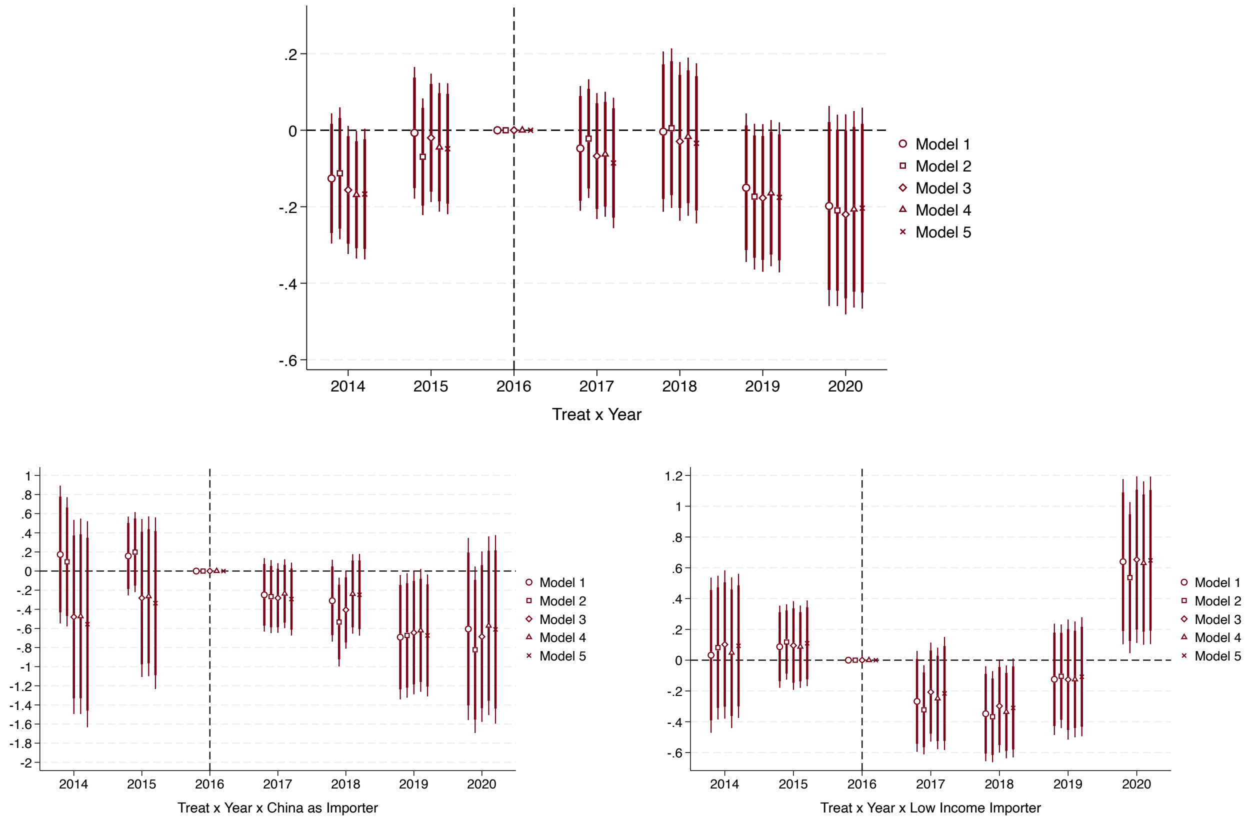

Figure 5: Placebo Test with Fake Treatment Year

This figure shows the results from estimation of Equation (7) after dropping observations for the years post the announcement of the ban. The left panel corresponds to 2015 as the fake treatment year and the right panel corresponds to 2016 as the fake treatment year. Each model corresponds to a different set of fixed effects and controls, as in Tables 2 to 4. The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

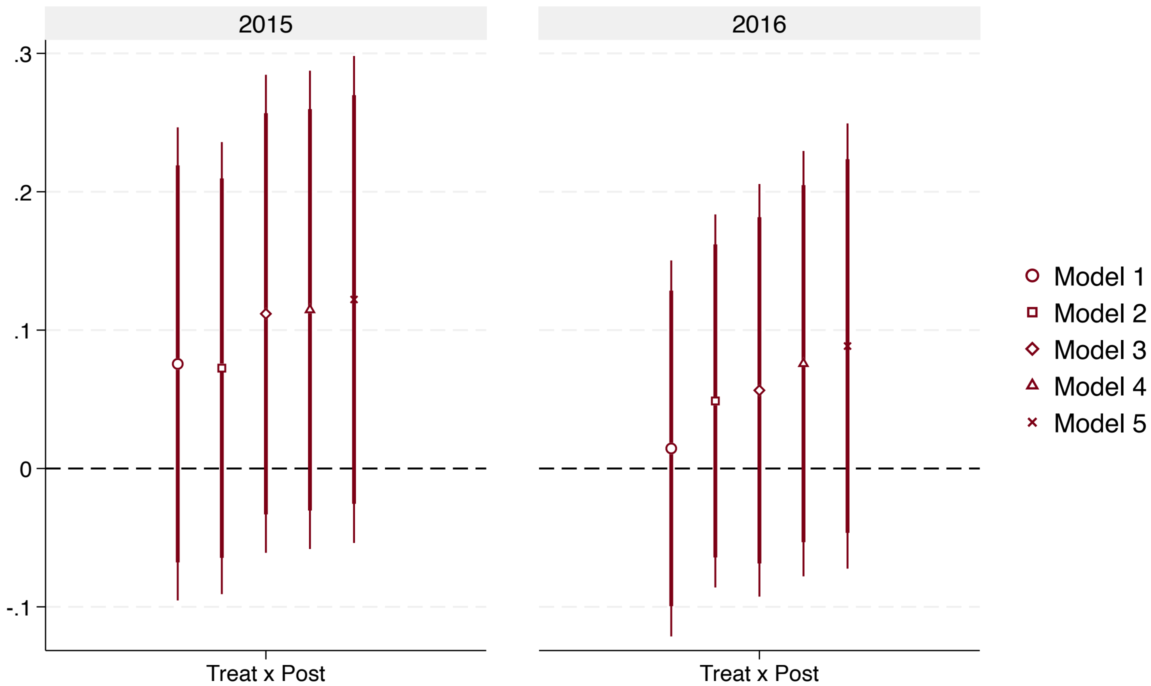

Figure 6: Placebo Test with Fake Treated Waste Type

This figure shows the results from estimation of Equation (7) after dropping observations for the treated waste types. Each panel corresponds to different waste types serving as the fake treated group. Each model corresponds to a different set of fixed effects and controls, as in Tables 2 to 4. The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

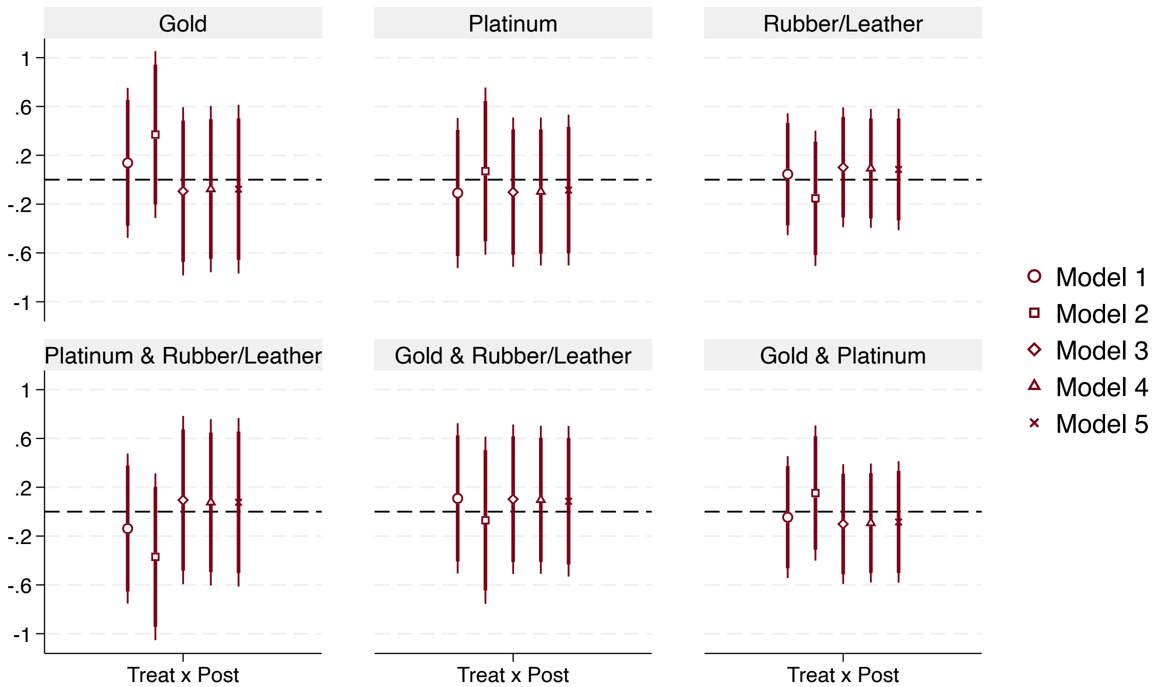

Table 1: China's Waste Imports in 2016

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
Metal	7.33	9,077.94
Organic	7.17	3,545.45
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: 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)	(5)
Treat×Post	-0.231***	-0.232***	-0.242***	-0.221***	-0.230***
	(0.0828)	(0.0852)	(0.0859)	(0.0824)	(0.0822)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.828	0.964	0.784	0.836	0.833
Observations	551,123	255,161	1,900,914	608,738	382,107

Table 3: 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.0719	-0.0677	-0.110	-0.126	-0.145
	(0.0953)	(0.101)	(0.0999)	(0.100)	(0.104)
Treat×$\mathbb{1}(year = 2015)$	0.0295	-0.0173	0.00263	-0.0180	-0.0445
	(0.0675)	(0.0664)	(0.0728)	(0.0741)	(0.0783)
Treat×$\mathbb{1}(year = 2017)$	-0.180**	-0.176**	-0.204**	-0.201**	-0.233***
	(0.0766)	(0.0752)	(0.0793)	(0.0787)	(0.0832)
Treat×$\mathbb{1}(year = 2018)$	-0.232**	-0.265***	-0.276***	-0.256***	-0.280***
	(0.0914)	(0.101)	(0.0974)	(0.0946)	(0.0973)
Treat×$\mathbb{1}(year = 2019)$	-0.372***	-0.386***	-0.397***	-0.390***	-0.416***
	(0.100)	(0.0940)	(0.103)	(0.101)	(0.105)
Treat×$\mathbb{1}(year = 2020)$	-0.191	-0.208	-0.233	-0.225	-0.238*
	(0.137)	(0.128)	(0.143)	(0.139)	(0.141)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.828	0.964	0.784	0.836	0.833
Observations	551,123	255,161	1,900,914	608,738	382,107

Table 4: Impact by Waste Type

This table presents the results from estimation of Equation (9). 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)	(5)
Glass×Post	-0.278***	-0.284***	-0.263***	-0.263***	-0.266***
	(0.0976)	(0.103)	(0.0980)	(0.0971)	(0.0980)
Metal×Post	-0.179**	-0.208***	-0.194**	-0.156*	-0.170**
	(0.0813)	(0.0791)	(0.0810)	(0.0820)	(0.0862)
Paper×Post	-0.386***	-0.323***	-0.365***	-0.353***	-0.377***
	(0.121)	(0.0822)	(0.124)	(0.123)	(0.122)
Organic×Post	-0.239*	-0.281**	-0.250*	-0.246*	-0.252*
	(0.128)	(0.127)	(0.143)	(0.138)	(0.140)
Plastic×Post	-0.542***	-0.472***	-0.752***	-0.726***	-0.753***
	(0.142)	(0.119)	(0.142)	(0.141)	(0.142)
Wood×Post	0.0105	0.104	0.0385	0.0433	0.0385
	(0.0783)	(0.121)	(0.0794)	(0.0787)	(0.0795)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.828	0.964	0.784	0.836	0.832
Observations	531,275	255,161	1,900,914	608,738	360,455

Table 5: Dynamic Impact - Extensive Margin

This table presents the results from estimation of Equation (8) after dropping all zero bilateral trade flows. 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)	(5)
Treat$\times\mathbb{1}(year = 2014)$	-0.0580	-0.0806	-0.117	-0.113	-0.122
	(0.0961)	(0.104)	(0.100)	(0.101)	(0.104)
Treat$\times\mathbb{1}(year = 2015)$	0.0478	-0.0246	0.0108	0.00745	-0.00358
	(0.0678)	(0.0674)	(0.0733)	(0.0737)	(0.0777)
Treat$\times\mathbb{1}(year = 2017)$	-0.184**	-0.177**	-0.206***	-0.191**	-0.209**
	(0.0787)	(0.0756)	(0.0796)	(0.0808)	(0.0881)
Treat$\times\mathbb{1}(year = 2018)$	-0.235**	-0.268***	-0.283***	-0.253***	-0.267***
	(0.0937)	(0.102)	(0.0975)	(0.0960)	(0.0999)
Treat$\times\mathbb{1}(year = 2019)$	-0.364***	-0.392***	-0.405***	-0.379***	-0.404***
	(0.102)	(0.0944)	(0.103)	(0.103)	(0.108)
Treat$\times\mathbb{1}(year = 2020)$	-0.187	-0.218*	-0.245*	-0.235*	-0.240*
	(0.139)	(0.130)	(0.144)	(0.140)	(0.144)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.786	0.960	0.666	0.796	0.805
Observations	132,813	129,387	141,467	147,017	120,315

Appendix to
“Global Impact of a Unilateral Waste Trade Regulation”

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Figure A.1: China’s Import Quantity of Treated and Control Waste Types

This figure shows China’s total import quantity of waste types 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. Actual imports of control waste types by China was positive, even though it appears to be near zero in the figure due to scaling. See, for example, Table 1 for quantity of imports of control waste types in 2016.

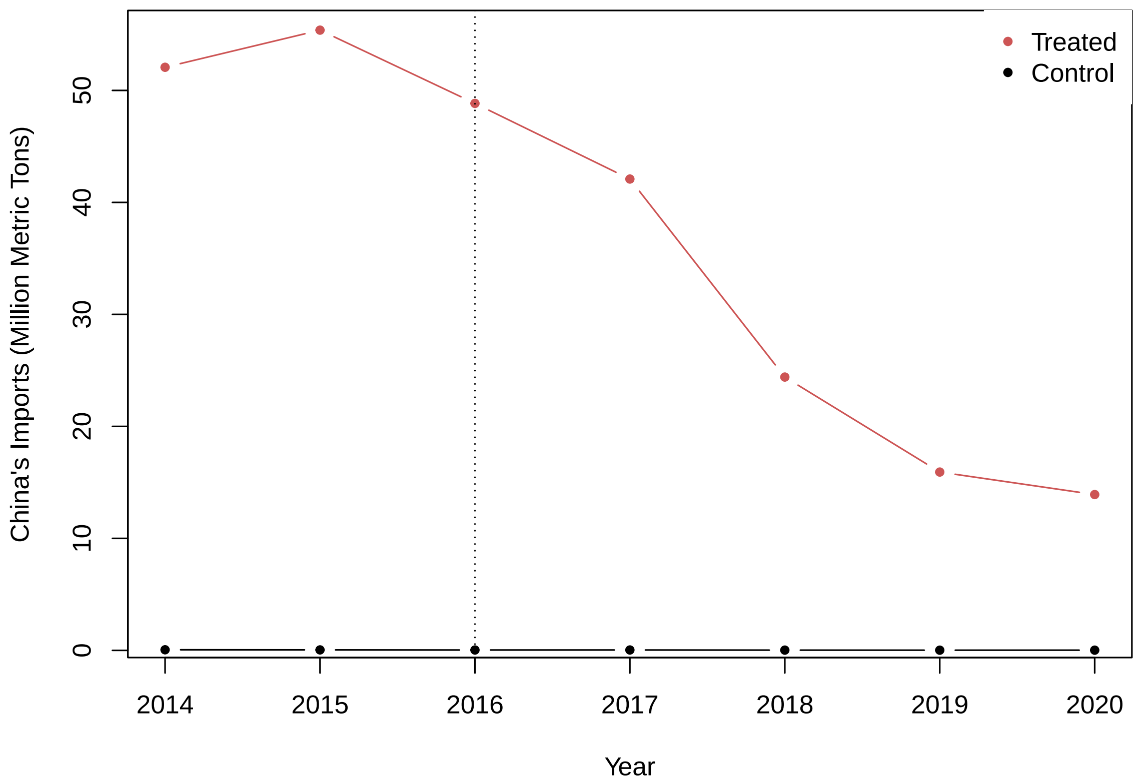

Table A.1: HS6 Categories of Waste

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, 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, 262190
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.2: 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

Figure A.2: Testing Parallel Trends Assumption - Alternative Control Group

This figure presents the results from estimating Equation (10). The hollow circles are point estimates, the thick lines are 90% confidence intervals, and the thin lines are 95% confidence intervals.

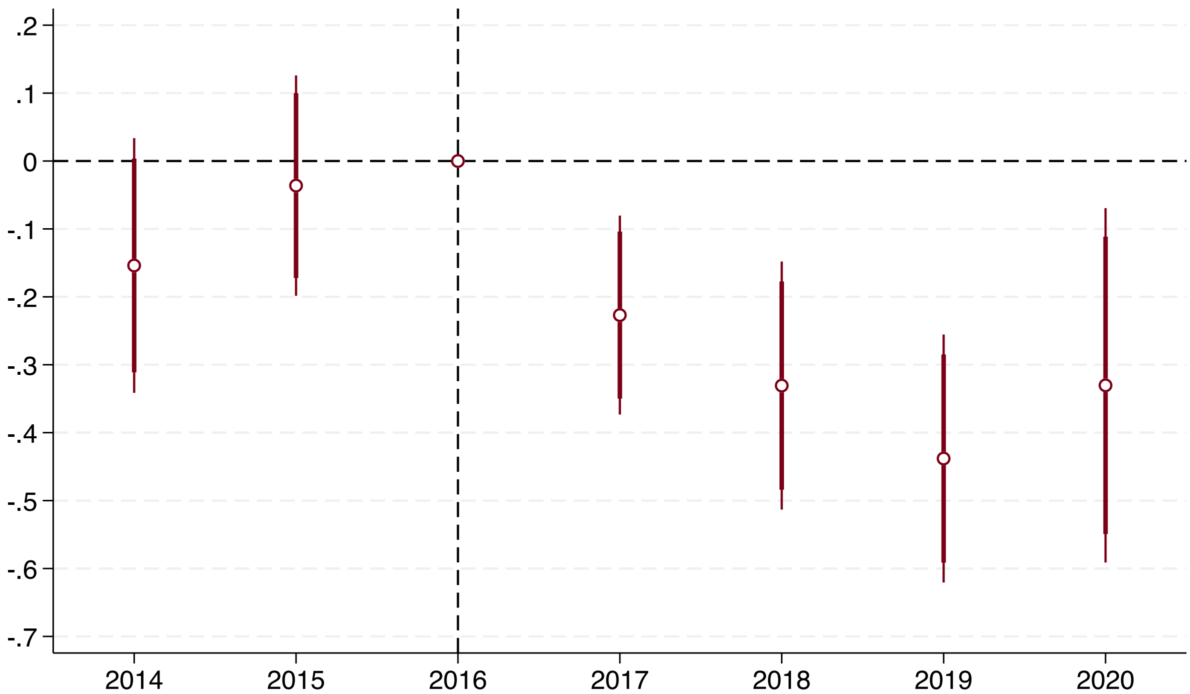

Table A.3: Dynamic Impact on China

This table presents the results from estimation of Equation (8) after adding the interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer. 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.0748	-0.0879	-0.0960	-0.114	-0.108
	(0.0981)	(0.0914)	(0.0968)	(0.0965)	(0.0976)
Treat×$\mathbb{1}(year = 2015)$	0.0115	-0.0540	-0.00316	-0.0274	-0.0295
	(0.0659)	(0.0614)	(0.0652)	(0.0655)	(0.0667)
Treat×$\mathbb{1}(year = 2017)$	-0.130*	-0.110	-0.144*	-0.144*	-0.163**
	(0.0759)	(0.0697)	(0.0766)	(0.0767)	(0.0804)
Treat×$\mathbb{1}(year = 2018)$	-0.145	-0.125	-0.169*	-0.159*	-0.175*
	(0.0901)	(0.0861)	(0.0900)	(0.0900)	(0.0913)
Treat×$\mathbb{1}(year = 2019)$	-0.223***	-0.218***	-0.255***	-0.239***	-0.250***
	(0.0823)	(0.0793)	(0.0834)	(0.0824)	(0.0845)
Treat×$\mathbb{1}(year = 2020)$	-0.0595	-0.0689	-0.0865	-0.0754	-0.0698
	(0.131)	(0.127)	(0.130)	(0.128)	(0.130)
Treat×$\mathbb{1}(year = 2014)$ ×China as Importer	0.122	0.0722	-0.540	-0.528	-0.615
	(0.371)	(0.346)	(0.520)	(0.524)	(0.551)
Treat×$\mathbb{1}(year = 2015)$×China as Importer	0.139	0.183	-0.299	-0.281	-0.355
	(0.202)	(0.208)	(0.417)	(0.423)	(0.454)
Treat×$\mathbb{1}(year = 2017)$×China as Importer	-0.167	-0.179	-0.206	-0.156	-0.216
	(0.193)	(0.191)	(0.183)	(0.182)	(0.191)
Treat×$\mathbb{1}(year = 2018)$×China as Importer	-0.169	-0.403*	-0.266	-0.0975	-0.108
	(0.210)	(0.229)	(0.199)	(0.204)	(0.210)
Treat×$\mathbb{1}(year = 2019)$×China as Importer	-0.619*	-0.629*	-0.566*	-0.546*	-0.599*
	(0.327)	(0.328)	(0.325)	(0.324)	(0.321)
Treat×$\mathbb{1}(year = 2020)$×China as Importer	-0.745	-0.963**	-0.820*	-0.703	-0.744
	(0.485)	(0.444)	(0.454)	(0.476)	(0.501)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.831	0.968	0.784	0.836	0.832
Observations	531,275	255,161	1,900,914	608,738	360,455

Table A.4: Dynamic Impact by Importer

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer and an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for low-income importer. 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.126	-0.113	-0.156*	-0.169**	-0.167*
	(0.0869)	(0.0880)	(0.0855)	(0.0850)	(0.0872)
Treat×$\mathbb{1}(year = 2015)$	-0.00681	-0.0693	-0.0198	-0.0445	-0.0484
	(0.0879)	(0.0778)	(0.0856)	(0.0859)	(0.0873)
Treat×$\mathbb{1}(year = 2017)$	-0.0475	-0.0219	-0.0675	-0.0628	-0.0856
	(0.0832)	(0.0792)	(0.0840)	(0.0834)	(0.0870)
Treat×$\mathbb{1}(year = 2018)$	-0.00364	0.00541	-0.0292	-0.0169	-0.0341
	(0.107)	(0.106)	(0.106)	(0.106)	(0.107)
Treat×$\mathbb{1}(year = 2019)$	-0.150	-0.174*	-0.177*	-0.164*	-0.175*
	(0.0991)	(0.0972)	(0.0985)	(0.0976)	(0.100)
Treat×$\mathbb{1}(year = 2020)$	-0.198	-0.209	-0.220*	-0.207	-0.204
	(0.133)	(0.128)	(0.133)	(0.131)	(0.134)
Treat×$\mathbb{1}(year = 2014)$×Low Income Importer	0.0324	0.0817	0.102	0.0485	0.0931
	(0.257)	(0.238)	(0.246)	(0.250)	(0.239)
Treat×$\mathbb{1}(year = 2015)$×Low Income Importer	0.0874	0.118	0.0952	0.0875	0.110
	(0.136)	(0.125)	(0.147)	(0.137)	(0.142)
Treat×$\mathbb{1}(year = 2017)$×Low Income Importer	-0.268	-0.322**	-0.207	-0.248	-0.216
	(0.167)	(0.148)	(0.164)	(0.168)	(0.187)
Treat×$\mathbb{1}(year = 2018)$×Low Income Importer	-0.348**	-0.367**	-0.298*	-0.336**	-0.310*
	(0.158)	(0.151)	(0.154)	(0.154)	(0.164)
Treat×$\mathbb{1}(year = 2019)$×Low Income Importer	-0.124	-0.105	-0.126	-0.125	-0.108
	(0.184)	(0.172)	(0.199)	(0.192)	(0.197)
Treat×$\mathbb{1}(year = 2020)$×Low Income Importer	0.640**	0.536**	0.653**	0.631**	0.648**
	(0.274)	(0.250)	(0.276)	(0.271)	(0.278)
Treat×$\mathbb{1}(year = 2014)$×China as Importer	0.173	0.0969	-0.480	-0.473	-0.556
	(0.368)	(0.345)	(0.518)	(0.521)	(0.550)
Treat×$\mathbb{1}(year = 2015)$×China as Importer	0.157	0.198	-0.282	-0.264	-0.336
	(0.210)	(0.214)	(0.421)	(0.426)	(0.458)
Treat×$\mathbb{1}(year = 2017)$×China as Importer	-0.249	-0.267	-0.282	-0.237	-0.293
	(0.196)	(0.195)	(0.186)	(0.184)	(0.194)
Treat×$\mathbb{1}(year = 2018)$×China as Importer	-0.310	-0.533**	-0.406**	-0.239	-0.248
	(0.218)	(0.237)	(0.207)	(0.212)	(0.218)
Treat×$\mathbb{1}(year = 2019)$×China as Importer	-0.692**	-0.673**	-0.644*	-0.620*	-0.674**
	(0.332)	(0.332)	(0.329)	(0.328)	(0.325)
Treat×$\mathbb{1}(year = 2020)$×China as Importer	-0.606	-0.823*	-0.686	-0.572	-0.610
	(0.486)	(0.444)	(0.455)	(0.477)	(0.503)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.831	0.968	0.784	0.836	0.832
Observations	531,275	255,161	1,900,914	608,738	360,455

Table A.5: Dynamic Impact by Neighborhood

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{t\neq2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer and an interaction between $\sum_{t\neq2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China's neighboring country as importer. 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.0541	-0.0387	-0.0656	-0.0792	-0.0796
	(0.0945)	(0.0961)	(0.0955)	(0.0944)	(0.0970)
Treat×$\mathbb{1}(year = 2015)$	0.0616	-0.0112	0.0479	0.0158	0.0117
	(0.0913)	(0.0794)	(0.0910)	(0.0912)	(0.0930)
Treat×$\mathbb{1}(year = 2017)$	-0.00627	0.0224	-0.0345	-0.0294	-0.0496
	(0.0697)	(0.0649)	(0.0712)	(0.0700)	(0.0733)
Treat×$\mathbb{1}(year = 2018)$	0.0432	0.0494	0.00894	0.0232	0.00880
	(0.0991)	(0.0965)	(0.0987)	(0.0978)	(0.0999)
Treat×$\mathbb{1}(year = 2019)$	-0.0979	-0.130	-0.138	-0.121	-0.132
	(0.104)	(0.101)	(0.104)	(0.103)	(0.106)
Treat×$\mathbb{1}(year = 2020)$	-0.180	-0.197	-0.203	-0.196	-0.193
	(0.144)	(0.140)	(0.145)	(0.142)	(0.146)
Treat×$\mathbb{1}(year = 2014)$×Neighbor Importer	-0.0842	-0.110	-0.0849	-0.116	-0.0764
	(0.240)	(0.221)	(0.230)	(0.232)	(0.229)
Treat×$\mathbb{1}(year = 2015)$×Neighbor Importer	-0.130	-0.104	-0.123	-0.0953	-0.0772
	(0.143)	(0.129)	(0.143)	(0.141)	(0.143)
Treat×$\mathbb{1}(year = 2017)$×Neighbor Importer	-0.330**	-0.361**	-0.280*	-0.311*	-0.301
	(0.164)	(0.146)	(0.167)	(0.169)	(0.187)
Treat×$\mathbb{1}(year = 2018)$×Neighbor Importer	-0.372**	-0.350**	-0.333**	-0.361**	-0.358**
	(0.162)	(0.167)	(0.158)	(0.165)	(0.164)
Treat×$\mathbb{1}(year = 2019)$×Neighbor Importer	-0.239	-0.167	-0.232	-0.251	-0.235
	(0.173)	(0.174)	(0.173)	(0.171)	(0.175)
Treat×$\mathbb{1}(year = 2020)$×Neighbor Importer	0.403	0.384	0.345	0.364	0.376
	(0.262)	(0.246)	(0.258)	(0.252)	(0.256)
Treat×$\mathbb{1}(year = 2014)$×China as Importer	0.101	0.0222	-0.570	-0.562	-0.643
	(0.370)	(0.347)	(0.520)	(0.523)	(0.551)
Treat×$\mathbb{1}(year = 2015)$×China as Importer	0.0891	0.140	-0.350	-0.324	-0.396
	(0.212)	(0.214)	(0.422)	(0.427)	(0.459)
Treat×$\mathbb{1}(year = 2017)$×China as Importer	-0.290	-0.311	-0.315*	-0.270	-0.329*
	(0.191)	(0.190)	(0.181)	(0.179)	(0.188)
Treat×$\mathbb{1}(year = 2018)$×China as Importer	-0.357*	-0.578**	-0.444**	-0.280	-0.291
	(0.215)	(0.233)	(0.203)	(0.208)	(0.215)
Treat×$\mathbb{1}(year = 2019)$×China as Importer	-0.744**	-0.718**	-0.684**	-0.664**	-0.717**
	(0.334)	(0.333)	(0.331)	(0.330)	(0.328)
Treat×$\mathbb{1}(year = 2020)$×China as Importer	-0.623	-0.837*	-0.703	-0.582	-0.621
	(0.489)	(0.448)	(0.458)	(0.480)	(0.506)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.831	0.968	0.784	0.836	0.832
Observations	531,275	255,161	1,900,914	608,738	360,455

Table A.6: 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)	(5)
Treat×Post	-0.238***	-0.255***	-0.244***	-0.226***	-0.234***
	(0.0807)	(0.0822)	(0.0829)	(0.0789)	(0.0788)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.844	0.966	0.796	0.853	0.852
Observations	940,840	338,834	2,982,865	1,084,993	695,439

Table A.7: 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)	(5)
Treat$\times\mathbb{1}(year = 2014)$	-0.103	-0.0883	-0.132	-0.141	-0.151
	(0.0971)	(0.100)	(0.0999)	(0.0986)	(0.101)
Treat$\times\mathbb{1}(year = 2015)$	-0.0131	-0.0516	-0.0205	-0.0372	-0.0559
	(0.0746)	(0.0704)	(0.0769)	(0.0764)	(0.0786)
Treat$\times\mathbb{1}(year = 2017)$	-0.200**	-0.206***	-0.215***	-0.203***	-0.228***
	(0.0790)	(0.0771)	(0.0808)	(0.0788)	(0.0812)
Treat$\times\mathbb{1}(year = 2018)$	-0.269***	-0.310***	-0.294***	-0.279***	-0.296***
	(0.0933)	(0.0981)	(0.0981)	(0.0940)	(0.0954)
Treat$\times\mathbb{1}(year = 2019)$	-0.387***	-0.412***	-0.394***	-0.384***	-0.403***
	(0.0997)	(0.0923)	(0.101)	(0.0986)	(0.101)
Treat$\times\mathbb{1}(year = 2020)$	-0.246*	-0.271**	-0.273**	-0.271**	-0.279**
	(0.133)	(0.125)	(0.137)	(0.132)	(0.134)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.844	0.966	0.796	0.853	0.852
Observations	940,840	338,834	2,982,865	1,084,993	695,439

Table A.8: Dynamic Impact on China - Alternative Control Group

This table presents the results from estimation of Equation (8) after adding the interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer. 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)	(5)
Treat$\times\mathbb{1}(year = 2014)$	-0.127	-0.118	-0.125	-0.134	-0.131
	(0.102)	(0.0923)	(0.0998)	(0.0982)	(0.100)
Treat$\times\mathbb{1}(year = 2015)$	-0.0453	-0.0933	-0.0352	-0.0506	-0.0508
	(0.0758)	(0.0680)	(0.0742)	(0.0731)	(0.0748)
Treat$\times\mathbb{1}(year = 2017)$	-0.163**	-0.151**	-0.154*	-0.153*	-0.170**
	(0.0817)	(0.0751)	(0.0815)	(0.0800)	(0.0834)
Treat$\times\mathbb{1}(year = 2018)$	-0.189**	-0.183**	-0.186**	-0.185**	-0.192**
	(0.0945)	(0.0864)	(0.0940)	(0.0918)	(0.0944)
Treat$\times\mathbb{1}(year = 2019)$	-0.251***	-0.254***	-0.247***	-0.245***	-0.251***
	(0.0869)	(0.0803)	(0.0871)	(0.0847)	(0.0875)
Treat$\times\mathbb{1}(year = 2020)$	-0.117	-0.142	-0.121	-0.132	-0.120
	(0.130)	(0.126)	(0.128)	(0.125)	(0.129)
Treat$\times\mathbb{1}(year = 2014)\times$China as Importer	0.160	0.109	-0.508	-0.431	-0.561
	(0.377)	(0.347)	(0.506)	(0.482)	(0.536)
Treat$\times\mathbb{1}(year = 2015)\times$China as Importer	0.194	0.223	-0.247	-0.211	-0.304
	(0.204)	(0.205)	(0.397)	(0.369)	(0.432)
Treat$\times\mathbb{1}(year = 2017)\times$China as Importer	-0.121	-0.131	-0.195	-0.175	-0.171
	(0.198)	(0.193)	(0.189)	(0.161)	(0.188)
Treat$\times\mathbb{1}(year = 2018)\times$China as Importer	-0.166	-0.343	-0.220	-0.0367	-0.151
	(0.209)	(0.228)	(0.206)	(0.194)	(0.200)
Treat$\times\mathbb{1}(year = 2019)\times$China as Importer	-0.594*	-0.596*	-0.505	-0.321	-0.559*
	(0.329)	(0.325)	(0.335)	(0.386)	(0.328)
Treat$\times\mathbb{1}(year = 2020)\times$China as Importer	-0.718	-0.880**	-0.761*	-0.508	-0.639
	(0.462)	(0.440)	(0.444)	(0.435)	(0.445)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.847	0.970	0.796	0.853	0.851
Observations	899,186	338,834	2,982,865	1,084,993	640,123

Table A.9: Dynamic Impact by Importer - Alternative Control Group

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer and an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for low-income importer. 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.131	-0.102	-0.136*	-0.141*	-0.142*
	(0.0828)	(0.0832)	(0.0803)	(0.0788)	(0.0811)
Treat×$\mathbb{1}(year = 2015)$	-0.0263	-0.0739	-0.0167	-0.0331	-0.0331
	(0.0868)	(0.0761)	(0.0843)	(0.0829)	(0.0850)
Treat×$\mathbb{1}(year = 2017)$	-0.0396	-0.0253	-0.0369	-0.0366	-0.0523
	(0.0794)	(0.0756)	(0.0798)	(0.0780)	(0.0814)
Treat×$\mathbb{1}(year = 2018)$	-0.0149	-0.0263	-0.0136	-0.0190	-0.0164
	(0.103)	(0.101)	(0.102)	(0.0995)	(0.102)
Treat×$\mathbb{1}(year = 2019)$	-0.142	-0.172*	-0.132	-0.137	-0.134
	(0.0939)	(0.0905)	(0.0935)	(0.0909)	(0.0943)
Treat×$\mathbb{1}(year = 2020)$	-0.217*	-0.244**	-0.221*	-0.230*	-0.218*
	(0.123)	(0.114)	(0.123)	(0.118)	(0.124)
1.treat#$\mathbb{1}(year = 2014)$×Low Income Importer	-0.275	-0.233	-0.190	-0.224	-0.193
	(0.347)	(0.338)	(0.327)	(0.328)	(0.327)
Treat×$\mathbb{1}(year = 2015)$×Low Income Importer	-0.210	-0.178	-0.173	-0.174	-0.167
	(0.273)	(0.265)	(0.262)	(0.255)	(0.258)
Treat×$\mathbb{1}(year = 2017)$×Low Income Importer	-0.572**	-0.601**	-0.493*	-0.512**	-0.495*
	(0.275)	(0.255)	(0.261)	(0.259)	(0.265)
Treat×$\mathbb{1}(year = 2018)$×Low Income Importer	-0.637**	-0.591**	-0.585**	-0.597**	-0.610**
	(0.272)	(0.242)	(0.260)	(0.257)	(0.262)
Treat×$\mathbb{1}(year = 2019)$×Low Income Importer	-0.430	-0.357	-0.423	-0.414	-0.433
	(0.291)	(0.259)	(0.288)	(0.281)	(0.286)
Treat×$\mathbb{1}(year = 2020)$×Low Income Importer	0.347	0.328	0.400	0.396	0.385
	(0.356)	(0.324)	(0.353)	(0.345)	(0.351)
1.treat#$\mathbb{1}(year = 2014)$×China as Importer	0.165	0.0930	-0.497	-0.423	-0.550
	(0.372)	(0.345)	(0.502)	(0.478)	(0.533)
Treat×$\mathbb{1}(year = 2015)$×China as Importer	0.175	0.204	-0.266	-0.229	-0.321
	(0.208)	(0.208)	(0.399)	(0.371)	(0.434)
Treat×$\mathbb{1}(year = 2017)$×China as Importer	-0.245	-0.256	-0.312*	-0.292*	-0.288
	(0.197)	(0.194)	(0.188)	(0.159)	(0.188)
Treat×$\mathbb{1}(year = 2018)$×China as Importer	-0.340	-0.499**	-0.393*	-0.203	-0.327
	(0.213)	(0.234)	(0.209)	(0.197)	(0.204)
Treat×$\mathbb{1}(year = 2019)$×China as Importer	-0.703**	-0.678**	-0.620*	-0.430	-0.675**
	(0.330)	(0.329)	(0.337)	(0.387)	(0.330)
Treat×$\mathbb{1}(year = 2020)$×China as Importer	-0.618	-0.778*	-0.661	-0.410	-0.542
	(0.460)	(0.438)	(0.442)	(0.433)	(0.444)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.847	0.970	0.796	0.853	0.851
Observations	899,186	338,834	2,982,865	1,084,993	640,123

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

This table presents the results from estimation of Equation (8) after adding an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China as importer and an interaction between $\sum_{t\neq 2016} Treat \times \mathbb{1}(year = t)$ and an indicator for China's neighboring country as importer. 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)	(5)
Treat×$\mathbb{1}(year = 2014)$	-0.115	-0.0911	-0.108	-0.116	-0.120
	(0.102)	(0.0984)	(0.102)	(0.100)	(0.103)
Treat×$\mathbb{1}(year = 2015)$	-0.0167	-0.0766	-0.0148	-0.0339	-0.0336
	(0.103)	(0.0892)	(0.102)	(0.100)	(0.103)
Treat×$\mathbb{1}(year = 2017)$	-0.0498	-0.0332	-0.0593	-0.0467	-0.0697
	(0.0814)	(0.0756)	(0.0817)	(0.0795)	(0.0828)
Treat×$\mathbb{1}(year = 2018)$	-0.0271	-0.0254	-0.0378	-0.0273	-0.0398
	(0.108)	(0.103)	(0.107)	(0.105)	(0.108)
Treat×$\mathbb{1}(year = 2019)$	-0.134	-0.168	-0.140	-0.131	-0.142
	(0.110)	(0.104)	(0.110)	(0.107)	(0.111)
Treat×$\mathbb{1}(year = 2020)$	-0.260*	-0.286**	-0.266*	-0.271*	-0.268*
	(0.144)	(0.134)	(0.144)	(0.139)	(0.144)
Treat×$\mathbb{1}(year = 2014)$×Nieghbor Importer	-0.0233	-0.0248	-0.0327	-0.0370	-0.00694
	(0.233)	(0.217)	(0.225)	(0.222)	(0.224)
Treat×$\mathbb{1}(year = 2015)$×Nieghbor Importer	-0.0577	-0.0147	-0.0321	-0.0228	-0.0188
	(0.148)	(0.135)	(0.148)	(0.143)	(0.146)
Treat×$\mathbb{1}(year = 2017)$×Nieghbor Importer	-0.286*	-0.302**	-0.226	-0.271*	-0.251
	(0.164)	(0.149)	(0.166)	(0.163)	(0.172)
Treat×$\mathbb{1}(year = 2018)$×Nieghbor Importer	-0.286*	-0.311*	-0.256	-0.292*	-0.274*
	(0.163)	(0.161)	(0.162)	(0.160)	(0.162)
Treat×$\mathbb{1}(year = 2019)$×Nieghbor Importer	-0.201	-0.160	-0.201	-0.228	-0.208
	(0.174)	(0.171)	(0.173)	(0.168)	(0.172)
Treat×$\mathbb{1}(year = 2020)$×Nieghbor Importer	0.490*	0.450*	0.460*	0.443*	0.470*
	(0.257)	(0.249)	(0.253)	(0.246)	(0.252)
Treat×$\mathbb{1}(year = 2014)$×China as Importer	0.149	0.0815	-0.526	-0.449	-0.572
	(0.377)	(0.348)	(0.506)	(0.482)	(0.537)
Treat×$\mathbb{1}(year = 2015)$×China as Importer	0.165	0.207	-0.268	-0.228	-0.321
	(0.215)	(0.213)	(0.403)	(0.375)	(0.438)
Treat×$\mathbb{1}(year = 2017)$×China as Importer	-0.235	-0.249	-0.289	-0.281*	-0.271
	(0.198)	(0.194)	(0.190)	(0.160)	(0.189)
Treat×$\mathbb{1}(year = 2018)$×China as Importer	-0.328	-0.500**	-0.368*	-0.195	-0.303
	(0.216)	(0.234)	(0.212)	(0.200)	(0.207)
Treat×$\mathbb{1}(year = 2019)$×China as Importer	-0.711**	-0.684**	-0.612*	-0.436	-0.668**
	(0.336)	(0.331)	(0.342)	(0.392)	(0.336)
Treat×$\mathbb{1}(year = 2020)$×China as Importer	-0.575	-0.737*	-0.616	-0.370	-0.492
	(0.466)	(0.442)	(0.448)	(0.439)	(0.450)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.847	0.970	0.796	0.853	0.851
Observations	899,186	338,834	2,982,865	1,084,993	640,123

Table A.11: Impact by Waste Type - Alternative Control Group

This table presents the results from estimation of Equation (9). 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)	(5)
Glass×Post	-0.273***	-0.284***	-0.254***	-0.251***	-0.254***
	(0.0973)	(0.101)	(0.0974)	(0.0948)	(0.0976)
Gold×Post	0.161	0.275	-0.0634	-0.0565	-0.0588
	(0.316)	(0.358)	(0.354)	(0.349)	(0.353)
Metal×Post	-0.217***	-0.246***	-0.231***	-0.198**	-0.214***
	(0.0815)	(0.0816)	(0.0811)	(0.0788)	(0.0825)
Paper×Post	-0.379***	-0.332***	-0.358***	-0.342***	-0.365***
	(0.120)	(0.0831)	(0.119)	(0.118)	(0.118)
Organic×Post	-0.230*	-0.269**	-0.223*	-0.220*	-0.223*
	(0.124)	(0.127)	(0.124)	(0.120)	(0.123)
Plastic×Post	-0.527***	-0.469***	-0.729***	-0.706***	-0.726***
	(0.140)	(0.119)	(0.135)	(0.131)	(0.135)
Platinum×Post	-0.132	-0.161	-0.106	-0.119	-0.108
	(0.314)	(0.351)	(0.314)	(0.310)	(0.314)
Wood×Post	0.0261	-0.0274	0.0461	0.0389	0.0485
	(0.0795)	(0.0862)	(0.0800)	(0.0783)	(0.0801)
Yarn×Post	-0.229***	-0.243***	-0.220***	-0.217***	-0.213**
	(0.0857)	(0.0917)	(0.0852)	(0.0836)	(0.0856)
Controls					
Country-Year Controls	✓	✓	—	—	—
Bilateral Controls	—	—	✓	—	—
Fixed Effects					
Type	✓	—	✓	✓	✓
Year	✓	✓	—	—	—
Bilateral	✓	—	—	✓	—
Type-Bilateral	—	✓	—	—	—
Country-Year	—	—	✓	✓	—
Bilateral-Year	—	—	—	—	✓
Pseudo-R^2	0.844	0.966	0.797	0.853	0.852
Observations	899,186	338,834	2,982,865	1,084,993	640,123