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The Future of Plastics Trade: Identifying Determinants and Impacts of the Shifting Global Plastic Scraps Network

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Approval of Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Ana Ortiz Salazar as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in International Politics and Political Science.

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Abstract

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Plastic waste management is an area of increasing concern for environmental and public health. Existing research shows that as of 2019, 79% of total generated plastic waste has accumulated in landfills or leaked into the environment, 12% incinerated, and 9% recycled. China's Operation National Sword, launched in 2017, banned the import of plastic waste and other materials, triggering ripple effects throughout the global plastic scraps trade network. The impacts are cross-sectoral and multi-scalar, cascading across markets, policy, the natural environment, public health, and have increased uncertainty about the future of the global trade of plastics. To understand shifts across the global plastic scraps network, the author of this dissertation first uses a Social Network Analysis (SNA) approach to explore the structural changes over time of the plastic trade network, especially due to China's Operation National Sword. Results show that Southeast Asian, and Western and Central European countries became the most important traders of plastic waste after China's Operation National Sword. A cross-sectional time-series multi-method analysis additionally shows that poorer countries with large manufacturing sectors were the most affected by the policy, becoming havens for plastic waste. Trade partners of top plastic traders such as China became more likely to import waste as well. Results from a System Generalized Method of Moments (SGMM) analysis reveals that wealthier countries trade more plastic scraps of mixed materials, while large manufacturers import more polyethylene plastic. Countries with higher environmental performance were better to prevent plastic import increases relative to their exports.

Dedication

To my parents, Claudia and Rafael, I would not have been remotely close to where I am today without you. To my sisters, Laura, María and Diana, thank you for your endless love and support. To my husband, Louis, you have been by my side every step of this journey. This is for you.

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Introduction

China launched Operation National Sword in 2017, banning post-consumer mixed plastic and paper waste imports to reduce the volume of contaminated material entering the country. The initiative had significant, global ramifications, triggering a ripple effect that stifled global plastic waste exports and increased imports across countries in Southeast Asia. National Sword's effects have also been cross-sectoral, with its impacts cascading across the global plastic scraps market, domestic recycling industries, and marine ecosystems.

The ramifications of National Sword are well documented, especially with respect to public health and environmental externalities. Literature on the subject has pointed to an increase in environmental and health risks for vulnerable communities in countries now receiving the plastic waste that China has declined, primarily through exposure to toxins from waste decomposition through air and water systems and the improper burning of plastic. Exposure to these toxins and carcinogens are tied to cardiovascular and respiratory disease, as well as cancer (Posnack, 2021; Verma, 2016). With respect to environmental externalities, waste burning and decomposition contribute to greenhouse gas (GHG) emissions, which are a significant driver of climate change, as well as the seeping of pollutants into oceanic environments that can harm marine ecosystems.

While research to date has largely focused on the immediate economic impacts of National Sword, namely the consequent shifts in plastic scrap import and export levels and the impacts on domestic recycling industries, few studies have attempted to explain the rerouting of plastic waste to certain countries. More specifically, they have not investigated which factors may have actually predisposed some countries to take China's place as the primary destination of the world’s plastic waste. The factors that are driving changes in the plastic trade network, and by consequence a range of social, economic, and environmental impacts, are important to understand: they could inform the design and implementation of policy, both international and domestic, that addresses how plastic waste is handled and thus mitigate or remedy inequalities in the environmental and economic burdens borne by plastic waste havens, or countries that import more plastic waste than they export. Furthermore, identifying the countries most affected by National Sword can shed light on the structural conditions that enabled other countries to send their plastic waste abroad, thus directing some policy solutions to also reduce overall waste generation in addition to waste handling, disposal, and recycling.

This study expands upon existing literature by estimating the effect of structural economic and relational measures on countries’ plastic scraps trade volumes, as well as their likelihood to become waste havens. Although macroeconomic variables (i.e., economic development and manufacturing industry size) are relevant explanatory factors of plastic scraps trade patterns, in isolation they are not able to illustrate the connectivity dynamics that predisposed some countries to take in a large fraction of plastic waste that was once going to China.

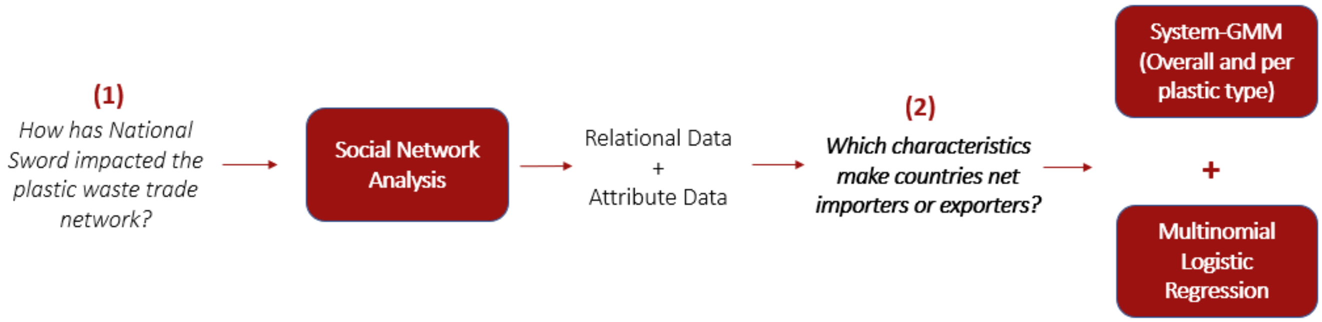
This study also offers methodological contributions to the existing literature by employing methods that recognize the endogenous nature of international trade processes, such as the relationship between economic development and trade, and manufacturing output and supply, producing unbiased estimations of the effects of economic and policy factors. As such, this research implements a dynamic panel data estimator, which is suitable to address endogeneity concerns. The robustness of the findings is also tested through an alternative estimation via maximum likelihood.

Research Design Overview

This research takes a quasi-experimental approach, using non-experimental data to make inferences about the effect of structural variables on countries' plastic trade tendencies. Specifically, this study combines relational with attribute measures to identify which characteristics make countries more prone to import or export plastic waste.

Figure 1 shows a flow diagram summarizing the methods implemented in this study. To evaluate the impacts of a shifting global plastic scraps network, a Social Network Analysis (SNA) approach is used, described in Chapter 1, to explore the network's topological changes over time. This chapter describes changes in the centrality—measured as eigenvector centrality—of trading countries in the plastic scraps network, showing how Western and Central European countries and Southeast Asian countries experienced abrupt changes in plastic trade patterns after National Sword. SNA approaches apply mathematical concepts of graph theory to quantify the characteristics of relational structures. In the context of this research, trade interactions between countries are mapped as a network where countries are nodes linked by plastic waste import or export transactions. The role and influence of each country in the global plastic waste trade network can then be quantified with measures of centrality.

Figure 1. Research Design Flow Diagram



Chapter 2 follows with a cross-sectional time-series multi-method analysis, quantifying the effect that changes in countries' level of development, network centrality, and manufacturing sector size have on plastic import and export amounts through a Generalize Method of Moments (GMM) dynamic panel data estimator. GMM estimators are built from an instrumental-variable approach with the goal of overcoming endogeneity or simultaneity between the explanatory variables and the dependent variable, especially when the process is dynamic, with past levels of the dependent variable included as explanatory variables. More specifically, the centrality measure produced through SNA complements other non-relational variables in a dynamic panel regression via GMM estimation in Chapter 2. This chapter analyzes disaggregated levels of plastic trade by type recognizing that the desirability of different plastic types can impact the effect of countries' characteristics on their plastic waste trade levels. For example, it is expected that large manufacturers will import more polyethylene (PE) plastic waste (i.e., the most used and produced plastic), and import mixed plastic scraps to a lesser degree, assuming a less profitable domestic market and available technology to process mixed material. It is important to note that although level of development and manufacturing economic sector size are found to be relevant determinants for differences within and between countries' plastic waste trade levels, limitations in the environmental performance measure only allow for the estimation of its effect across countries.

The most immediate effects of level of development, environmental performance, and manufacturing sector size, particularly before the plastics ban, on countries' probability to become waste havens are also estimated using a multinomial logistic regression. Countries are classified based on their pre- and post-ban plastic trade tendencies. They are specifically categorized as net importers if they import more plastic than they export—assumed to be potential waste havens—or net exporters if they export more plastic than they import. Chapter 3 presents a description of plastic trade and policy patterns for selected countries and a discussion of the implications of the findings. This analysis concludes, in Chapter 4, with an outline of the limitations of this study and suggested pathways for future research.

Plastics Scraps Trade and the National Sword Policy

Up until 2018, China was the primary destination for plastic scraps or waste – herein used interchangeably – accounting for an average of 73% of global plastic imports from 2003 through 2016.[1] As one of the largest manufacturers in the world, China exercised demand for raw materials such that it was profitable to import plastic scraps from other countries. Given that producing plastic from scratch consumes more energy and generates more material residue than using recycled plastics to manufacture new products, producers perceived importing plastic scraps as an environmentally beneficial economic opportunity.

[1] This percentage includes plastic scraps exports to Hong Kong.

However, plastic scraps are often contaminated in commingled and single-stream recycling processes. This reduces the quality, and thus the profitability, of the material. The diversity of plastic's chemical and physical properties also complicates its recycling, since material collection, sorting, and recovery processes can vary across polymer types (OECD, 2018). Additionally, lax regulations on the transnational trade of plastic waste have created a loophole for exporters to mix electronic scraps (e-scrap) and organic waste into recyclable plastic material shipments without meaningful consequence. These complexities, alongside a lack of sorting and recycling technologies, reduce the market value of plastic scraps, its reutilization, and recycling. Consequently, as of 2019, it is estimated that 79% of total generated plastic waste has accumulated in landfills, 12% has been incinerated, and only 9% has been recycled (Jambeck et al., 2015; Geyer et al., 2017; OECD, 2022).

The 1989 Basel Convention, the most comprehensive international agreement regulating the transboundary movement and disposal of waste, introduced new amendments to plastic waste regulations that went into effect in 2021. However, the Convention has not been ratified by the United States, one of the top exporters of plastic scraps. Furthermore, the Convention still allows non-halogenated polymers, such as polyethylene and polyethylene terephthalate (PET), to be exported without "prior informed consent" from the receiving country so long as the plastic is "destined for recycling in an environmentally sound manner and almost free from contamination and other types of wastes" (Secretariat of the Basel Convention, n.d.). This kind of exception creates opportunities for exporting countries to continue to send their plastic waste abroad without much hesitation.

Motivated by the growing number of unauthorized plastic imports, the low quality and recycling potential of imported material, and increasing environmental pollution, China implemented Operation Green Fence (OGF) in 2013, under which customs officials were required to conduct extensive inspections of arriving containers to enforce quality control (i.e., minimal levels of non-recyclable waste present in the containers; Resource Recycling, 2020). However, the initiative was only partially successful in reducing illegal trade and was only slated to last for ten months. Chinese officials ultimately announced Operation National Sword in 2017, a much stricter effort that targeted criminal activity surrounding illegal permits and increased quality controls. A few months after its implementation in 2018, China also set limits to contamination levels for most recyclables and banned specific types of solid waste imports, including ethylene polymers such as recyclable PET, PE, polyvinyl chloride (PVC), and polystyrene (PS)—all among the most common plastic polymers produced worldwide (Nerland et al., 2014). As of 2021, the ban was updated to include almost all solid waste imports.

Operation National Sword can also be perceived as a political tool by the Chinese government to put pressure on Western economies. Soon after China announced the import ban on solid waste to the World Trade Organization (WTO), the United States, Canada, Australia, South Korea, and some European Union countries expressed concerns about the lack of specificity and detail of the notification. They requested China to adhere to notification obligations—providing clarification about the restrictions—as the ban impacted multi-billion markets (World Trade Organization, 2017). The announcement of the ban was perceived to be purposefully vague, as lack of clarification on the new requirements would affect shipments if they did not comply with the new regulations.

Given China's status at the time as the largest importer of plastic scraps, the effect of this policy change on the global plastics market was drastic, evidencing international over-dependence on China as the world's plastics bin. As the profitability of recyclable plastic decreased, recycling companies in North America and other regions stockpiled material and were sometimes forced to send it to landfill. As countries looked for alternative destinations to export plastic scraps, countries in Southeast Asia show overwhelming increases in their plastic scrap imports. During OGF, Southeast Asian countries received substantial amounts of plastic scrap, sorting and cleaning with the goal to meet China's strict requirements before re-exporting scraps to China. Consequently, when China stopped receiving foreign plastic after National Sword, those countries were forced to handle the plastic domestically. For example, in 2018, Malaysia, Indonesia, and Thailand experienced an increase in imports of 59%, 149%, and 262% respectively from 2017 levels. Some Chinese recycling companies have also relocated to other countries with more flexible regulations and to enjoy tariff exemptions under the ASEAN-China Free Trade Agreement, where they produce pellets of recycled plastic to export to China (Yoshida, 2021). Unfortunately, most of 2018's top importers have waste mismanagement rates exceeding 50%, including but not limited to India (87%), Indonesia (83%), China (76%), Thailand (57%), and Malaysia (57%), based on 2010 figures (Jambeck et al., 2015).[2]

As responses to National Sword, Western countries that heavily relied on China were also forced to adapt their domestic waste management practices. The New South Wales government, for example, announced a $47 million support package to help local government and industry to

[2] The authors define mismanaged waste as "waste that arise through littering or dumping in low quality landfill or open dump sites."

adapt to the changes (New South Wales government, 2018). Through the *Waste Less, Recycle More* initiative, the government aims to support curbside recycling and promote industry innovation. Similarly, the United States' Environmental Protection Agency (EPA) developed a Solid Waste Infrastructure for Recycling (SWIFR) grant program which will request input to guide the development of new waste and recycling programs. This grant is part of the Infrastructure Investment and Jobs Act bill passed in 2021, which allocated $357 million to "developing programs for recycling infrastructure and recycling education…" (Quinn, 2022).

National Sword's impacts extend beyond trade and operations. Newer, leading importers often lack the processing capabilities to adequately handle the incoming waste. As a result, they have been significantly burdened by the environmental and public health impacts from inappropriately managed plastic, including the toxins and greenhouse gases (GHGs) emitted from overfilling landfills and improperly burnt plastic. Specifically, the most commonly used plastics (e.g., PE, PET, and PS) release methane and ethylene when exposed to solar radiation, the rate of which increases with time (Royer et al., 2018). These same plastics also produce GHG emissions when incubated in water for long periods of time. In 2010 alone, it is estimated that between 4.8 and 12.7 million metric tons (MMT) of plastic waste generated by coastal regions entered the ocean, which falls between 1.7% and 4.6% of the total plastic generated by these regions (Jambeck et al., 2015). Most recently, 22 MMT of plastic materials leaked into the environment in 2019 alone (OECD, 2022). Similarly, the informal burning of plastic releases toxic chemicals that are harmful to human health. For instance, burning PVC releases vinyl chloride and benzol, which are carcinogenic compounds (Alabi et al., 2019). Overall, plastics contribute about 3.4% of global GHG emissions throughout their lifecycle (OECD, 2022). Plastic waste management is thus an area of increasing concern with respect to environmental and public health.

At the local and national levels, plastic waste management has significant environmental, social, and public health implications. For example, in low-income countries, over 90% of waste is dumped in unregulated landfills or is openly burned (World Bank, 2022). As aforementioned, unregulated landfills and plastic burns are tied to significant acute and chronic disease health risks in neighboring communities, primarily through pollutants seeping into the air and waterways. In addition, in developing countries, the recycling sector heavily relies on informal workers who collect and recycle 15 to 20 percent of waste. Research has brought to light poor working conditions and the lack of labor protection laws in this informal industry, posing serious threats to the livelihoods of workers.

As the new top importers follow China's footsteps and impose their own restrictions, the future of plastic scraps trade is more uncertain than ever. It is unclear whether governments will rely on alternative domestic processing methods or instead continue to look for other destinations to which to send their plastic waste. Although the environmental and market impacts of National Sword have been studied before, few researchers have examined the factors that predispose countries to become plastic waste havens in the first place. Moreover, analyses of National Sword's environmental and economic consequences have not provided estimates or approximate quantifications of how structural differences in economic development, industry size, environmental regulations, and other relevant factors have affected countries' plastic waste trade levels. Ignoring economic development differences, especially, overlooks the unequal distribution of environmental and socioeconomic burden brought by increased plastic imports among countries with inadequate environmental stringency and processing capacity.

However, the waste trade network has been studied through various empirical approaches and research methodologies, including social network analysis (SNA), gravity trade models, and panel data models. This research recognizes the value of all of these approaches but implements a more holistic and multi-method approach, while also introducing new estimations methods to quantify shifts in trade levels while accounting for the aforementioned structural differences and impact distributions.

Chapter 1 provides a descriptive analysis of the shifting plastic waste trade network, specifically through the lens of SNA. It includes an overview of existing research on the impact of Operation National Sword and earlier national regulations on the global plastic trade network. Chapter 1 finally expands upon previous research by mapping trade networks that account for more recent years, while discussing how node-level relational measures have evolved. Chapter 2 discusses determinants of international waste trade (overall and plastic) as well as previously implemented methodological approaches. The first section of Chapter 2 includes econometric tests for relevance of these established determinants in the context of plastic scraps trade and robustness to the implementation of different estimation approaches. Chapter 3 includes descriptive case studies of plastic trade and discussion of policy strategies for important regions in the market of plastic waste in relation to the results from the preceding chapters. Chapter 4 concludes with a summary of this study's findings, its limitations and possible research extensions.

Chapter 1 | The Shifting Plastic Waste Trade Network: Before and After National Sword

To better understand the impact of National Sword on the global plastics trade, we must uncover and assess the direct impact of China's import ban on other trading countries over time. To do this, we can treat the trade system as a network: shifting our focus toward the composition and structural properties of trade relations and their change over time. To this end, we can use a Social Network Analysis (SNA) approach, commonly used in literature to explore the topological evolutions of networks and the relational characteristics of the individual nodes therein. It also provides quantitative measures of those characteristics.

Mapping relational structures has facilitated researchers to visualize channels through which nodes, usually representing individuals, organizations, or other entities, can influence each other. These configurations, known as sociograms in the context of interpersonal relationships, are used to visualize and identify influential nodes and non-reciprocal or asymmetrical relationships. In the context of plastic waste trade, influential nodes are top traders, importing or exporting large amounts of plastic scraps with many countries. Several measures of influence or centrality have been developed in the SNA framework. Some measures emphasize nodes' number of connections, their distance to other nodes, their importance as bridges connecting other nodes, or the prestige of their connections. The centrality measure discussed in this descriptive analysis will focus on the latter, considering the trading profile of nodes' connections, with the assumption that countries trading with influential countries like China were more likely to assume more central roles once National Sword was implemented. For example, Abdollahian and Yang (2013) use SNA metrics to examine the global trade system, which they state are able to measure the relative importance of countries "embedded in the larger context of global trade." Asymmetrical relationships can also be explored, were some Southeast Asian countries receive large amounts of plastic waste, but do not export as much.

This chapter will discuss how researchers have identified and quantified the effects of National Sword through SNA. The review of this literature will show how SNA has been used to measure the effects not only on each individual country, but also on the trade network as a whole. Later in this chapter, SNA is applied to complete a similar assessment of the plastics trade network post-National Sword, expanding upon previous studies by including additional years within the analysis and incorporating other measures of connectivity and centrality that tell a more complete story of the network's evolution over time.

How did National Sword Impact the Plastic Scraps Trade Network?

Multiple studies have shown how National Sword, despite being a domestic policy, has had an observable ripple effect that can be observed within and across countries in the plastic scraps trade network. Several analyses point to a shift in the network, whereby China's role as the most central node was consequently assumed by other countries after the plastics ban.

Wang et al. (2020), for example, analyze the spatiotemporal evolution of the network, showing that the heterogeneity index (i.e., a measure of the overall variance of each node's number of ties) had remained constant at high levels during the 2000s but started increasing after 2010 – when China implemented OGF. High levels of heterogeneity are characteristic of a network with few highly connected countries, which in turn reflects high vulnerability to targeted "attacks," or in this context, vulnerability to restrictions on imports and exports by top trading countries. Their findings suggest that, even after China's efforts to reduce their role as the top importer of plastic scraps, exporting countries continue to send plastic waste to only a limited number of countries.

The density of the network or the degree of connectivity, as well as nodes' closeness centrality (i.e., the average number of trading partners shared with all other countries), have in turn decreased after National Sword (Wang et al., 2020; Zhao et al., 2021). A lower density reflects lower connectivity or a smaller number of connections relative to all possible connections in a network, indicating that China's plastics ban triggered a reduction in overall plastic waste trade. In other words, some countries were forced to find alternative means to manage their plastic waste other than exporting it, and some importing countries stopped importing plastic waste. Similarly, the reduction in the average closeness centrality of nodes indicates an increase in the average distance or "steps" from one country to all other countries, again reflecting a shrinkage of the plastic scraps trade.

Using an Ecological Network Analysis (ENA), an application of network analysis to ecosystems formed by interactive elements linked by the "flow of energy or matter," Huang et al. (2019) identify China, the United States, Germany, and the European Union as the "major controllers" of the supply in the global plastic waste trade network. They find that most European countries heavily depend on Germany to export their waste, whereas countries like Canada and Mexico also rely on the United States. Pacini et al. (2021) similarly show that, in 2018, Germany acted as the most important trade hub in the network, with other important hubs such as Belgium, Italy, Turkey, and the Netherlands clustered under the influence of Germany. They also show that countries in which logistical facilities and harbors have a high presence tend to be connected to top trading countries, such as in the case of Malaysia and Thailand.

These network analyses illustrate some of the impacts, or non-impacts, of National Sword. Despite China's ban on imports, plastic waste exports did not necessarily cease. However, overall trade decreased, shrinking the overall size of the trade network. These analyses also reveal significant players and intermediary countries in the trade network, showing their importance in the trade network.

The Plastic Waste Network's Evolution: The Emergence of Influential Nodes

The aforementioned studies provide insight into the evolution of the plastic scraps trade network after the implementation of Operation National Sword, and they reveal how SNA offers useful perspectives to understand the impacts of the ban. In this section, SNA is similarly applied to more recent data, in this case incorporated to expand existing research and to lay the foundations for subsequent analyses in this study.

For the present analysis using SNA, bilateral trade data were collected from the United Nations (UN) Comtrade Database. Trade is measured in kilograms of plastic scraps imported for each year between 1999 and 2020. We use these data to construct a network of 119 countries with UCINET software (Borgatti et al., 2002). Subsequently, we estimate country-level measures of eigenvector centrality and clustering coefficients.

In this analysis, eigenvector centrality is based on the idea that a large number of trade connections to other highly-connected nodes makes a node more influential (i.e., "central") than a node with the same number of connections but connected to poorly-connected nodes. An eigenvector centrality estimate can therefore be used to assess the degree to which a country trades with other countries that in turn have many other trading partners. Unlike degree centrality, eigenvector centrality does not only consider the number of trade connections of a given country, but it also takes into account how well-connected that country's connected trade partners are. As such, two countries with the same number of connections can have different eigenvector centrality scores if one of those countries is connected to countries that are highly connected to other countries. As a result, an eigenvector centrality score shows whether a given country is more likely to import more plastic scraps given the overall plastic trade connections of its trade partners. More specifically, for a given network G with adjacency matrix $A = (a_{i,j})$, where $a_{i,j} = 1$ if country i is connected to country j, the eigenvector centrality score of country i is defined as:

$$X_i = \frac{1}{\lambda}\sum_{j \in G} a_{i,j} x_J$$

where, for country i, the centrality scores x_J of all its j connections are summed recursively. λ is a constant that, when expressed in the vector notation of the equation, is the largest eigenvalue of the adjacency matrix that produces a non-zero eigenvector with non-negative entries. The intuition is that, as is the case with some Southeast Asian countries that are used as "third-parties" for sorting and pre-processing plastic, once these countries trade with China, they will show large eigenvector centrality scores (and therefore high levels of both imports and exports of plastic waste).

Similarly, the clustering coefficient is also estimated to measure a node's tendency to form trade clusters. In this context, a clustering coefficient assesses the level of connectivity of a given node—i.e., the density of a node's trading neighborhood. In other words, a clustering coefficient measures how many connections exist among a country's trading partners relative to the total number of possible connections they could have. For our purposes, the clustering coefficient is included to assess changes in countries' tendencies to trade with a limited number of countries. Top traders before the National Sword policy are expected to exhibit low clustering scores after it.

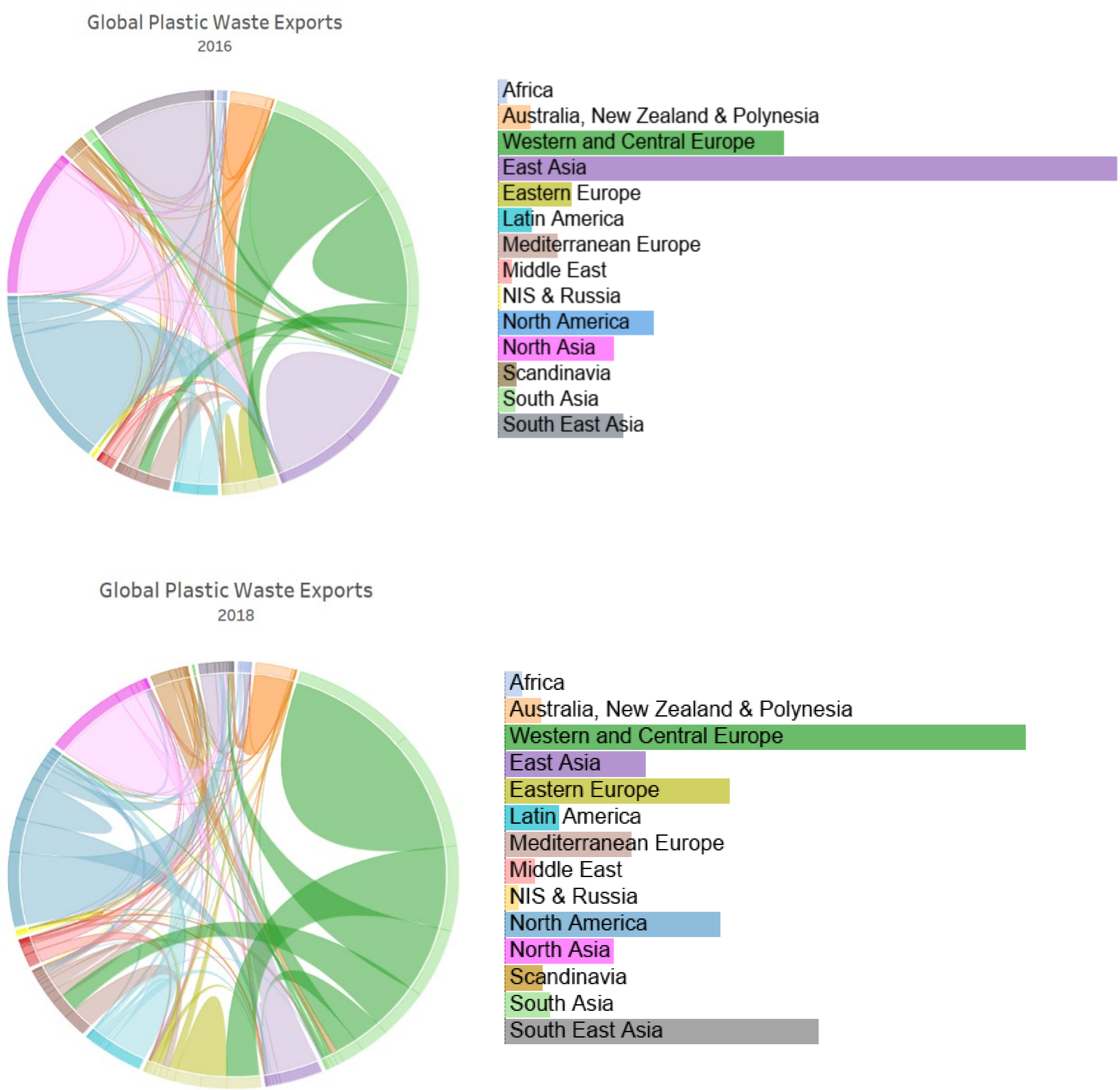
As evidence of the radical structural changes experienced by the network, Figure 2 shows chord diagrams of the plastic trade network by region in 2016 (before the China ban was announced) and 2018. A chord diagram visualizes connections between entities (in this case, regions), wherein fragments of the circumference or arcs are representative of the size of flows between regions (in this case, the portion of total plastic waste exported). The horizontal bar charts show the fraction of total imports accounted by each region.[3] The colors of the bar graphs correspond to those of the chords. In 2016, most regions sent their scraps to East Asia (i.e., mainland China and Hong Kong), as represented by the weight of each outgoing chord (as a fraction of total imports). The chord that comes out but remains in East Asia represents plastic waste that was exported to Hong Kong and re-exported to mainland China. The bar graph also shows that Western and Central Europe (i.e., Austria, Belgium, France, Germany, Ireland, Netherlands, Switzerland, and the United Kingdom) accounted for the second largest fraction of imports. However, most of the imports came from within the region. In other words, Western and Central European countries mostly imported from other Western and Central European countries given their laxer intraregional trade regulations. North Asia and Southeast Asia (i.e., Japan, South

[3] NIS stands for Newly Independent States

Korea, Cambodia, Indonesia, Malaysia, Laos, Myanmar, the Philippines, Singapore, Thailand, Vietnam, and Brunei) had the third largest combined fraction of imports, with most (if not all) chords coming from other regions. Also evident in Figure 2, is that almost the totality of their exports went to East Asia. This exemplifies the role that those nearby countries played as intermediary processers for China before the ban.

Figure 2 also shows that North America was responsible for an important fraction of imports before the ban. Yet, most of North America's plastic imports mainly came from within the continent. Overall, Africa, Oceania, the Middle East, Scandinavian countries, NIS and Russia, South Asia, and Latin America made up small portions of total trade, with East Asia alone manifesting a larger volume than all of them combined.

Figure 2. Chord Diagrams of Plastic Scraps Trade Before (2016) and After ONS (2018)



In 2018, after the implementation of National Sword, plastic waste exports changed destinations. Directionality and partnerships also changed. For example, Europe increased the intra-trade of plastic waste. From the number of chords going toward Southeast Asia, it is also evident that more countries redirected plastic exports to this region. The largest portion of plastic imports to this region came from North America, North Asia (i.e., Japan and South Korea), and Western and Central Europe. Although countries in Western and Central Europe substantially increased trade after the ban, it was mostly with countries within the region or with Eastern and Mediterranean Europe countries. Figure 2 also shows that most of Hong Kong's and China's plastic waste exports went to Southeast Asia.

Given the differences in the sizes and trade partners for imports and exports, it is important to consider imports in the context of *net* trade. This is because net trade values account for exports. For instance, looking at differences between imports and exports in Figure 2, countries in Southeast Asia import substantially more than they export, whereas many European countries are mostly net exporters (i.e., they export more plastic than they import). Particularly, Southeast Asian countries imported almost 10 times more plastic waste (from other regions) than what they exported after the ban in 2018.

Figure 3 shows country-level eigenvector centrality trends for selected countries over the 1999-2020 period (blue trend, left Y-axis). Evident in Figure 3, drastic trend changes occurred due to National Sword. It is also possible to identify gradual shifts in centrality occurring since the early 2010s, when OGF regulations were implemented. Figure 3 also shows the trend of plastic imports (in logged kilograms) over time (red trend, right Y-axis).[4] Although for countries like China, the relationship between centrality and levels of imports is more evident, it is important

[4] The countries in Figure 3 are those with average centrality scores larger than 0.1 and who exhibited more evident changes during the period of analysis. Trends for all countries in the analytic sample are included in Figure A in the Appendix.

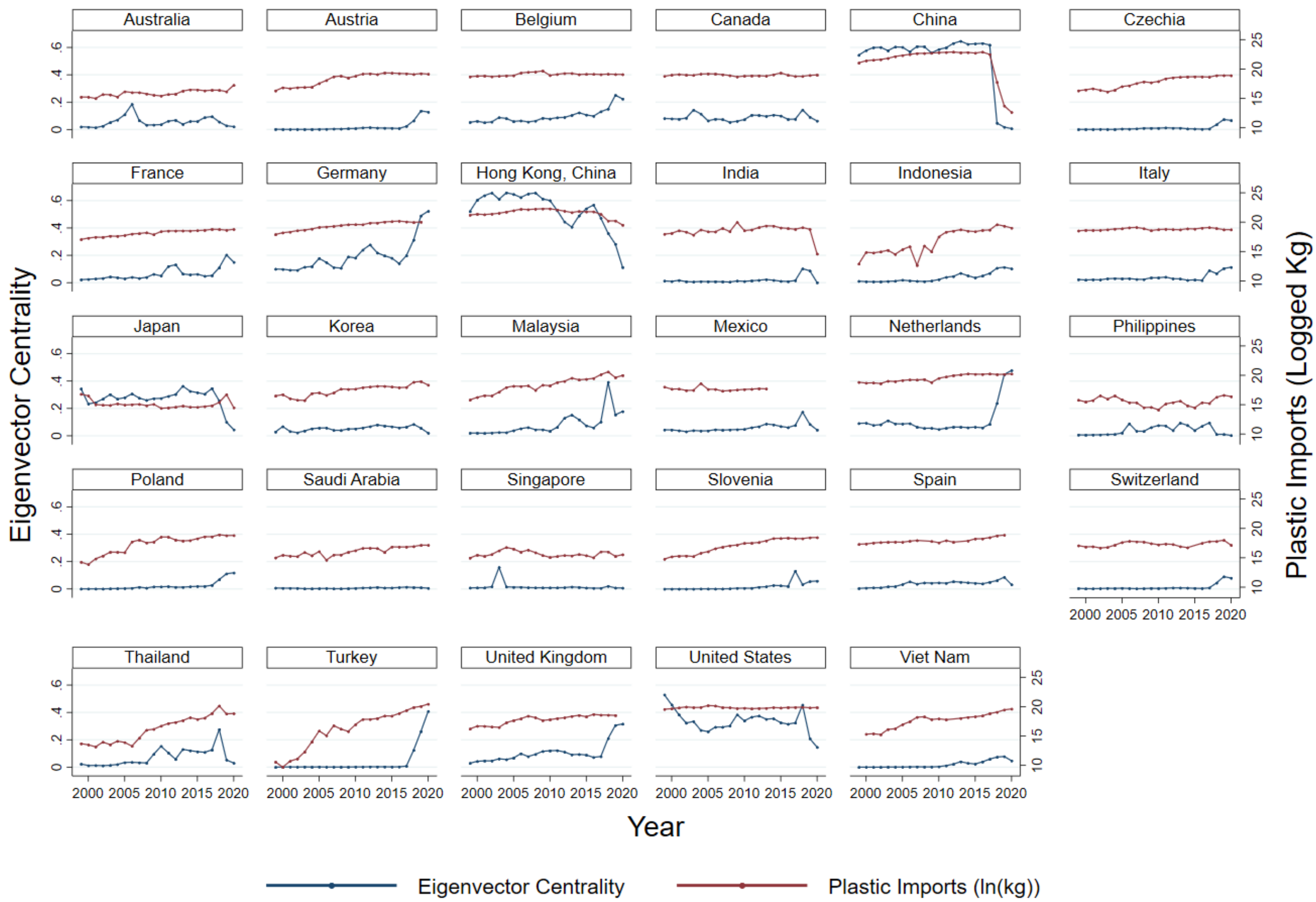
to consider that the units of plastic imports are in a logarithmic scale. Turkey, for example, shows a sharp increase in eigenvector centrality since 2017—from almost 0 in 2016 to 0.41 in 2020, which is a susbtantial increase considering that the total range of this centrality score is from 0 to 0.66. Although Turkey's increase in plastic imports seems gradual, the total amount of plastic imports increased by 395% between 2016 and 2020.

Levels of imports for the United States appear stable relative to changes in other countries. Yet, its eigenvector centrality shows high variability. More specifically, while the U.S. continued importing between 420M and 440M kilograms of plastic scraps after the ban, its eigenvector centrality decreased from 0.32 (before the ban) to 0.15 (after the ban). In other words, although its imports seem unaffected by China's policies, the profile of its trading partners (i.e., whether it traded with top or bottom plastic traders) did change. Although self-reported trade data for the United States is unavailable for a couple of years after the ban's implementation, its overall export levels recentlly decreased by more than 60% relative to its 2015 levels. Yet the United States increased plastic scraps exports to other regions immediately after the ban, sending, for example, 12 times more plastic to Thailand, five times more to Malaysia, Turkey and Germany, and four times more to the Netherlands (per self-reported exports data in 2016 and 2018).

As expected, both China and Hong Kong experienced sharp drops in eigenvector centrality after the ban. Interestingly, while for China its eigenvector centrality dropped together with its imports, for Hong Kong a similar drop occurred without a drastic decline in its imports. Differently, the Netherlands, Germany, and the United Kingdom experienced sharp increases in their eigenvector centrality; import trends remained basically uninterrupted. For example, the Netherlands did not report imports from Thailand and Malaysia (both highly connected countries) in 2016, but it did report imports from Thailand in 2018 and from Malaysia in 2019. The United Kingdom also gradually increased imports and exports during the 1999-2017 period, but trade started to decline slowly since 2010, and more evidently since 2017. Most of their exports were redirected to Southeast Asia. Countries like Thailand and Malaysia experienced substantial increases in both level of plastic imports and eigenvector centrality immediately after the ban, but then manifested similar decreases the following year. Both of these countries quickly followed China's footsteps, implementing plastic imports restrictions of their own: Thailand announced a total ban of plastic imports by 2025, while Malaysia is phasing out imports gradually (Ananthalakshmi, 2018; Wladeck, 2022).

Critically, Figure 3 shows radical differences between key plastic trade trends like imports and those of network centrality (here assessed using the eigenvector centrality). Most of the world nations manifest relatively stable import trends, with smooth changes, if any, from before to after China's ban. This is not the case for trade connectivity. Figure 3 shows that China's ban had a detectable effect on eigenvector centrality's volatility. Clearly, for China both imports and plastic trade network connectivity covary to an imporant degree. This is not the case for many of the other key players in the plastic global market. This situation highlights the importance of trade connectivity as a measure of trade dynamics not captured by traditional macroeconomic measures like imports. Given that the overall production and consumption of plastic remained practically unchanged from before to after the ban, most of the trade dynamics occur in bilateral trade patterns depending on pre-established connectivity and trade partners.

Figure 3. Eigenvector Centrality and Plastic Imports (Logged Kilograms) for Select Countries (1999-2020)



While observed changes in plastic waste trade levels bring attention to top traders, considering the profile of trading partners can highlight the conditions in which plastic scraps are processed as well as the quality of traded material. For instance, Japan and the United States did not experience substantive changes in plastic imports, but their eigenvector centralities decreased. Japan substantially reduced trade with China, but it also started trading with more European countries and some in Southeast Asia and Africa, each region with varying processing technology and capabilities. Whereas plastic waste in African and Southeast Asian countries is less likely to be recycled, recycling rates in a country like Germany (between 60-70%) imply a smaller portion of plastic going to landfills and entering the ocean. The increase in trade between the United States, and Europe and Southeast Asia has similar implications. For example, a report by the United Nations Environment Programme (UNEP) evaluating waste management in 10 Association of Southeast Asian Nations (ASEAN) member countries shows that open dumping and open burning of waste are prevalent in these countries, and that the recycling sector is mostly comprised of informal workers (Jain, 2017).

The clustering coefficient of these countries (Figure B in the Appendix) aligns with the described changes of eigenvector centrality. As countries trade with more countries, hence import more plastic waste, their clustering coefficient decreases. Increases in the number of trade partners drive this measure down as more partners imply more possible connections among those partners that do not always exist. For example, since 2010, more countries started importing to Turkey, Indonesia, and Vietnam, but they did not increase trade with each other. They disproportionally sent plastic waste to these three countries, but not to each other. If plastic scraps were being more equally distributed across traders, the clustering coefficient of all traders would be higher and more similar.

Figures 4 and 5 show a more disaggregated picture, displaying the 2016 and 2018 network connections, where nodes with darker colors and bigger nodes have the highest degree centralities (i.e., highest imports of plastic scraps). As such, the size and color of the nodes represent ranks in imports and not exports. The weight of imports between each pair of nodes determines the intensity of the color (bluer for lower weights and redder for higher weights) and the thickness of the edges. The location of the nodes also represents a country's centrality in the network. Comparing the networks provides a more holistic picture of the dynamics of plastic waste trade than would be observed by looking only at the countries individually or in aggregate.

The 2016 network shows China and Hong Kong as the most central nodes in the plastics imports network. Although Hong Kong is as large a node as China, the edge between the two captures in part one aspect more directly detectable in the data: that most of the imported plastic scraps arriving to Hong Kong were re-exported to mainland China. The edges from India and Vietnam to China and Hong Kong are again examples of the role as intermediary processers played by countries in South and Southeast Asia. Other Southeast Asian and European countries are also centrally located (although with significantly lower import levels than China), including Germany, Italy, Spain, Belgium, and France among others. The United States is also central; indeed, it is one of the top importers in 2016. Its exports to Hong Kong are among the largest bilateral transactions in the world. In fact, 42% of its exports were directed to Hong Kong alone.

Figure 4. Plastic Scraps Trade Network in 2016

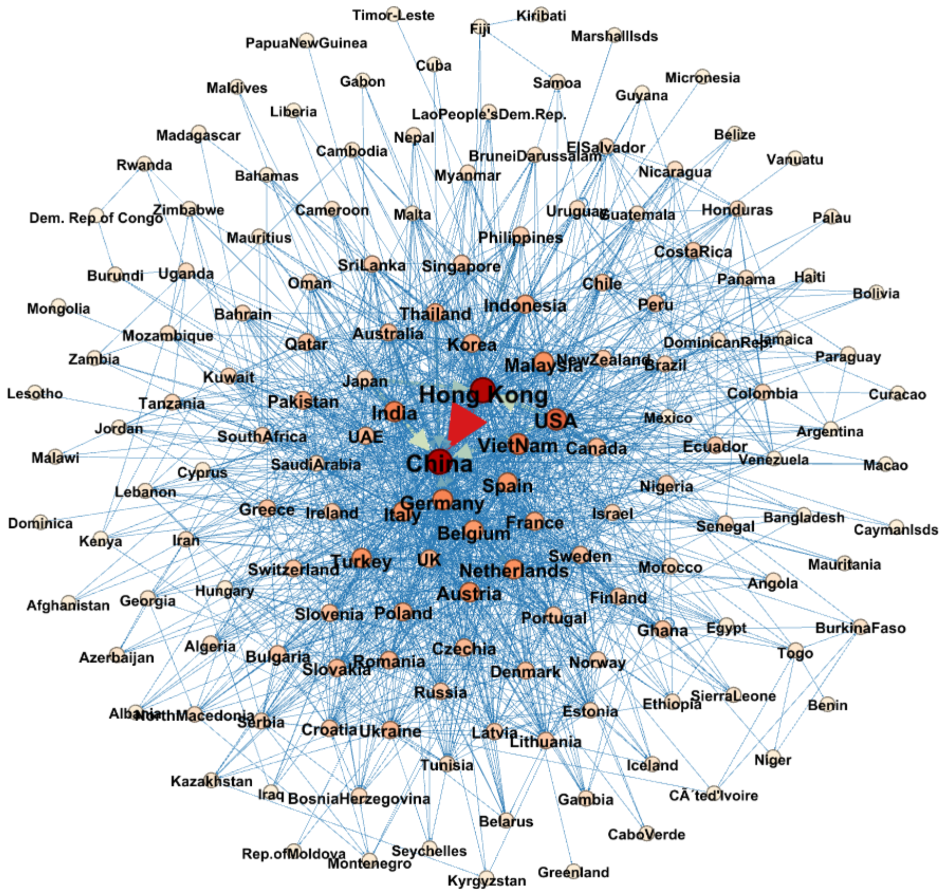
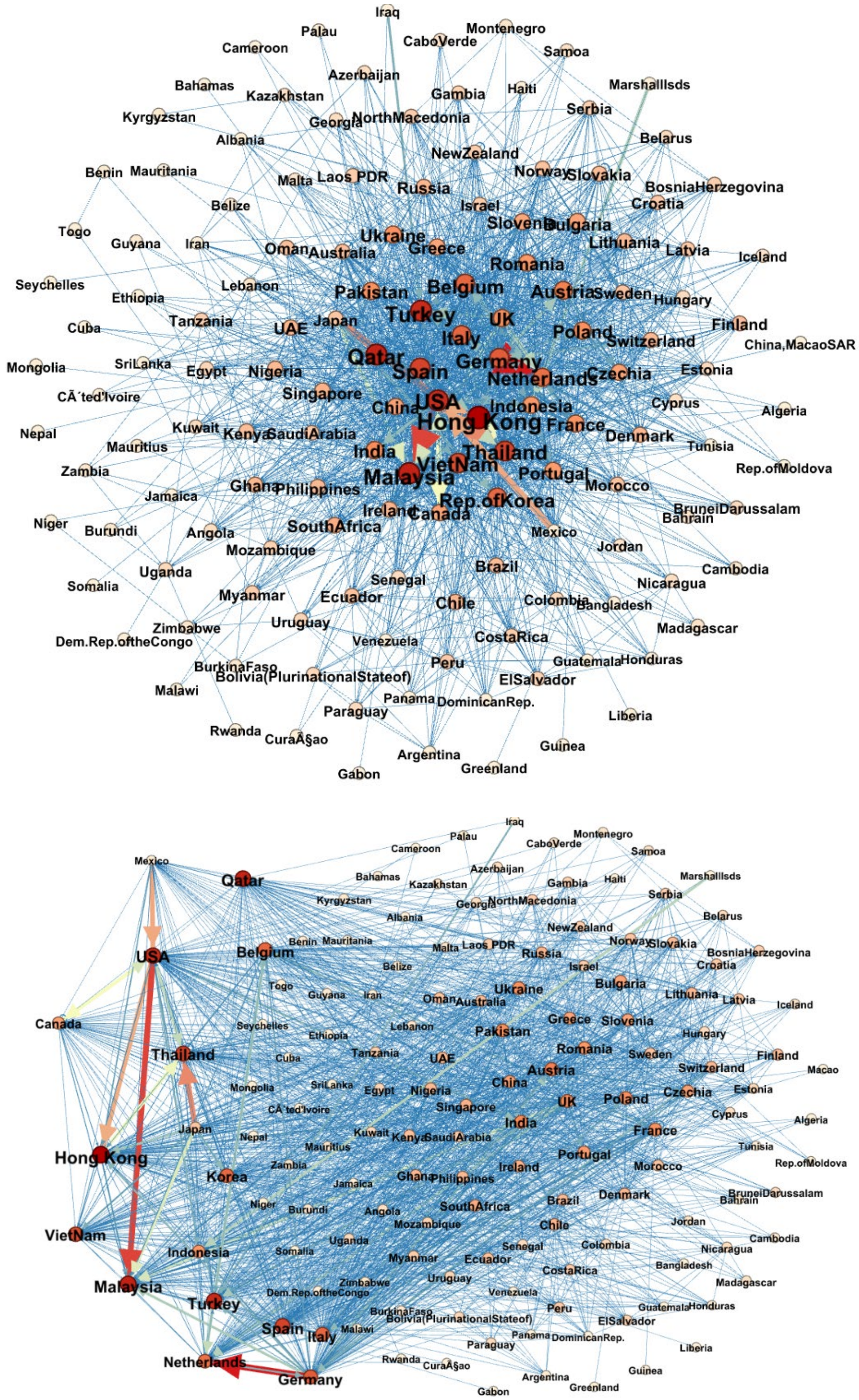


Figure 5. Plastic Scraps Trade Network in 2018



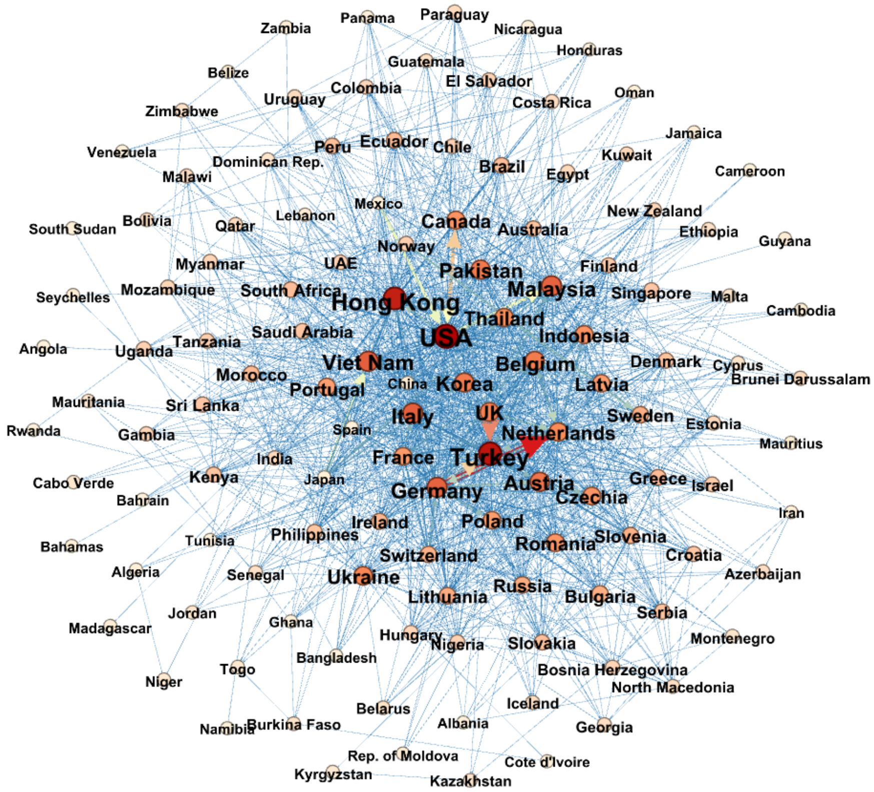
Note: The bottom network replicates the 2018 network but rotates the image thus placing most central nodes at the left so that connections are more visible.

Differently, In Figure 5, the 2018 network shows several equally central nodes. While in 2016 Hong Kong and China were the only two most central ones, Malaysia, Thailand, Germany, Qatar, Turkey, Vietnam, the Netherlands, Germany, Spain, Italy, Belgium, South Korea, and the United States became central by 2018. Most notably, Malaysia received the highest fraction of plastic scraps from the United States, and a smaller but significant portion from Japan's and Indonesia's. While China was no longer among the most important plastic traders, Hong Kong continued to receive plastic scraps from 78 countries, with the largest amount coming from the United States. Although the centrality of Southeast Asian countries decreased by 2020, a few of them such as Malaysia, Thailand, and Indonesia sustained high import levels.

Figure 5 also shows that, although Germany continued to be an important European importer, it also exported the second highest amount of plastic to the Netherlands (a piece of information also revealed in self-reported data). While Japan experienced reductions in plastic waste imports, it is Asia's biggest packaging waste producer, now exporting its waste to Thailand, Malaysia, and South Korea in 2018 (Lee, 2022). Turkey and Qatar remained large recipients of foreign plastic waste. For example, Turkey became the largest export destination for plastic scraps from the United Kingdom, as well as the largest non-European destination of Germany's plastic waste exports due to the lax domestic enforcement of licensing and inspection of recycling facilities laws (Human Rights Watch, 2022). Qatar's plastic imports decreased overall by 2018; yet, after the ban, governmental efforts have mainly focused on strategies to increase domestic waste management (Mohamed, 2021).

A more recent 2020 plastic trade network is visualized in Figure 6, showing an overall reduction in trade of plastic scraps and an even smaller (relative to 2018's network) number of central countries. The combined effect of the COVID-19 pandemic and growing plastic trade restrictions across Southeast Asian countries brought the network's density downward. Intraregional trade in North America increased by 2020, with the United States receiving plastic from (and sending to) countries within the continent (i.e., from and to Mexico and Canada). Europe also increased its plastic trade within the European region by more than 11% relative to 2016 levels. This is also reflected by the fact that, in 2020, OECD countries accounted for 89% of global reported exports and 67% of imports (Brown et al., 2022). Interestingly, Turkey became the largest recipient of the European Union plastic waste exports by 2020. More European countries increased their number of trade partners and, as a consequence, the amount of plastic imported. Exports from Germany to the Netherlands and from the United Kingdom to Turkey were the largest reported (in weight).

Figure 6. Plastic Scraps Trade Network 2020



Despite these shifts in the destination of plastic scraps also implying potential changes in their processing and management (i.e., whether they are recycled, incinerated, or landfilled), the utilized reported data does not distinguish between intermediary or transit countries and final destinations of plastic. In other words, re-exports are not distinguished from exports. Therefore, not all imported plastic can be assumed to be processed domestically. Furthermore, given that trade data is self-reported, values available for download from the United Nations (UN) Comtrade are constantly updated, especially for more recent years. At the time of writing, available data for 2021 was incomplete and thus excluded from the analysis, and 2020 figures were updated several months after data collection for this analysis. As such, estimates and descriptions for more recent years should be interpreted with caution.

SNA is a valuable tool through which to analyze and illustrate the changes in the global plastic trade network triggered by National Sword. However, SNA is a descriptive analysis, and alone it cannot necessarily offer insight into the specific mechanism underlying changes in the trade network. It is important to also investigate the specific characteristics that predisposed certain countries to more easily accept incoming plastic pairings and scraps from countries who could no longer rely on China to receive their exported waste. Importantly, as evinced by SNA results, trade connectivity matters. The origin and destiny of plastics after China's ban seem to follow patterns pre-established in trade among nations that are not readily captured by traditional trade measures. It seems, therefore, that the future of plastic trade—and with it its environmental and public health implications—can be usefully described by trade connectivity. Indeed, this study proposes the idea that measures resulting from SNA may become useful descriptors and tools for quantification in the context of other statistical tools.

Chapter 2 | The Determinants of Plastic Scraps Trade

This chapter explores and identifies the characteristics of countries that may have made them more prone to importing plastic post-National Sword. It begins with a discussion of the existing literature on economic and structural factors that drive plastic imports, as well as trade of other waste types that might be relevant in the context of plastic scraps. Their effect on the transboundary movement of plastic scraps is then estimated using appropriate methodologies for dynamic panel data, with a focus on disaggregated trade data by plastic type given differences in each type's recycling potential and determinants for demand. This chapter also introduces an innovative macro-level measure of environmental performance and incorporates structural economic country-level characteristics, with special attention toward observed changes within the years immediately before and after National Sword. It also incorporates eigenvector centrality, calculated in the previous chapter, as a relevant measure of trade connectivity useful to explain countries' plastic scraps trade levels. The latter section of this chapter examines changes in countries' probabilities to import more plastic than they export, an indicator of potential waste havens, distinguishing between the countries increasingly importing of plastic with high recycling potential from those receiving plastic that is more difficult to process.

Literature Review: Why Do Countries Import Waste?

Research on countries' motivations to import waste has largely focused on the overall trade of waste, which includes both hazardous and non-hazardous waste. However, few studies address the conditions that make countries more prone to specifically import plastic scraps. Among the country-level characteristics discussed in the literature as correlated to patterns of international waste trade, the strength of environmental regulations has been commonly used to test whether bilateral differences in environmental policy stringency increase the trade of waste between two countries.

Kellenberg (2012), for example, constructs an environmental regulation index with survey responses from the *Global Competitiveness Report* (GCR) across 102 countries. Certain survey questions relate to perceptions of each country's stringency of "air, water, chemical, and toxic waste regulations relative to other countries in the world." Kellenberg's findings show that the relative environmental stringency gradient between countries is an important and robust determinant of bilateral waste trade. Although the survey responses do not capture perceptions of regulations on non-toxic waste such as plastic scraps, global data of that granularity are not available. Kellenberg shows the findings' robustness by using an alternative "environmental sustainability indicator" as a measure of environmental stringency. However, the GCR survey respondents mostly include company executives who might not provide a representative picture of nation-level perceptions. Alternative measures of environmental policy stringency could potentially be used in the context of plastic scraps trade. Similarly, the Basel Convention ratification has been included in analyses of international waste trade to control for its effect on overall waste trade reduction over time (Baggs, 2009; Kellenberg, 2012). Historically, the Convention's effect has been most noticeable on hazardous waste trade, but new amendments concerning plastic waste, introduced in 2021, will make the Convention relevant for analyses of 2021 data and future years.

D'Amato et al. (2012) are among the few authors that study how policy, and economic and institutional characteristics affect countries' plastic waste trade flows. They analyze polyethylene export flows of 27 European Union countries from 2004 to 2007. Through a negative binomial regression, the authors find that the number of kilograms of waste per capita destined to landfill is negatively associated with PE exports. Their waste management policy measures are proxied by the amount of waste that is landfilled. They argue that their results show that more landfilled waste per capita implies a weaker waste management policy, and thus less recyclable waste available to be exported. In the same way, a higher recycling rate negatively affects polyethylene scraps exports, which is assumed to be used in domestic production of PE. Counterintuitively, their results also show that countries with more patent applications of waste material recycling technologies tend to export more polyethylene plastic waste. On the other hand, they find that measures of geographical distance do not have a statistically significant effect on polyethylene plastic waste exports.

Lower levels of development are also a commonality among recent top net importers of plastic waste. During the late 1980s and early 1990s researchers focused on the lack of enforcement of waste trade regulations, which allowed developed countries to send hazardous waste to developing countries. Strohm (1993) discusses the political context of the international waste trade and whether "North-to-South" waste imports occur due to a sovereign free choice from the South to accept the risk in exchange for the economic benefit, or if they constitute transfer of risk to vulnerable groups. The author explores the interaction between a desire for greater environmental protection, but greater consumption of manufactured products in Western countries, and how these affect domestic waste management policies. She notes that overwhelmed domestic disposal capacities create the need for international waste trade since waste can be more cheaply dumped or incinerated in developing countries. Strohm claims that the "Prior Informed Consent" regime, where waste recipient nations consent is enough, fails when the information that guides the recipient's decision to consent is inadequate. For example, environmental risk evaluations about shipments often fail to reach officials in the recipient country.

In the same way, Clapp (1994) describes how developing countries allied politically to strictly regulate trade of hazardous waste with less-industrialized countries through the Basel Convention. She also shows that although some perceive the environmental risk that developing countries take as the price for the economic benefit of receiving the developed world's waste, the environmental impact they suffer also "threatens their future economic prospects." Cleanup costs of hazardous waste dumps, lower agricultural productivity due to contamination of groundwater, and diminished public health all combine to harm their economic growth.

Higashida and Managi (2014), Brooks et al. (2018), and Kellenberg (2012) also identify that, over the last two decades, an exponentially increasing proportion of waste has been going to developing countries. While some developed countries are among the top importers of waste, their share of imports is low when compared to their share of world exports. A similar trend is observed when only considering plastic waste: 87% of plastic waste exports between 1988 and 2018 came from high-income countries (Brooks, 2018). In fact, D'Amato et al. (2012) show that upper-middle income countries tend to export substantially more polyethylene scraps. Similarly, they find that countries with lower labor wages attract more PE waste exports from European

Union countries, which they associate to a "pollution haven" incentive for exporting countries "to exploit the wage differential."

Another economic driver considered by existing research is that higher capital-to-labor (capital/labor) ratios can lead to increased waste imports, assuming that the ratio reflects the country's technological recycling capabilities (Baggs, 2009). Kellenberg (2015) notes that this argument contradicts the idea that developing countries are the main destinations of the developed world's waste, given that developing countries tend to have low capital/labor ratios. However, in the context of plastic waste, these findings are consistent when looking at *absolute* plastic waste imports (i.e., import quantities not adjusted by export quantities), which show countries like the United States, the Netherlands, and Germany among the top importers. An additional relevant economic factor, recycling productivity across countries, has been measured with recycling wage rates. Alternatively, it has been proxied with gross domestic product (GDP) per capita on the rationale that countries with high productivity overall also tend to have a highly productive recycling sector (Kellenberg, 2012). Population size is also a common structural control, especially considering that the amount of produced waste in a country is a direct product of the number of people (Lebreton and Andrady, 2019).

Literature discussing the properties of different plastic types and their relevance in the treatment process can also inform analysis of countries' motivations to import specific plastic types that align with their processing capabilities and demand. Out of the two major categories of plastic material, thermoset polymers are less relevant when discussing the international plastic scraps trade since they tend to be infusible and insoluble after their initial forming, thus making the material undesirable for recycling purposes. Thermoplastics, on the other hand, soften to a malleable state or melt into liquid when heated, making them recyclable and processable through various methods. One important characteristic for the categorization of thermoplastic polymers is their glass transition temperature (Tg). The flexibility of polymers such as PVC and PS, for example, is reduced when they are cooled below their respective Tg (Grigore, 2017). Furthermore, given that most types melt at different temperatures, they are often processed separately.

The processing methods available in each country also offer a factor for consideration when examining plastic waste trade. Most curbside and drop-off recycling programs in Europe and the United States take high density PE (HDPE) and PET, while PVC is less commonly accepted given its high chlorine content and hazardous additives (North Carolina Department of Environmental Quality, n.d.). Recycling of PS is also limited because it is commonly contaminated with food or other organic materials, and because it is expensive to transport due to its low density. Taking these properties into consideration can then be useful to give meaning to observed import levels of each plastic type. Specifically, PE and PET can be considered the most desirable types of plastic scraps and pairings to import, while PS and PVC are expected to be less desirable and thus in lower demand.

Most of the reviewed literature estimates the effect of several economic factors on the international trade of waste using gravity models of bilateral trade (Baggs, 2009; Kellenberg, 2012; Higashida and Managi, 2014). The use of the gravity model implies that countries with larger economies trade more waste than smaller countries because (1) they consume more and thus produce more waste to export; or (2) they have a more developed disposal and processing capacity to import more waste (Kellenberg, 2015). The model also assumes that longer distances between countries entail higher costs of transportation, which in turn decrease trade between any two countries. However, considering that plastic scraps are mainly transported internationally via sea freight, distance between trading countries might not be the most appropriate proxy for shipping prices. Over time, other factors such as number of maritime lines, product characteristics, port efficiency, and trade restrictions have become important factors affecting prices of maritime transports (Sánchez et al., 2003; Clark et al., 2004). Furthermore, by definition, the gravity model is estimated with dyadic data, which considers each country pair as the unit of analysis. Thus, the included covariates in a cross-sectional time-series data model need to be transformed to become relative measures (i.e., variables that vary by country-pair). Accordingly, the gravity model might not be an appropriate estimation method when the research question concerns country-level characteristics that are evaluated in absolute terms and not relative to other countries.

Dynamic Modeling of Plastic Scraps Trade

An additional challenge in the analysis of trade is the simultaneous relationship between trade levels and other economic factors. For instance, trade drives economic growth (Frankel and Romer 1999), but economic growth is often associated with more economic openness, hence more trade (Commission on Growth and Development and International Bank for Reconstruction and Development, 2008). Similarly, modelling dynamic processes, where trade levels depend on their past realizations, requires methodologies that address the violation of exogeneity assumptions in econometric models. Dynamic panel data estimators (Anderson and Hsiao, 1982;

Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998), developed with these limitations in mind, are the main estimation approach of this section.

Data

To operationalize each country's trade of plastic scraps, data on imports and exports of plastic waste, parings, and scraps (in kilograms) were collected from the UN Comtrade Database. The compiled data go from 1999 to 2020, constituting 21 years of data for 119 countries. Given that some countries do not have data available for plastic trade for all the years of the analysis, the number of countries per year varies, making the data unbalanced. The waste categories collected include ethylene, styrene, and vinyl chloride polymers, as well as other types of plastic that are not classified elsewhere.[5] Again, it is important to note that national trade data in the UN Comtrade Database is reported voluntarily and may exclude certain data (e.g., illegally traded plastics), and thus may not be fully representative of a given country's actual plastic waste trade. Misreporting issues can be partially overcome by mirroring reported imports data, assuming that countries will be less likely to underreport imports than exports. All plastic trade variables are normalized through a logarithmic transformation.

Between 31-34% of total plastic trade reported during the period of study were categorized as ethylene polymers (PE) waste, pairings and scrap.[6] The biggest fraction, however, comprises

[5] The specific UN Comtrade HS commodity codes used are 391510 (Ethylene polymers waste, pairings and scrap), 391520 (Styrene), 391530 (Vinyl Chloride), and 391590 (Not elsewhere classified).
[6] Due to misreporting, the proportion differs when looking at exports and imports. As such, both estimates are given as lower and upper bounds. The baseline used only includes countries with complete information of plastic types traded.

"other" plastic not classified elsewhere, accounting for 56-58% of total plastic traded. This commodity category includes plastic without an assigned commodity code as well as scraps of mixed types such as polyethylene terephthalate (PET) and polypropylene (PP; Brown, 2022). Styrene polymers make up about 5% of plastic trade, and vinyl chloride polymers make up between 5-8%. Considering the recycling potential and desirability of each of these plastic categories, these proportions align with the expected demand and production rate of overall PE and PET. As aforementioned, most recycling facilities and technology are equipped to process PE, which is also the most commonly used plastic worldwide. Nevertheless, the fact that "uncategorized" plastic makes up more than half of all plastic traded is concerning, since mixed materials have a lower recycling potential and determining whether the destination country possesses the technological capacity to process it is harder if the plastic's characteristics are unknown. Furthermore, this commodity code might also present an opportunity for countries to export unwanted plastic waste legally.

Table 1 reports summary statistics for the sample of study of 1,906 complete observations. Summary statistics for the earliest and latest year are also included. Average plastic trade levels, as well as ethylene polymers and uncategorized scraps, have grown over time despite China's initiatives and despite overall trade going down drastically after National Sword's implementation. Data quality and availability have also improved in later years. Accordingly, the average of both imports and exports of ethylene and uncategorized plastic scraps have increased for the analytic sample. The overall average of logged plastic imports, for example, is equivalent to about 3,470,000 kilograms, about the amount imported by Singapore in 2016; while the maximum equates to 8,900,000,000 kilograms, China's total imports in 2012.

Table 1. Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Logged Plastic Imports (Kg)				
Full Sample (N=1,906)	15.06	2.98	0.00	22.91
2000	14.64	2.73	4.47	19.65
2020	15.38	3.22	3.47	20.44
Logged Plastic Exports (Kg)				
Full Sample	15.92	2.49	0.00	21.60
2000	14.97	2.68	6.87	20.14
2020	16.01	1.97	10.59	19.84
Logged Ethylene Plastic Imports (Kg)				
Full Sample	12.34	5.12	0.00	22.21
2000	11.73	5.19	0.00	18.13
2020	13.19	5.13	0.00	19.90
Logged Ethylene Plastic Exports (Kg)				
Full Sample	12.69	5.57	0.00	20.67
2000	11.72	5.47	0.00	19.01
2020	12.80	5.53	0.00	20.19
Logged Other Plastic Imports (Kg)				
Full Sample	14.11	3.47	0.00	22.25
2000	13.32	3.45	0.00	19.51
2020	14.24	4.05	0.00	19.55
Logged Other Plastic Exports (Kg)				
Full Sample	15.24	3.03	0.00	21.48
2000	13.70	4.28	0.00	19.56
2020	15.18	2.56	0.00	18.88
Environmental Performance Index				
Full Sample	57.40	12.56	25.1	90.68
2000	54.80	8.32	33.7	76.20
2020	51.02	15.22	27.6	81.50
Logged GDP Per Capita (2010 US Dollars)				
Full Sample	9.02	1.30	5.91	11.39
2000	9.13	1.24	6.26	11.21
2020	8.88	1.26	6.44	11.36
Manufacturing Sector (% of GDP)				
Full Sample	14.77	5.65	2.60	48.80
2000	16.51	5.69	4.32	30.86
2020	13.57	4.90	3.11	26.18
Eigenvector Centrality				
Full Sample	0.026	0.078	0	0.646
2000	0.020	0.066	0	0.456
2020	0.039	0.098	0	0.523
Weighted Average Distance to Top 5 Exporters (miles)				
Full Sample	6,891.9	2,409.1	2,830.0	14,628.8
2000	6,321.2	2,292.2	3,987.7	13,536.8
2020	7,122.5	2,906.6	3,840.7	14,016.0
Weighted Average Distance to Top 5 Importers (miles)				
Full Sample	7,002.6	2,827.1	2,824.1	16,458.2
2000	6,770.3	2,763.1	3,987.1	15,554.9
2020	7,512.2	2,566.7	5,195.8	13,716.4

An independent variable of interest is the centrality measure described in Chapter 1, here included as a measure of the connectivity profile of countries' trading partners. Again, a larger score indicates a high degree of plastic trade connectivity—i.e., that a given country trades plastic with highly influential countries in the overall plastic trade (i.e., top importers). This centrality measure is not only a property of the trading country itself but of the robustness of its trading network. Including this variable in the analysis is critical as it offers an alternative perspective to plastic trade dynamics than those traditionally developed in macroeconomic research. Table 1 shows that the average centrality increased substantively from the earliest to latest year of the analysis. While plastic waste imports were primarily concentrated in East Asia in 2000, plastic waste trade was redistributed among more countries after the ban, increasing the average eigenvector centrality score in the sample.

As a measure of environmental stringency, the Environmental Performance Index (EPI) out of the Yale Center for Environmental Law and Policy and the Center for International Earth Science Information Network (CIESIN) at Columbia University is used. The EPI ranks 180 countries on "climate change performance, environmental health, and ecosystem vitality" (Wolf et al., 2022). The index, going from 0 to 1 (with 1 representing the best performance), aggregates 40 performance indicators that measure how close countries are to meeting established environmental targets. Although this is a macrolevel indicator, this variable aims to test the claim that better environmental performance reduces waste trade levels. Nevertheless, this measure has a moderately strong correlation with GDP per capita (~0.60), so mixed results are expected (as discussed in the literature). In other words, while wealth has been found to be associated with lower levels of plastic waste imports, larger differences in environmental performance between trading partners increase waste imports. The analytic sample consists of countries of varying EPI scores, with an overall minimum of 25.1 (e.g., Myanmar's score in 2019) and maximum of 90.7 (e.g., Finland's score in 2016). Although average EPI scores in the sample are lower in 2020 than 2000, the range of variation and maximum value are larger.

As additional independent variables, the size of the manufacturing sector (percentage value added of GDP) and GDP per capita (in constant 2010 USD) are obtained from the World Bank's "World Development Indicators." GDP per capita, a proxy for level of development, tests the literature finding that developing countries tend to import more plastic waste than developed countries (hence that wealthier countries export more plastic waste). Both measures remain relatively stable over time, but average GDP per capita is lower in 2020 and the variance increases, possibly signaling unequal growth across the sample of countries. Similarly, the size of the manufacturing sector as a percentage of GDP decreases, which is expected as most countries shift to service-based economies.

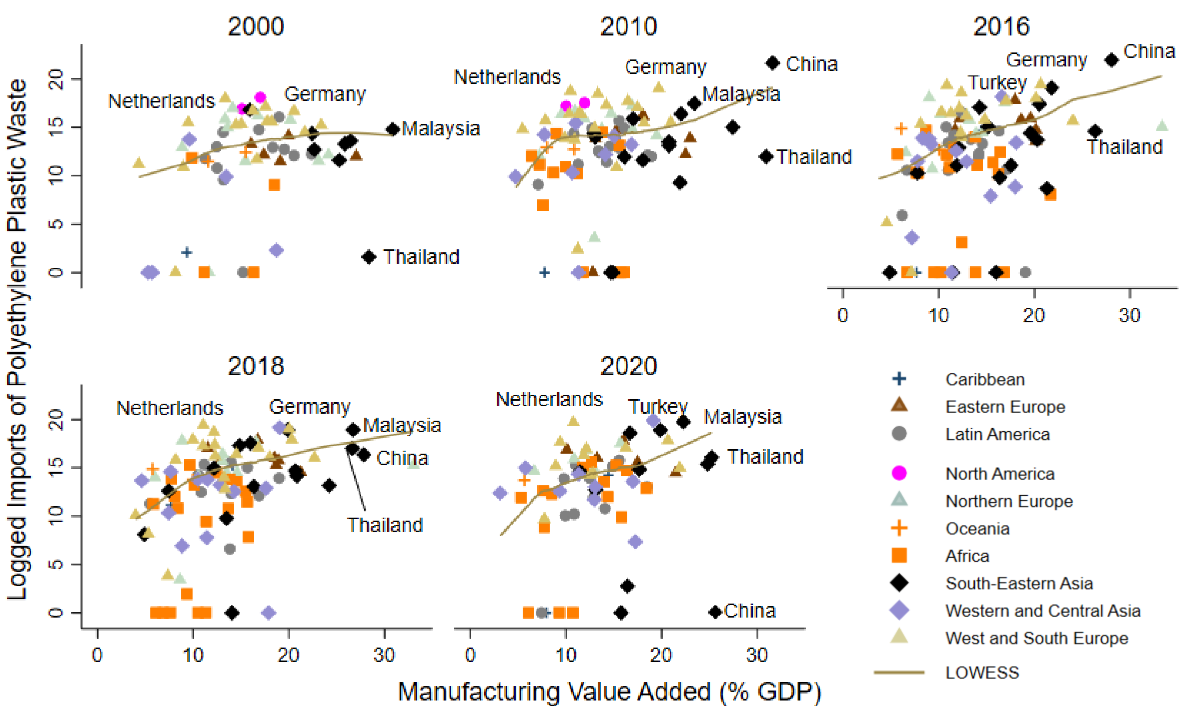
As discussed in the literature review, it is expected that large manufacturing countries will show the largest trade of plastic waste. Figures 7 and 8 visualize the relationship between imports of plastic scraps and the size of a country's manufacturing sector with scatterplots of logged imports of mixed and polyethylene plastic scraps (in kilograms) and manufacturing sector for select years, where each region is also distinguished by color and shape. The earliest (2000) and latest (2020) years in the sample are included, as well as a baseline year before the implementation of OGF (2010) and National Sword (2016), and a year after (2018).

Figure 7 shows Locally Weighted Scatterplot Smoothing (LOWESS) trends in selected years for the relationship between imports of polyethylene plastic waste and the manufacturing value as percent of GDP. Figure 7 shows that, in spite of the presence of countries with zero or near-zero imports, the relationship became increasingly positive and linear over time before the implementation of National Sword. Similarly, Figure 8 shows in the Y-axis the imports of “other” plastic waste as a function of manufacturing value. Both figures 7 and 8 show that in 2016—the year immediately before the ban—the strength of the relationship was the tightest, with plastic imports increasing almost linearly as manufacturing value added increased.

There are other qualitative aspects of the associations illustrated in the figures worth mentioning. For instance, both figures show that, although the relationship remained positive after National Sword’s implementation, its slope decreased afterward, illustrating the effects of the policy. Importantly, these effects are noticeable even though nations, overall, did not shift their overall location in the Euclidean space. In other words, the dispersion of nations across imports and manufacturing levels did not drastically change: what changed is their specific locations within the same area in the Euclidean space. China’s ban generated a reaccommodating process that seems to be dictated by factors related to imports and manufacturing yet not captured by the overall dispersion of the data. We argue about the possibility that trade connectivity is responsible in part for such dynamics.

Also interesting, is that imports trends of both types of plastic are almost identical. More countries reported no imports of polyethylene scraps, while almost all countries in the sample reported some level of mixed plastic scraps imports. This is expected given that most plastic products are often made of multiple types of plastic, and so their classification as exclusively PE plastic is not common. Should other factors not accounted for in the figures be responsible for the similarity of the trends between plastics with such different implications, those factors may be related to aspects that dictate trade and manufacturing yet, again, not readily captured in the dispersion of the data. Network location matters. And location of nations relative to other nations, too. This is one of the contributions of this study, as trade connectivity could play an important yet unobservable role in typical macroeconomic indicators.

Figure 7. Scatterplots of Manufacturing Value Added and Imports of Polyethylene Scraps by Year



Looking at specific regions, the figures also show that the 2016 trend most closely resembles that of Southeast Asian countries (black diamonds), which follows an almost non-positive relationship in the earliest year of the analytic sample. They continued to be among the top importers of plastic scraps after the ban, yet some large manufacturers reported very small imports in 2020. China, for example, decreased polyethylene imports by 99.6% from 2016 to 2018. According to recent data, China reported zero imports in 2020. It seems, therefore, that China's ban generated a cascade of effects across other plastic trade nations and on the distribution of the types of plastics those nations used to trade on. For example, Turkey, the largest plastic trader in Western and Central Asia, increased its imports of mixed plastic waste by more than 180% from 2016 to 2018.

Turning to African countries, they did not report much plastic waste trade data during the earliest years of the study period, and thus most of our missing data come from those nations. This missingness also has methodological implications, making the panel data unbalanced. What we can detect in the data, nevertheless, is that, over the years, African countries have maintained mid-size levels of manufacturing value added and of mixed and polyethylene plastic imports. On the other hand, Western and Southern European countries have moderately reduced levels of imports of both mixed and polyethylene plastic scraps while manifesting large variation in their manufacturing value added levels. Overall, Western and Southern European countries tend to be above the fitted trend, signaling the relevance of other factors other than manufacturing driving plastic scraps trade in this region.

Variation in plastic trade is also detected in other key European nations; for example, Germany decreased its polyethylene plastic imports by 33% from 2016 to 2018, while the Netherlands' import levels remained practically unchanged. Similarly, North American countries, primarily the United States and Canada, were among top importers during the earlier years of the study period in spite of manifesting relatively low- to mid-size levels of manufacturing value added. Taken together, China's ban triggered many changes in plastic type trade in spite of having no effect on the overall use of plastics and manufacturing. Findings bring to light the possibility that the distribution of the size of plastic trade and the type of plastic—i.e., which countries increased or decreased plastic imports or exports, and of what type of plastic, and their overall shares in the global plastic trade—is due to other trade-related factors, like network connectivity.

Figure 8. Scatterplots of Manufacturing Value Added and Imports of Mixed Plastic Scraps by Year

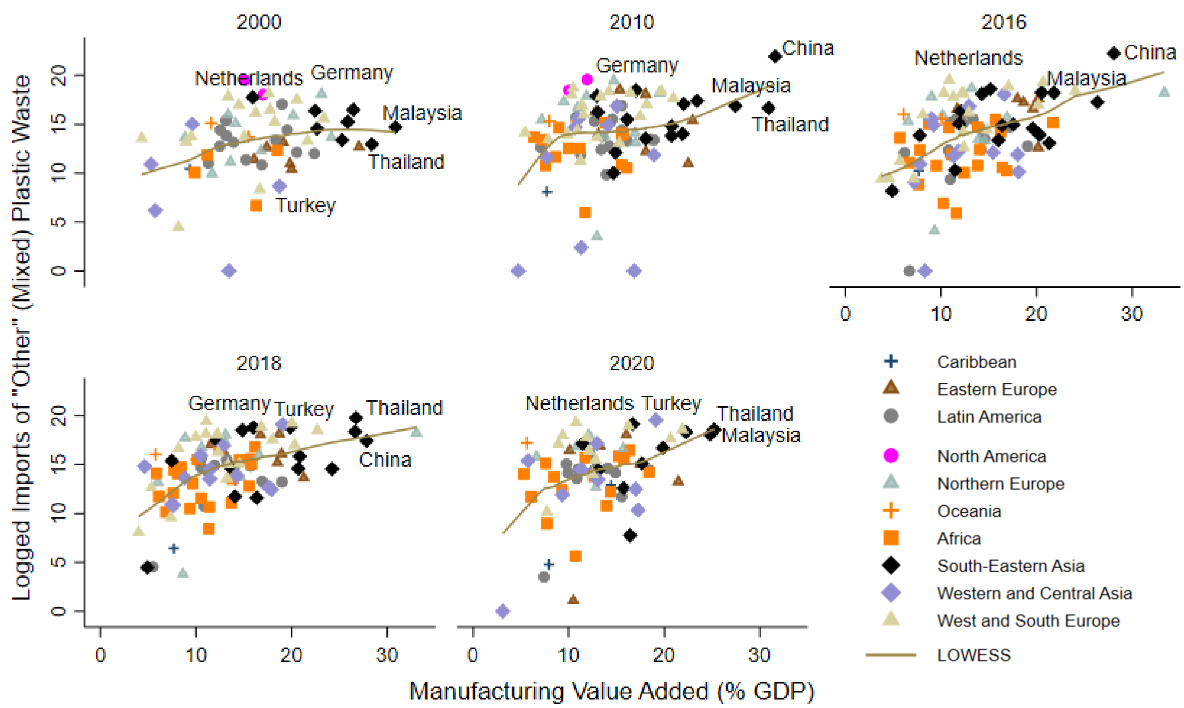
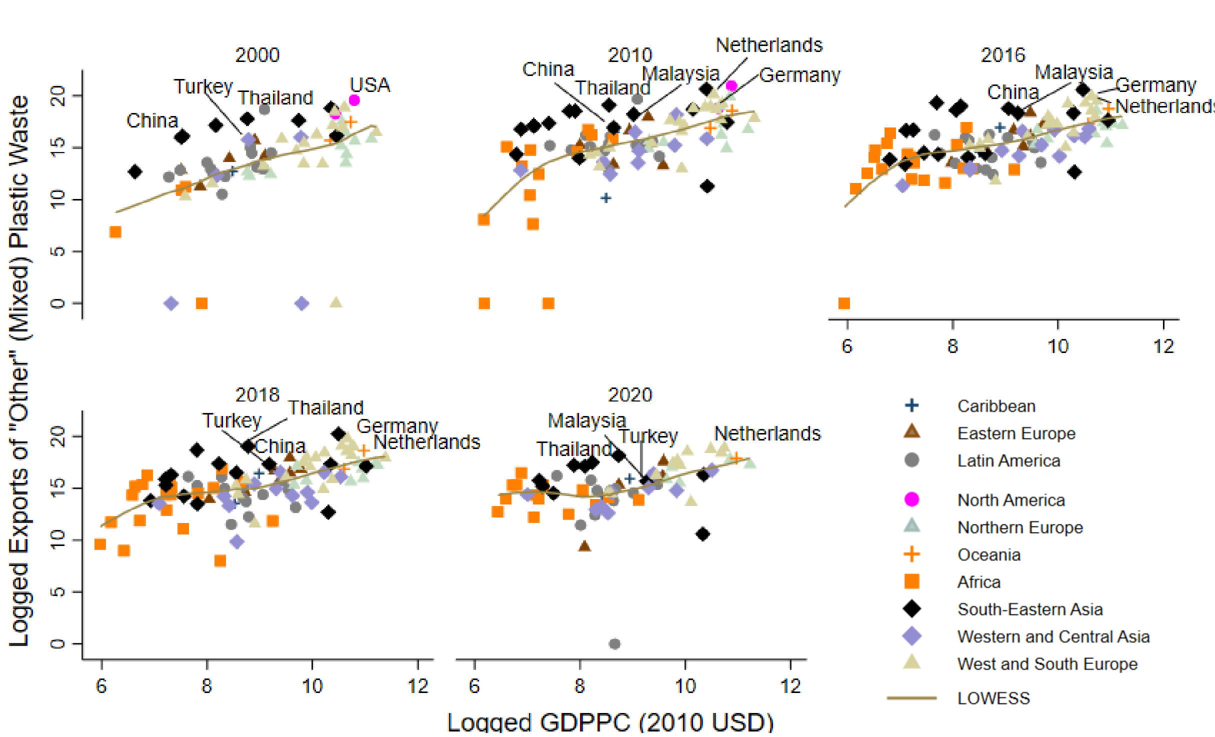


Figure 9 shows the relationship between exports of mixed plastic scraps and logged GDP per capita. For comparison purposes, the panels in Figure 9 are for the same years as those in figures 7 and 8, and each region is also distinguished by color and the shape of the marker. Since mixed or uncategorized plastic scraps are assumed to have the lowest recycling potential—or at least lower than PE plastics—it is expected that countries with larger imports of this type of plastic will be more likely to become waste havens after China's ban. Importantly, Figure 9 illustrates once again that overall levels of both exports and economic development did not change much—e.g., the area of variation in the Euclidean space remains similar from before to after China's ban—suggesting that there are qualitative aspects of plastic trade making nations change their location in the association even though levels remained quite stable. Plastic trade and economic development remain stable, roles of nations do not. We argue that network connectivity is an important aspect of these associations that goes beyond traditional models developed in macroeconomic theory.

Figure 9. Scatterplots of GDP per capita and Exports of Mixed Plastic Scraps by Year



In Figure 9, Southeast Asia is the region with the largest variation in GDP per capita, still showing a moderately positive relationship between development and plastic exports. Thailand and

Malaysia, for example, manifest mid- to high-economic development relative to other countries in the region. Although not evident due to the logarithmic scale, Thailand's plastic exports decreased by 36% from 2016 to 2018. Turning to the Americas, the trend is also similar among Latin American countries, which show low to medium levels of development and exports. The United States was also the top exporter of uncategorized plastic waste during earlier years, and although it stopped reporting disaggregated data in later years, it continues to be one of the top exporters of overall plastic scraps. Lastly, countries in Western and Southern Europe are mostly rich and with large amounts of plastic scraps exports. Nevertheless, looking at the Netherlands and Germany, they both moderately decreased exports and imports of plastic scraps in 2018. Unlike Figures 7 and 8, in Figure 9 the trend fits well the pattern of European countries. In the following section these relationships are statistically tested and quantified while also controlling for relevant confounders such as population and geographical proximity to top traders.

Methods

In addition to gravity models of trade, other methodologies prove useful for analyzing the determinants of plastic scraps trade, especially when recognizing that levels of trade tend to be stable in the absence of exogenous shocks such as Operation National Sword. An appropriate estimation method should not only account for the dynamicity of plastic trade, but it should also be able to isolate effects of structural variables, whose estimates can be biased in panel data settings given their correlation to country-specific heterogeneity. Generalized Method of Moments (GMM) for dynamic panel data estimators are especially suitable for these cases

(Anderson and Hsiao, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998).

Given that a dynamic model of plastic trade includes a lagged version of the dependent variable as a regressor, estimations through fixed effects approaches will be biased due to the correlation of the autoregressive term and the error term. GMM for dynamic panel data models overcomes this issue by augmenting an instrumental variable approach, using transformed versions of the endogenous variables as instruments. Specifically, Anderson and Hsiao (1982) proposed to take first differences of the model equation to get rid of the constant and panel-specific effects terms. The researcher can then use lagged versions of the variables (or their differences) as instruments of the endogenous regressors. Arellano and Bond (1991) extend this approach, noting that using all available information for instrumentation can increase efficiency. With difference GMM, issues of under-identification that arise when more instruments than parameters are available can be overcome, implying that all available lags can serve as instruments for the endogenous covariates. Furthermore, unlike standard two-stage least square (2SLS) standard instruments, GMM-type instrumentation does not drop observations as lag length increases. As such, with this type of estimator, all available lags can be used as instruments without reducing the sample size. Arellano and Bover (1995) and Blundell and Bond (1998) further augment the difference-GMM estimator, proposing a simultaneous system of equations estimation. In addition to an equation of first differences instrumented with lags, the equation in levels is estimated with first differences (and their lags) as instruments. The intuition behind system GMM is that past levels of the dependent variable convey little information about future changes, especially if the coefficient estimate of the autoregressive parameters is close to one, making lags of the levels poor instruments for the differences.

System-GMM estimation can overcome other data and econometric limitations. Because the bias introduced by endogenous covariates can decrease as more time periods are included in the analysis, this estimation is particularly suitable for panel structures with many panels relative to its number of periods, which is a characteristic of the data used in this analysis (119 countries over 21 years). System-GMM can also produce robust estimates to the presence of heteroskedasticity within the panels. Lastly, in addition to the autoregressive parameter, this estimation method can produce less unbiased and more precise estimates of the effect of other endogenous covariates. Accordingly, a system-GMM dynamic panel data model is implemented to estimate the effects of economic and structural variables on plastic scraps trade. Specifically, for each plastic waste category (including overall plastic waste), the system-GMM model estimates equations with the following econometric specification, separately for imports and exports:

$$log(P)_{it} = \alpha + \gamma[log\ (P)_{i(t-1)}] + \beta[log\ (G)_{it}]\ + \rho E_{it} + \lambda C_{it} + \theta M_{it} + \sum_{j=1}^{n} \delta_j X_{it} + T + \varepsilon_{it} \qquad (1)$$

where $log(P)_{it}$ is the natural log of kilograms of plastic imports (exports) for country i in time t. The term $\gamma log\ (P)_{i(t-1)}$ stands for the 1-year lagged version of the dependent variable and its respective coefficient γ.[7] $log\ (G)_{it}$ is the natural log of GDP per capita for country i in time t. E_{it} is the environmental performance index, C_{it} is our independent variable of interest: the

[7] The model for ethylene polymers includes an additional 2-year lag (t-2) as it reached statistical significance in model specifications.

eigenvector centrality score for country i in time t. M_{it} is the size of the manufacturing sector for country i in time t. The term $\sum_{j=1}^{n} \delta_j X_{it}$ is a vector of *n* covariates X_{it} (assumed to be endogenous) for country i in time t, each with its respective coefficient δ_j. These covariates include logged population size and the weighted average distance to top exporters (importers).[8,9] Lastly, T stands for year fixed effects.

Given the observed changes in eigenvector centrality after the implementation of ONS, an interaction term between a pre- and post-ONS dummy variable and eigenvector centrality will be introduced to the models as well. Data on other determinants discussed in the literature, including recycling sector productivity and port efficiency, were not as widely available as those used in the present analyses and thus are not included in these models. To assess goodness of fit, the Andrews-Lu (2001) moment selection criteria (MMSC) AIC and BIC are reported in addition to Hansen's J-statistic. MMSC-AIC and MMSC-BIC are based on Hansen's J-test statistic, but they are adjusted to offset increases in controls X_{it} that occur for any additional, respective instrument even if they are valid instruments.

[8] Given the propensity of System-GMM to overfit endogenous variables due to instrument proliferation, this study tests for over-identification using a series of Sargan-Hansen and difference-in-Hansen tests, which are also used as guides for instruments selection. The tests indicate that lags t-3 and t-4 as instruments for the autoregressive term in the differenced equation, and lags t-2 and t-3 for the other covariates are valid, while the first lag of first differences for the equation in levels are valid instruments for the models of ethylene and uncategorized plastic imports and exports. The tests output table A is included in the Appendix. As suggested by Arellano (2003) and Roodman (2009), I curtail (i.e., truncate) the number of instruments and collapse the instrument set to further avoid instrument proliferation.

[9] Using the Arellano-Bond test for serial autocorrelation (Arellano and Bond, 1991), the study finds no evidence of second-order autocorrelation. Results are included in the Appendix (Table B).

Results

System-GMM (SGMM) parameter estimates for four models excluding connectivity measures are listed in Table 2. Models 1 and 2 report the estimated effect of the covariates on logged imports and exports of ethylene polymers—assumed to be the most desirable type of plastic scraps—respectively. Models 3 and 4 are for logged imports and exports of “uncategorized” plastic scraps—assumed to be the least desirable type of plastic waste. The interaction term and the pre- post-ONS dummy did not reach statistical significance, and so are reported in Table C in the Appendix. Results for the model of overall plastic waste are also included in Table D in the Appendix.

As expected from the literature, results confirm that wealthier countries trade more plastic, all else equal (Table 2). Specifically, they trade more uncategorized plastic. On average, a one-percent increase in GDP per capita is associated with a 0.60% increase in kilograms of uncategorized traded plastic. Considering the large range of variation in plastic trade for the countries in the sample, an average 0.60% increase in imports can translate into an average increase of 24,000 kilograms for a country like Norway, or an increase of 388,000 kilograms for a country like Vietnam. This effect is robust to the specifications in both models of uncategorized plastic scraps. As such, countries with higher levels of economic development not only import more plastic, but they also export more plastic. These effects are robust when controls are included in the models.

Table 2. SGMM Parameter Estimates, Plastic Imports and Exports by Type (Excluding Eig. Centrality)

VARIABLES	Model 1 Logged Imports Ethylene	Model 2 Logged Exports Ethylene	Model 3 Logged Imports Other	Model 4 Logged Exports Other
Logged Plastic Imports (Type for given model) (t-1)	0.346***		0.292***	
	(0.064)		(0.125)	
Logged Plastic Imports (Type for given model) (t-2)	0.166***			
	(0.0512)			
EPI	-0.0129	-0.015	0.017	-0.007
	(0.039)	(0.044)	(0.020)	(0.016)
Logged Plastic Exports (Type for given model)	0.138*		-0.113	
	(0.079)		(0.107)	
Logged GDPpc (constant 2010 USD)	0.4349	0.313	0.595**	0.608**
	(0.544)	(0.564)	(0.269)	(0.309)
Manufacturing (% GDP)	0.207**	0.077	0.130*	0.013
	(0.113)	(0.103)	(0.067)	(0.047)
Logged Population	-0.407	0.078	0.184	0.218
	(0.722)	(0.970)	(0.637)	(0.320)
Weighted Average Distance to Top 5 Exporters	-0.00003		-0.0002	
	(0.00024)		(0.0001)	
Logged Plastic Exports (Type for given model) (t-1)		0.612***		0.578***
		(0.075)		(0.095)
Logged Plastic Exports (Type for given model) (t-2)		0.221***		
		(0.053)		
Logged Plastic Imports (Type for given model)		0.228**		0.036
		(0.121)		(0.076)
Average Distance to Top 5 Importers		0.00024		0.00006
		(0.0003)		(0.0001)
Time Fixed Effects	Yes	Yes	Yes	Yes
Constant	4.75	-6.55	2.11	-3.36
	(15.39)	(18.69)	(11.78)	(6.37)
Observations	1,906	1,906	1,904	1,904
Number of countries	119	119	119	119
R-squared	0.628	0.717	0.573	0.762

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The size of a country's manufacturing sector also has a positive, statistically significant effect on imports of both ethylene and uncategorized polymers. As hypothesized, countries that manufacture more goods as a percentage of their total GDP import more plastic: a one-percent increase in the size of the manufacturing sector is associated with a 0.21% increase in kilograms of polyethylene plastic scraps imports and 0.13% of uncategorized plastic. This finding is consistent with the fact that ethylene polymers are the most widely used type of plastics, since the demand of this material is high for large manufacturers. Given that uncategorized plastics comprise more than half of plastic scraps trade, and that using reused plastic for the production of goods can make the manufacturing process cheaper, it is also not surprising that larger manufacturers import more plastic waste, pairings, and scraps. Most countries in South and East Asia have large manufacturing sectors, with average GDP value added percentages ranging from 15-28%. On the other hand, European Union countries' average values are about 15-16%. Notably, the effect of manufacturing is not statistically significant for plastic exports. Thus, even assuming that large producers also generate the most waste, these countries do not necessarily export the most waste.

The autoregressive coefficient estimates indicate that plastic scraps import levels are less stable over time compared to export levels. This might be attributed to global shifts since the early 2010s due to China's Operation Green Fence initiative and its eventual complete ban via Operation National Sword in 2017. Although import patterns changed, exporters continued to send plastic waste abroad, only changing destinations. This is, again, one of the reasons why countries changed their specific location in figures 7, 8 and 9 even though import and exports of plastic, and macroeconomic conditions overall, did not drastically change levels globally. In more detail, the scatterplots in figures 7, 8, and 9 show that countries in Southeast Asia were already large traders of plastic waste even before the implementation of ONS. Although their trade levels were expected to be high even without ONS, the observed growth rates in imports, specifically, would not have been as high. One of the reasons for the movement and relocation of countries in the plastic trade market follow plastic-trade network connectivity.

Another aspect of the data is that import levels are positively associated and statistically significant predictors of export levels, and vice versa, which is also evidenced in the similarity of the estimated effects on imports and exports. The estimated coefficients of additional controls of population size and geographical distance did not reach statistical significance. The null effect of the distance measure might be a result of the estimation method. The measure is a weighted average of the distance between a given country and the top 5 exporters (or importers for models 2 and 4) where the weight assigned to each distance is based on the portion of global plastic trade that the country exports (or imports). Although this variable is shown to be relevant in models of bilateral trade, our results show that its effect dilutes in models that consider other countries—i.e., when the network of traders (not merely bilateral trade associations) is accounted for. At the theoretical level, these null effects are expected since trade is multilateral by nature, trade has become increasingly globalized, and variables of connectivity in trade networks (like eigenvector centrality) should capture most of the essential variation in plastic trade.

To assess the explanatory contribution of the eigenvector centrality measure (described in Chapter 1), six additional models are estimated through SGMM. Parameter estimates from these models are reported in Table 3. In Table 3, models 1 to 3 use imports of polyethylene (PE) plastic waste as the dependent variable. Model 1 is a base model with only autoregressive terms, and uses PE exports as an independent variable, too. Model 2 incorporates to Model 1 all control variables. While Model 3 follows the specification in equation 1, Model 2 excludes eigenvector centrality. Similarly, Models 4 to 6 replicate these models using imports of mixed or uncategorized plastic as the dependent variable.

Goodness-of-fit statistics improve drastically from model 1 to 2 and from model 4 to 5. Overall, models 3 and 6, which use both attribute and relational characteristics, fit better the plastic imports data. The coefficients of attribute variables (i.e., manufacturing, GDP per capita, population, and weighted average geographical distance to top exporters) remain relatively stable even after the inclusion of eigenvector centrality.

Again, eigenvector centrality—our variable of interest—measures how well connected a country is by emphasizing the connections of its trading partners. Eigenvector centrality does not only consider the profile of a country's immediate trading partners, but "second-degree" connections, which are countries with whom a country could indirectly trade plastic waste through the trading partners they have in common—i.e., nodes in the network. Given that this variable assesses the degree of connectivity of a given country through direct and indirect plastic trading partners, this variable contains essential variation as to how countries would adapt to the effects imparted by China's ban.

Table 3. SGMM Parameter Estimates, Plastic Imports by Type

VARIABLES	Model 1 Logged Imports Ethylene	Model 2 Logged Imports Ethylene	Model 3 Logged Imports Ethylene	Model 4 Logged Imports Other	Model 5 Logged Imports Other	Model 6 Logged Imports Other
Logged Plastic Imports (Type for given model) (t-1)	0.301***	0.357***	0.367***	0.318***	0.281***	0.303***
	(0.084)	(0.062)	(0.060)	(0.083)	(0.070)	(0.067)
Logged Plastic Imports (Type for given model) (t-2)	0.109	0.178***	0.189***			
	(0.069)	(0.049)	(0.051)			
EPI		-0.009	-0.0190		0.015	0.004
		(0.039)	(0.039)		(0.021)	(0.019)
Logged Plastic Exports (Type for given model)	-0.020	0.153*	0.154*	0.147	-0.167	-0.156*
	(0.158)	(0.080)	(0.079)	(0.213)	(0.131)	(0.088)
Logged GDPpc (constant 2010 USD)		0.352	0.288		0.649**	0.578**
		(0.524)	(0.558)		(0.308)	(0.288)
Manufacturing (% GDP)		0.215*	0.210*		0.136**	0.106
		(0.118)	(0.118)		(0.069)	(0.071)
Eigenvector Centrality			11.92**			8.660*
			(4.968)			(4.411)
Logged Population		-0.352	-0.474		0.160	-0.122
		(0.700)	(0.871)		(0.681)	(0.612)
Weighted Average Distance to Top 5 Exporters		0.00005	-0.00011		-0.0002	-0.0002*
		(0.00024)	(0.00025)		(0.0001)	(0.0001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.97**	3.81	5.69	7.502**	3.162	8.853
	(3.56)	(14.94)	(17.95)	(3.292)	(12.43)	(11.25)
Observations	1,895	1,895	1,895	1,893	1,893	1,893
Number of countries	119	119	119	119	119	119
Hansen's J-statistic	0.555	7.51	7.60	17.63	16.26	18.6
MMSC-AIC	-5.45	-18.49	-22.40	7.63	-23.74	-27.40
MMSC-BIC	-13.78	-54.62	-64.08	-6.26	-79.32	-91.32

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The addition of eigenvector centrality improved MMSC-AIC and MMSC-BIC in both polyethylene and mixed plastic scraps models.[10] [11] The estimated coefficient for eigenvector centrality is substantively and statistically significant across models. Specifically, a one-unit increase (i.e., going from being a country that does not trade plastic waste to being the most central country in the network) is associated with an almost 1,200% increase in polyethylene waste imports ($\hat{\beta} = 11.92$) and more than an 860% increase in mixed plastic waste imports ($\hat{\beta} = 8.66$). This is a 93% increase in PE waste imports and 67% in mixed scraps imports with a one-standard deviation increase in eigenvector centrality ($\sigma = 0.078$) which are substantive increases considering that the sample's total range of variation is 0.646. This is, for example, the difference in the 2018 centrality score between Germany (0.31) and Malaysia (0.39).

The distribution of eigenvector centrality is highly skewed to the right. Yet, the estimated coefficient remains statistically and substantively significant even when countries with centrality scores smaller than 0.01 are excluded from the models. This robustness check only includes 460 observations—i.e., it excludes from the analysis those nations that either do not significantly belong to the global plastic trade network, or that trade plastic waste only in the periphery of nations that operate at the core of the network. In this robustness exercise, as expected, the coefficient estimate for eigenvector centrality shrinks to 6.9 ($p < 0.05$), bringing to light that plastic trade is not only explained by connectivity but also, almost equally important, by not being connected to the plastic trade network (Table F, Appendix). That considering the totality of

[10] The estimated effect of eigenvector centrality is not statistically significant and small in the models of exports. These results are included in table E in the Appendix.
[11] The distribution of eigenvector centrality is notably skewed to the right and cannot be normalized via logarithmic transformation due to zero inflation, which would drop an important number of observations.

the sample (i.e., connected and unconnected nations) retrieves a larger size of the coefficient, suggests that eigenvector centrality covers a single dimension ranging from low- to high-connectivity. Once we include unconnected nations into the sample, the effect increases because it is now capturing the variation of well-connected nations in relation to those that are not connected.

One possible limitation of the present study lies in the similarity between the dependent variable and aspects of the way the eigenvector centrality measure is developed. Total plastic trade is a product of the number of countries with whom a country trades plastic waste, and at the same time, a country's number of trade partners is also affected by the determinants of total amount of plastic waste traded. Given such similarity, we would need to further investigate the extent to which the centrality score measures a different variable from the dependent variable, or whether it measures the same phenomena that we are aiming to explain. Yet, it is important to note that our SGMM models account for lags of our dependent variable. This suggests that our estimated effects for eigenvector centrality are independent from variation attributable to the dependent variable.

More generally, we can also investigate the correlations between the dependent variables and eigenvector centrality. To do this, Table 4 shows correlation matrices between eigenvector centrality, and logged imports and exports of PE and mixed plastic before and after the implementation of ONS. The correlation between imports of both PE and mixed plastic waste, and eigenvector centrality before ONS is positive and moderate, with correlation coefficients of 0.32 and 0.39, respectively. The correlation between exports of both plastics and eigenvector centrality is even smaller. As expected, the correlations become moderately stronger after the implementation of ONS, with the correlations between imports of PE and mixed plastic waste, and eigenvector centrality increasing to 0.42 and 0.46, respectively. Especially after the ban, eigenvector centrality was a relevant determinant of plastic waste trade. We thus believe that, given the moderate levels of correlation between these variables and the way our SGMM models control for lagged variation of the dependent variable, our estimates bring support to our hypothesis.

It is also important to note that the models reported in Table 3 additionally control for indicators traditionally believed to be explanatory variables of trade. One good example of such control is the level of economic development. Interestingly, the coefficient estimate for GDP per capita shrinks (from model 2 to model 3, and from model 5 to model 6) once the model accounts for connectivity. Commonly excluded from macroeconomic models of trade, our results show that increased mixed plastic waste imports due to higher economic development can be partially explained by changes in the profile of country partners and the connectivity among them. So, changes among trade partners, and in the size of trade among them, occur independently from the economic development of the countries involved in trade networks. In this sense, our connectivity variable seems to represent variation attributable to other aspects of trade that are not captured by traditional macroeconomic variables. For example, trade agreements can be theorized to have a substantial impact on plastic waste trade independent from geographical proximity and economic development. Overall, the positive effect of eigenvector centrality indicates that countries that trade with top importers are more likely to import plastic waste as well.

Table 4. Correlation Matrix Before and After the ONS

Pre-ONS (2000-2017)

	Eigenvector Centrality	Imports of Mixed Plastic (Logged)	Imports of PE Plastic (Logged)	Exports of Mixed Plastic (Logged)	Exports of PE Plastic (Logged)
Eigenvector Centrality	1				
Imports of Mixed Plastic (Logged)	**0.384**	1			
Imports of PE Plastic (Logged)	**0.319**	0.647	1		
Exports of Mixed Plastic (Logged)	**0.320**	0.492	0.440	1	
Exports of PE Plastic (Logged)	**0.277**	0.511	0.543	0.538	1

Post-ONS (2018-2020)

	Eigenvector Centrality	Imports of Mixed Plastic (Logged)	Imports of PE Plastic (Logged)	Exports of Mixed Plastic (Logged)	Exports of PE Plastic (Logged)
Eigenvector Centrality	1				
Imports of Mixed Plastic (Logged)	**0.459**	1			
Imports of PE Plastic (Logged)	**0.422**	0.739	1		
Exports of Mixed Plastic (Logged)	**0.490**	0.510	0.482	1	
Exports of PE Plastic (Logged)	**0.364**	0.415	0.560	0.560	1

Coefficient estimates for GDP per capita are not null, however. Our results also reaffirm the previously established relationship between economic development and plastic waste trade. As with overall international trade, wealthier countries exhibit higher levels of plastic trade. Nevertheless, results suggest that they mostly trade uncategorized plastic scraps, which, again, include mixed materials that are harder to recycle. If they export mostly to countries without the technology to recycle properly, the portion that is actually reutilized and recycled is even lower. The finding that a larger manufacturing sector is associated with more imports of both ethylene and uncategorized plastics, but not exports, is intuitive but also revealing. The countries with the largest average manufacturing sectors (as GDP valued added) are, in descending order, China, Thailand, Malaysia, Ireland, and Indonesia, four of which are among the most impacted Southeast Asian countries. The effect of manufacturing remains stable when centrality is included in the model.

Despite the inclusion of time fixed effects that capture the effects of the implementation of important policies such as National Sword, Green Fence, and amendments to the Basel Convention, the immediate effects of China's plastics ban are still unclear. Moreover, results so far have suggested that there is a close tendency for those who import plastic waste to also export it. Nevertheless, if it is assumed that plastic that is not re-exported is handled domestically, looking at differences between exports and imports levels (i.e., whether countries are net exporters or net importers) might provide a clearer picture of the factors that make countries more likely to be potential waste havens. The next part of this analysis will thus focus on the changes between 2016 and 2018, estimating countries' probabilities of being net importers before and after National Sword.

Multinomial Logistic Regression: Modeling Plastic Trade Tendencies

Results from the dynamic panel data analysis uncovered large manufacturers and wealthier countries as the countries with largest levels of plastic trade. Yet, other classification methodologies can be implemented to examine changes in probabilities of countries becoming net importers, or assumedly, potential waste havens, before and after the implementation of National Sword. The following analysis attempts to determine which of the previously analyzed factors characterized net importers before the National Sword policy and which factors prevented countries from becoming waste havens after the China ban.

Methods

To categorize countries as potential waste havens and others, countries that imported more plastic waste than they exported in a given year are flagged, creating a dummy variable where those countries are assigned a value of 1 and others 0. Then, a categorical variable is created considering the years 2016 and 2018, the most immediate years before and after National Sword was implemented. This variable takes the value of 1 if a given country imported more than it exported in both 2016 and 2018, a value of 2 if it no longer had an import surplus in 2018 (i.e., 2016 dummy = 1 and 2018 dummy = 0), a value of 3 if it did not import more than it exported in either year (i.e., both years = 0), and a value of 4 if in 2016 it did not have an imports surplus but did import more than it exported in 2018 (i.e., 2016 dummy = 0 and 2018 dummy = 1). After this categorization, 102 countries remained in the analytic sample.[12]

A multinomial logistic regression is implemented to estimate the effects of the covariates on the country-specific categories before and after National Sword. As an extension of binary logistic regression, multinomial logit estimates the changes in the log odds of observing each category of the dependent variable through maximum likelihood estimation. One of its underlying

[12] Countries excluded did not have available data for both 2016 and 2018.

assumptions, the independence of irrelevant alternatives, states that the addition/deletion of alternative outcome categories does not affect the odds among the remaining options. In other words, if any of the four categories were removed as an option, the estimated changes in the log odds per every unit change in the independent variables should not be statistically differentiable from the ones in the model with all options included. Considering how the dependent categorical variable was constructed, where 2016 and 2018 outcomes were combined into single categories, this assumption is tested accordingly via a Hausman-McFadden test (1984)[13]. Equation 2 shows the econometric specification of the multinomial logit model:

$$Y_{ij} = \alpha_j + \beta_j log\ (G)_i + \rho_j E_i + \theta_j M_i + \varepsilon_{ij} \qquad (2)$$

where Y_{ij} is the probability of observing each j outcome for country i, regressed on an outcome-specific intercept, α_j, the natural log of GDP per capita, $\log{(G)}$, with one coefficient β_j per outcome, the environmental performance index, E_i and the size of manufacturing sector, M_i. Due to the limited sample size, other covariates are not included to simplify the model. However, estimates of the model controlling for population size, which does not substantially alter the coefficients or levels of statistical significance, are included in the Appendix in Table G.

[13] The test compares coefficient estimates of the model with different subset of outcomes included/excluded for statistically significant differences.

Results

Table 3 reports the estimated changes in relative risk ratios of observing each outcome, with outcome 3 (i.e., never being a net importer) as a baseline comparison. Relative risk ratios are the probability of observing one outcome over the probability of observing the baseline category (i.e., the log odds coefficient exponentiated). The first column shows the estimates for outcome 1, being a net importer before and after the ban. Column 2 reports them for being a net importer before the plastics ban, but not after it. And lastly, column 4 shows results for being a net importer after the plastics ban, but not before it.

Table 5. Multinomial Logistic Regression Parameter Estimates, Status 2016 and 2018

	(1) Net importer both years	(2) Net importer only 2016	(4) Net importer only 2018
Logged GDPpc (constant 2010 USD) (2016)	0.670	0.354**	1.301
	(0.275)	(0.174)	(0.452)
EPI (2016)	1.057	1.212***	0.948
	(0.048)	(0.078)	(0.037)
Manufacturing (% GDP) (2016)	1.077	1.118	1.088*
	(0.062)	(0.078)	(0.055)
Constant	0.076	0.000*	0.341
	(0.142)	(0.000)	(0.510)
Observations	102	102	102
Pseudo R^2	0.067	0.067	0.067
Wald Chi^2	19.89**	19.89**	19.89**

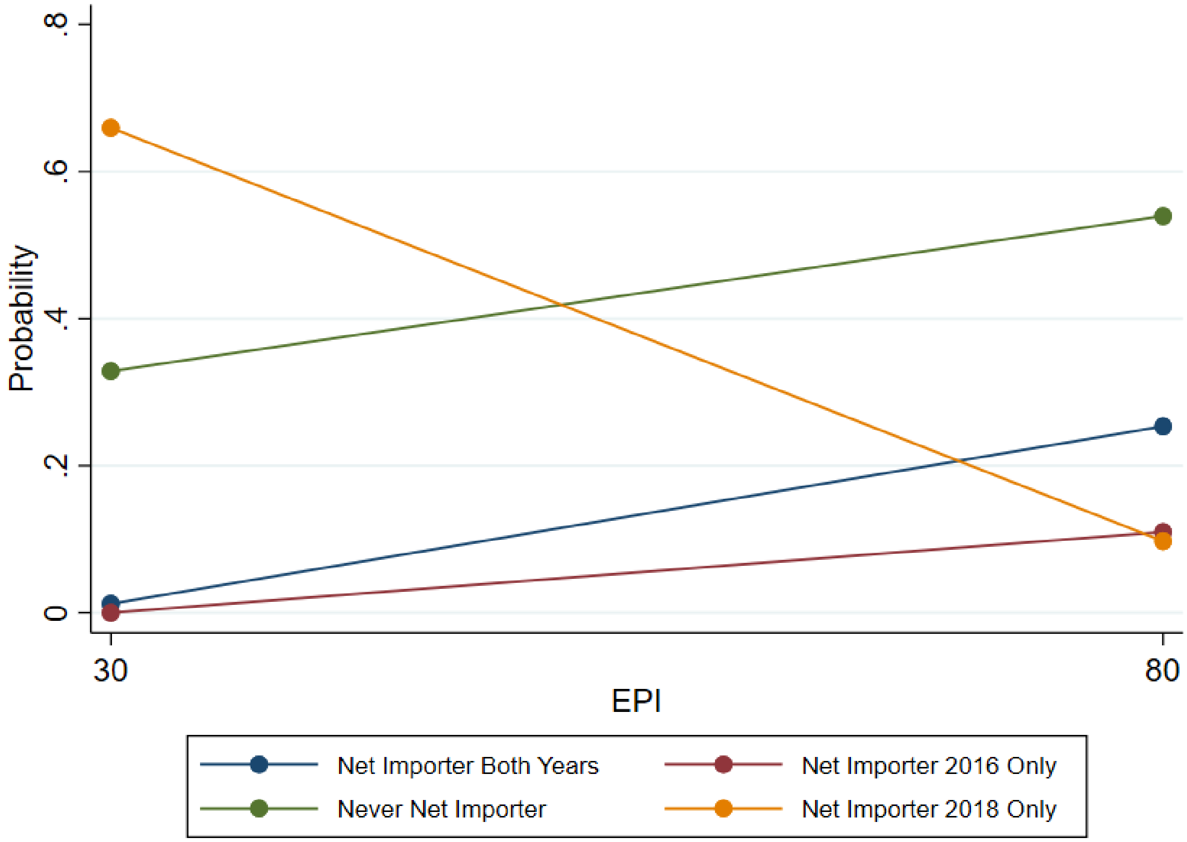
Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The Hausman-McFadden test and a generalized version of the test, each comparing the coefficients of the complete model and three additional models that remove one category of the dependent variable at a time, find no evidence for statistically significant systematic differences in the coefficients (Table H, Appendix). Consequently, the test does not suggest that the independence of irrelevant alternatives assumption is violated.

The coefficient estimates for EPI suggest that as environmental performance increases, countries are more likely to have been a potential waste haven in 2016 (i.e., importing more than what they exported) and to have no longer been one in 2018 than to have never been one at all. More specifically, increasing the environmental performance score by one unit, the relative risk of having been a net importer in 2016 but not in 2018, relative to never having been one at all, is expected to increase by a factor of 1.21 ($p < 0.01$). In other words, the relative risk of having been a potential waste haven in 2016 and no longer being one in 2018 is 1.21 times more likely given a one-unit increase in EPI. Considering that EPI scores in the analytical sample vary from 37.10 to 90.68 (Table H in Appendix), a 20% change in the relative risk of observing outcome 2 relative to outcome 3, associated with a one-unit increase of EPI, is a substantive increase.

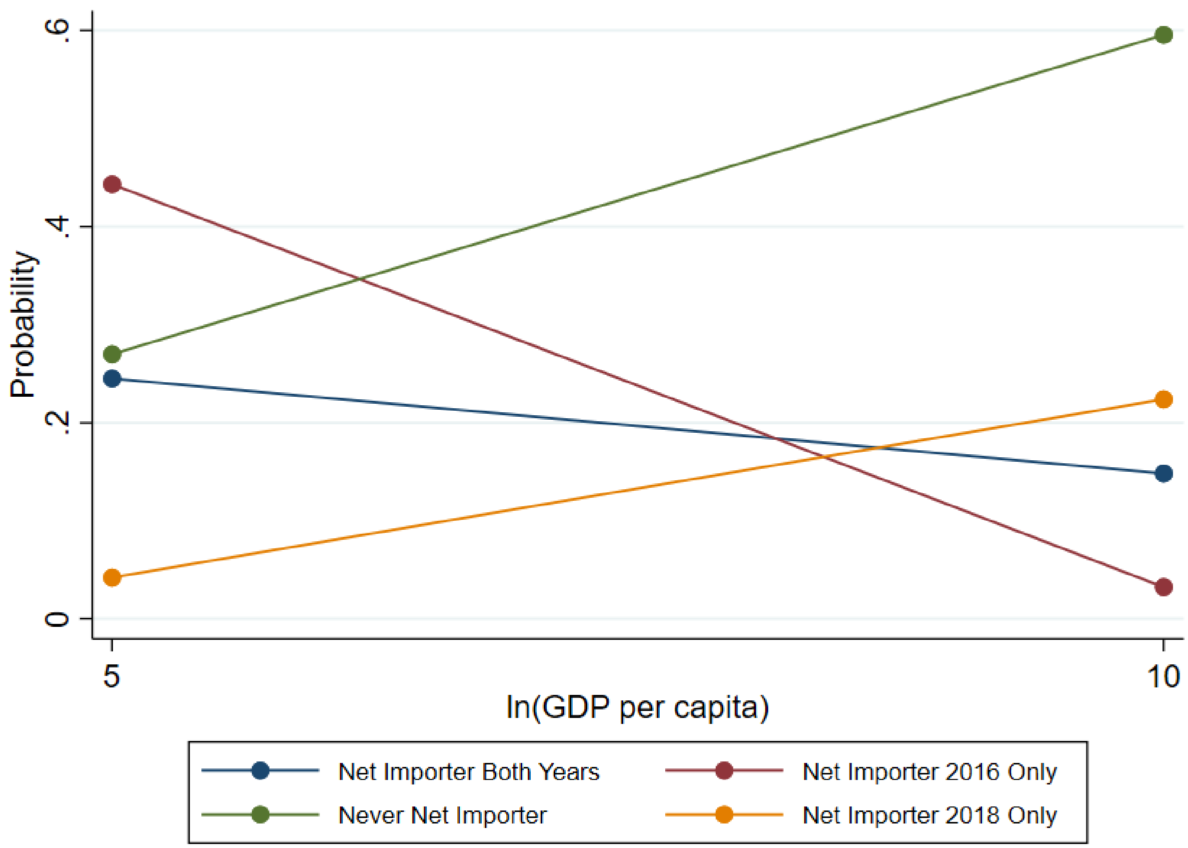
To facilitate the interpretation of these results, Figure 10 visualizes the predicted probabilities of each outcome at different levels of environmental performance. As environmental performance improves, countries are also more likely to never have been potential waste havens. In the same way, they are less likely to have become a waste haven after National Sword. However, they are also more likely to have been net importers in both years. Overall, this result suggests that greater environmental performance *prevented* countries from becoming potential waste havens, but it did not help *correct* behaviors immediately after National Sword was implemented. Thus, countries who were already importing more than they exported before the plastics ban were more likely to remain net importers despite high environmental performance scores.

Figure 10. Predictive Margins of Probability as EPI Scores Increase



The effect of logged GDP per capita is also statistically significant on the probability of being a net importer before the plastics ban and no longer being one after it (relative to never being one at all), showing a decrease of the relative risk by a factor of 0.35 with every one-unit increase in the log of GDP per capita. This is a 65% relative decrease associated to a one-unit increase in the economic development measure. In the context of the included sample of countries, this log difference in GDP per capita is approximately equivalent to the difference in 2016 levels between Indonesia and Romania. As shown in Figure 11, a higher level of economic development decreases the probability of being a net importer before the plastics ban, and it increases the probability of not being a net importer before and after the ban. This implies that poorer countries were more likely to be net importers even before National Sword. However, a higher level of economic development increases the probability of becoming a net importer in 2018. These results are consistent with the overall findings of this study: poorer countries tend to import more than they export; yet, even some wealthy countries also experienced increases in imports immediately after National Sword's implementation.

Figure 11. Predictive Margins of Probability as Logged GDP Per Capita Increases



Nonetheless, the clearest result is the effect of a large manufacturing sector in the probability of being a net importer of plastic scraps. The effect is consistently positive across all categories of the dependent variable, but only statistically significant for outcome 4 relative to outcome 3 ($p<0.1$). A one-percentage point increase in the value added of a country's manufacturing sector increases the probability of not being a net importer in 2016, and becoming one after National Sword was implemented, by about 9% relative to never being a net importer. Accordingly, only the probability of never being a net importer decreases with the increase of the manufacturing sector value added. Manufacturing countries thus have tended to be net importers regardless of changes in international plastic waste trade policies.

Overall, results from the multinomial logit regression coincide with those of the dynamic panel data analysis. Poorer countries with large manufacturing industries are more likely to import more plastic than what they export. Given the non-comparability of the environmental performance index over time, this analysis took advantage of the cross-sectional comparability of the index, showing that it can affect the likelihood of a country becoming a waste haven.

Chapter 3 | Case Studies and Discussion

China and Southeast Asia

Results from our analyses showed that the manufacturing sector is critical for the desirability of plastic scraps imports. Before ONS, China's plastic imports were driven by the low-cost, recycled raw materials demand of the manufacturing industry that could not be met domestically. Whereas plastic imports increased from 2003 to 2004 by 35%—when the manufacturing sector accounted for about 32% of GDP—they decreased by 11% a decade later, from 2012 to 2013. Interestingly, 2013 was the first year of OGF's implementation. Yet, a few years later, plastic imports decreased once again by 34% (from 2016 to 2017)—when 28% of GDP value added was attributed to manufacturing.

Whereas in 2016 (before the ban) about 41% of China's imports were polyethylene (PE) scraps and 52% were mixed plastic, about 72% of plastic imports were mixed and 25% were PE in 2018—right after the ban. Yet, the composition of China's plastic exports was similar before and after the ban, with about 86% of plastic exports categorized as mixed or "other" plastic scraps in both years. The ban clearly affected the plastic composition of plastic imports alone—i.e., without affecting the plastic composition of exports. China became a large producer and exporter of mixed plastic scraps—relative to its own import levels—after the ban. Chinese plastic imports before the ban (by far the largest across the globe) were smoothly absorbed by and re-directed among plastic traders after the ban depending on their connections.

Although the initial goal of the Chinese government was to reduce the contamination level of scraps imports, this goal shifted with ONS toward a complete elimination of foreign-produced contamination. With a recycling rate of only 30%, and a production of over 60 MMT of plastic every year, the implementation of China's ONS did not stop the country's growing use of plastic in packaging, product manufacturing, and other sectors (Lai, 2022). Moreover, once imports collapsed after the ban bringing down imports by a factor of about 30, China's plastic scraps exports remained unaltered. China's role in the plastic market shifted from the top importer to an important exporter of plastics.

Meanwhile, Hong Kong experienced reductions in both imports and exports, showing a different trend from that of mainland China after the ban. Analyzing self-reported bilateral plastic trade from China and Hong Kong to other regions (i.e., excluding plastic trade between Hong Kong and China) during the most immediate years before and after ONS' implementation, total combined plastic scraps exports shifted from 55,000 MT in 2016 to 276,000 MT in 2018, an increase of over 400%.[14]

Figure 12 shows the distribution of China's and Hong Kong's combined plastic exports by regional destination in 2016 and 2018. Figure 12 shows that 48% of combined plastic exports went to South and Southeast Asian countries while only 4% to Europe, before the ban in 2016. By 2018, 85% of plastic scraps exports went to 12 South and Southeast Asian countries, while merely 1% went to over 30 European countries. Accordingly, China's unilateral move to ban imports of plastic waste was accompanied by their own (and that of Hong Kong) shift of export partners, who after the ban mainly received mixed plastic waste from them.

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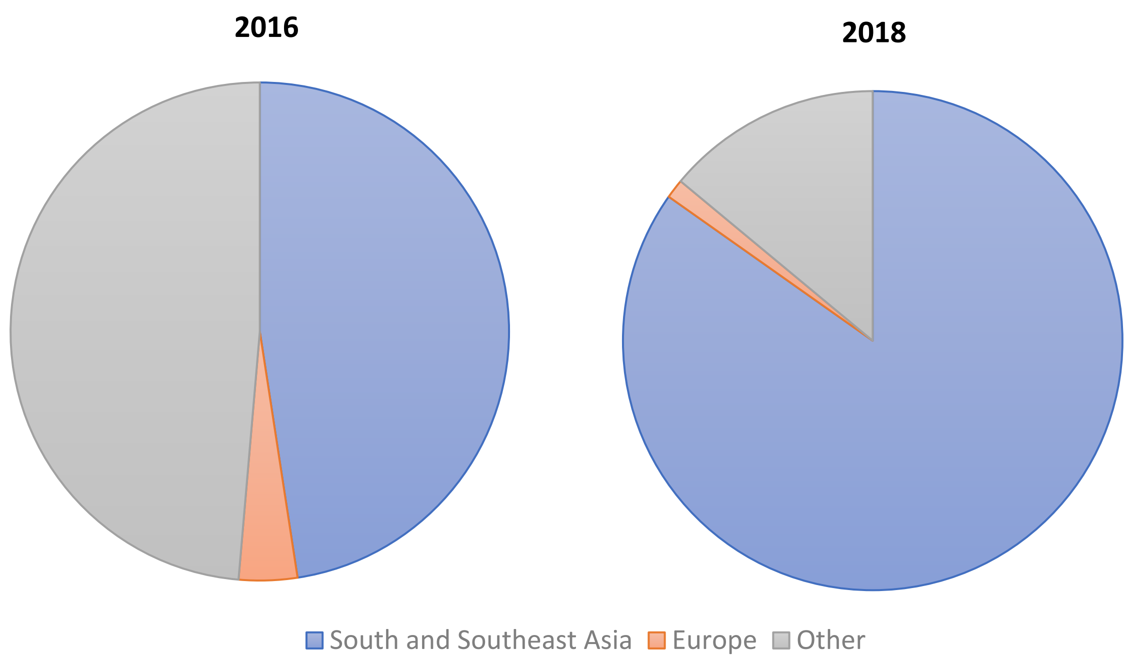
[14] Due to discrepancies between total plastic trade and total bilateral trade reports this figure might omit unreported transactions.

Figure 12. China's and Hong Kong's Plastic Scraps Exports by Destination - 2016 and 2018



This in-depth description shades some light on where the plastic ends up its process—beyond understanding the different paths (i.e., countries) it goes through. Particularly, there seems to be evidence to state that, after the ban, countries with high eigenvector centrality scores, such as those in Southeast Asia, became direct recipients of the plastic waste that would have otherwise accumulated in mainland China. Furthermore, countries with whom China traded plastic the most before the ban became, as a result, not only large recipients of plastic arriving from all China but also from other continents.

Despite that China's imports of foreign plastic scraps after the ban collapsed to practically zero, the country's demand for raw materials did not diminish. The profitability of the recycling industries in Southeast Asian countries is thus partially driven by this demand—and, to an important degree, these are the trade dynamics that create trading networks, and the ones that got activated after the ban. Importantly, the dynamics that nourish trade partnerships add meaning to plastic trade beyond macroeconomic variables. For example, in figures 7 through 9, macroeconomic activity changed very slowly in time, including before and after China's ban, whereas plastic trade based on connectivity shuffled the roles of countries.

As discussed in Chapter 2, Southeast Asian countries tend to have large manufacturing industries and, thus, a stable large demand for raw materials, including plastic. Taking Malaysia as an example, this study showed that it was one of the most affected countries in Southeast Asia, with an overall growth in plastic imports of 200% from 2016 to 2018. This growth did not happen in isolation, as Malaysia also manifested one of the sharpest increases in eigenvector centrality immediately after the ban. Malaysia has been among many ASEAN countries welcoming Chinese recycling enterprises who have moved facilities, investment, and equipment away from China after the ban reduced the available scraps to produce plastic pellets.

There are other case studies that suggest that trading follows policy outcomes—which in turn follows network connectivity—independently from macroeconomic ones. For example, research points out that China's domestic policy focus has also aligned with their trade policy, phasing out single-use plastics and increasing recycling and incineration capabilities (Lai, 2022). Similarly, although Thailand imposed bans of waste imports after the rapid influx of plastic waste post-ONS, the domestic recycling industry (primarily composed of informal workers) advocated for a slower timeline since they heavily relied on foreign plastic scraps. The ban, which was consequently reversed, is expected to take effect in 2025 (Campbell, 2022). In the meantime, China is the main destination of plastic pellets produced in Thailand, accounting for about 60% of exports (The Nation, 2022). This shuffling of roles in imports and exports between "good" and "bad" plastic scraps clearly follows connectivity patterns that cannot be captured by neither traditional macroeconomic nor gravity models of trade.

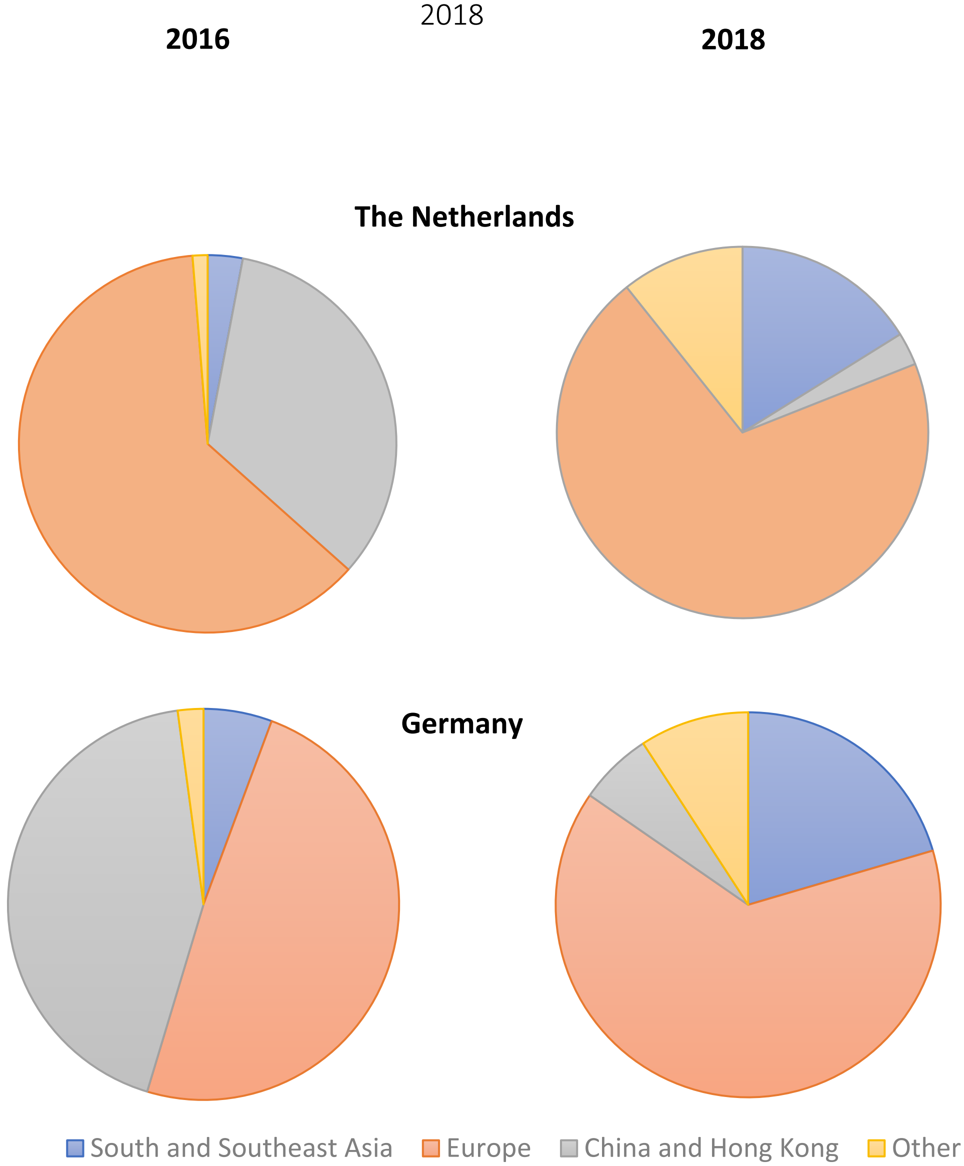
Overall, ASEAN countries have limited recycling infrastructure for plastic. Due to the low profitability of plastic, there is low incentive for the private sector to invest in plastic recycling infrastructure (Jain, 2017). Countries like Cambodia, Myanmar, and the Philippines lack comprehensive strategies to increase recycling rates. A UNEP 2017 report explains that these countries often fail to segregate waste and, instead, they directly dispose of it in dumpsites or openly burn it (Jain, 2017). Accordingly, as long as ASEAN countries have an incentive to fulfill raw plastic material global demand, regulations remain lax, and therefore domestic demand for scraps from the manufacturing industry remains high, they will continue to be the center of plastic waste accumulation. These trends, again, are better illuminated by trade connectivity considering that overall manufacturing industry output in ASEAN countries, remained unchanged after the ban.

Western Europe

In Chapter 1 we showed that European countries are also important players in the plastic scraps trade network. A closer look into the Netherlands and Germany—both countries accounting for over a third of global exports and imports originating from Europe in 2016 and 2018—shows a similar but less drastic picture to that of China. As shown in Figure 13, in 2016, the Netherlands sent 34% of plastic waste exports to China and Hong Kong, 62% to other European countries, and only 3% to the rest of South and Southeast Asia. Differently, Germany relied more heavily on

China, sending 49% of plastic exports to Hong Kong and mainland China, 43% to the rest of Europe, and 6% to South and Southeast Asia. In 2018, after the ban, both countries increased exports to other European nations and to a lesser extent to South and Southeast Asia. Specifically, 21% of Germany's and 16% of the Netherlands' exports went to South and Southeast Asia, while 64% and 70%, respectively, went to other European countries.

Figure 13. The Netherlands' and Germany's Plastic Scraps Exports by Destination - 2016 and 2018



Unlike China, these countries' imports were more evenly composed of PE and mixed scraps—e.g., 48% of Germany's plastic imports in 2016 were PE plastic scraps and 41% were mixed plastic waste. This percentages moderately changed in 2018, with 40% of imports being PE plastic scraps and 48% reported as mixed scraps. The Netherlands similarly maintained almost an even composition of imports (i.e., about 50% PE and 50% mixed) during 2016 and 2018. Germany's manufacturing sector is also one of the largest manufacturers in Western Europe, a significant driver of plastic scraps trade as seen in Chapter 2. Interestingly, China's ban did not change the composition of plastic imports in Germany and the Netherlands; it changed the origin and destiny of plastics and their volumes on the basis of pre-established connectivity.

In terms of exports, the Netherlands primarily exported mixed plastic both in 2016 and 2018 (i.e., over 50%), whereas Germany exported more PE waste than other plastic scraps. Even though recycling rates in Europe are the highest in the world, with Germany leading waste recovery at over 65%, the country exports more plastic than what it imports. In fact, the data shows that in recent years, both the Netherlands and Germany have often been ranked among the global top-5 plastic waste exporters, with Germany as the top exporter in 2018 and the Netherlands reaching second place in 2020. After the implementation of ONS, Germany exported twice as much plastic as it imported. The Netherlands, however, imported more overall plastic than it exported. Nevertheless, in 2018, the largest amount of plastic waste exported to the Netherlands came precisely from Germany (about 43%). Thus, without considering the bilateral transactions that make up the plastic waste trade network, the role of a country like the Netherlands in global plastic waste trade would be undistinguishable from that of a country like Malaysia.

Results from Chapter 2 are consistent with the behaviors of Germany and the Netherlands: developed countries tend to export, and to some extent import, more plastic waste. Yet, our analysis shows that increasing imports in wealthier European countries are predominantly coming from within the region, showing that the sharp increases in eigenvector centrality they experienced are primarily due to increased intraregional trade. Despite the lack of an accurate estimate of national plastic waste generation for each of these countries, the fact that they are the primary exporters of global plastic waste, suggests that they do not possess the capacity to process a large portion of the waste they generate or import. This theoretical framework seems to fit well with our regression estimates. Connectivity is a primary driver of both imports and exports, and the paths plastics go through.

Domestically, Germany's waste management and sorting policies and systems are considered the most effective in the world—e.g., in 2020, Germany reported an overall recycling rate of 70% (Federal Statistical Office of Germany, n.d.). It also reported that 16% of waste was landfilled, and about 12% was treated for energy recovery, which generally entails combustion or incineration, and anaerobic digestion. Looking at residues and waste (specifically from manufacturing and other economic activities), 48% was recycled, 25% was treated for energy recovery, and 19% was landfilled. The results of our analysis, especially the stability of the manufacturing industry over time, suggest that it is not expected that China's ban would generate drastic changes in existing infrastructure—which is rather linked to stable budgeting and operational environmental policy strategies—especially in large plastic traders. Contrarily, changes in plastic trade and processes after the ban followed changes in connectivity. At the theoretical level, part of connectivity and bilateral trade would be a function of the existing infrastructure and policy framework that allow to meet supply and demand of plastic, in volume and for specific processing.

For example, at a more general level, European countries have heavily relied on “waste-to-energy” strategies, incinerating their waste to produce energy, with countries like Britain burning almost 50% of their waste (Gardiner, 2021). However, carbon footprint concerns have pushed the EU to reduce funding for new incinerating facilities, and instead be redirected toward waste prevention, reuse, and recycling. As reflected in our regression estimates, it is thus expected that plastic trade connectivity within European nations would allow changes in the movement of plastic after the ban without contradicting existing policy.

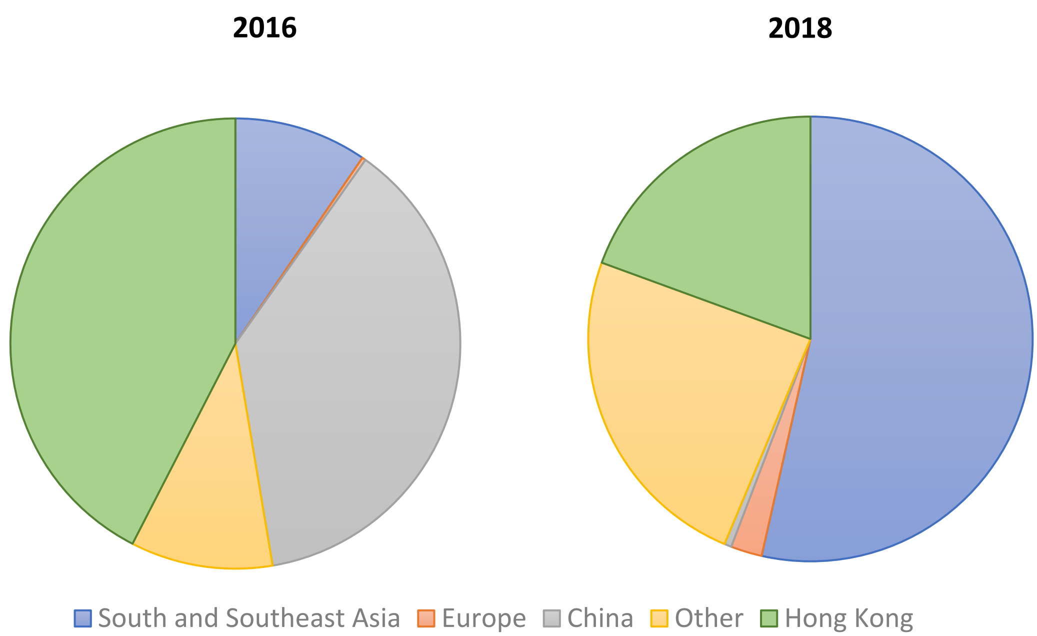
The Netherlands also outperforms other developed countries in recycling and waste management. It recently followed Germany’s footsteps and introduced a plastic bottles “deposit” program (Government of the Netherlands, 2022). Under this program, purchasers are charged a small deposit on plastic bottles, which they can recover once they return the bottles to the place of purchase. Yet, like in other European countries, national guidelines and criteria defining which waste counts as recycled often include waste that is sorted and shipped overseas when calculating recycling rates. Nuances like these are not captured in our data. Our trade variables are crude measures of import and export volume, and as such they certainly include measurement error. The quality of our inferences relies, therefore, on the robustness of our regression estimates.

North America

Although more recently the United States does not rank as high as European nations on exports of plastic scraps, it continues to send a large portion of its plastic waste to Southeast Asia. The United States did not report total plastic waste exports for some years after the ONS was implemented. However, reported data for total imports and exports in 2015 and 2020 show that, in 2015, the United States exported more than five times as much plastic as it imported. By 2020, it was still exporting more plastic than it imported but to a lesser extent (i.e., 1.4 times as much exports as imports). Figure 14, which visualizes the United States' plastic waste exports by destination in 2016 and 2018, shows that before ONS, most of its exports (about 80%) were going to Hong Kong and China.

In 2018, 66% of exports went to South and Southeast Asia and 30% went to Hong Kong. Results from the social network analysis in Chapter 1 suggest that Hong Kong was delayed in fully implementing the ONS. Yet, Figure 12 shows that, in spite of continuing to receive plastic from other regions, Hong Kong also exported most of plastic waste to South and Southeast Asia after the ban. Contrarily, most of the United States' imports in 2018 (66%) came from within the North American region—specifically, from Mexico (40%) and Canada (26%).

Figure 14. The United States' Plastic Scraps Exports by Destination - 2016 and 2018



As aforementioned, the United States has recently introduced policies to increase the domestic processing of their plastic waste, not only motivated by ONS but by new international regulations and restrictions from Southeast Asian governments. The Environmental Protection Agency (EPA) reported that only 9% of overall plastic waste in 2018 was recycled. Aiming to increase this rate, EPA recently developed a Solid Waste Infrastructure for Recycling (SWIFR) grant program which will request input to guide the development of new waste and recycling programs (United States Environmental Protection Agency, 2020). These domestic and foreign policy implementations represent an important factor regulating where plastic would go after China's ban. It is expected that variation that arises from factors like these would be directly and indirectly captured by our connectivity variable.

Once again, this case-study examination of selected countries showcases the different implications of changes in trade in Western countries versus Southeast Asian countries. More developed nations and nations with large manufacturing industry (including China) possess better infrastructure and technology to process plastic waste, but they re-export a large fraction of their waste to South and Southeast Asia, where it accumulates in landfills. If this is so, then trade connectivity is serving multiple purposes in our models. This is, again, due to the fact that our variables are rough measures of the volume of plastic trade without differentiating qualitative aspects of that trade. This lack of specificity in our variables should be explored in future research to help determine the different roles of connectivity.

Chapter 4 | Limitations, Future Research, and Concluding Remarks

This study presented an investigation of the global plastic waste trade network, describing its evolution after the implementation of China's Operation National Sword—the most important plastic waste regulation of the century. This analysis also emphasized the importance of trade connectivity in determining national and regional plastic waste trade levels. Although macroeconomic variables (i.e., economic development and manufacturing industry size) are still relevant explanatory factors of plastic scraps trade patterns, they are not suitable to illustrate the network dynamics that predisposed some countries to take in a large fraction of plastic waste that was once going to China. Accordingly, this study illustrated how trade connectivity offers a new perspective on plastic trade independent from traditional macroeconomic approaches.

Findings showed that large manufacturing countries continue to attract foreign plastic waste, becoming the newest waste havens of the world. Particularly, Southeast Asian countries tend to have large manufacturing industries and, thus, a stable large demand for raw materials, including plastic. Four of the top five manufacturers in the analytic sample are East and Southeast Asian countries. Results thus showed that countries with large manufacturing industries import more mixed plastic scraps, and to a larger extent, more PE plastic waste.

Our findings show that, while wealthier countries also take a substantial portion of the world's plastic waste, they still contribute the most to overall plastic exports, especially uncategorized and mixed plastic with lower recycling potential. Estimates indicated that economic development was a determinant for both imports and exports of mixed plastic waste, but not for

PE scraps. Nevertheless, a closer look to plastic trade patterns in Western European, countries that accounted for over a third of trade originating in Europe, before and after ONS, and that occupy the highest levels of economic development in the analytic sample, showed that increases in their imports were predominantly driven by plastic waste trade within Europe. Differently, Southeast Asian countries' imports were, for the most part, coming from other regions.

These are the dynamics that cannot be captured without considering the relational and qualitative context of plastic waste trade. As our social network analysis showed, Southeast Asian countries who received almost half of China's and Hong Kong's combined exports before the ban, experienced increases in eigenvector centrality even since Operation Green Fence in the early 2010s, and sharper increases after ONS. This was not the case for other key plastic traders. For example, although Germany also experienced similar increases in eigenvector centrality, it exported the largest portion of plastic to the Netherlands. Southeast Asian countries, on the other hand, imported more plastic waste than they exported, rarely sending it to other regions. This study showed that all these dynamics were a function of trade connectivity, independent from macroeconomic conditions.

We also show that observed changes in eigenvector centrality reflect other drivers of the demand for plastic scraps, such as shifts of plastic pellets production from China to Southeast Asian countries. Similarly, eigenvector centrality also showed other changes in country-specific policies that facilitated the relocation of countries within the plastic waste trade network.

This connectivity measure also partially explained effects initially attributed to higher levels of economic development. In other words, as recycling enterprises and plastic pellets producers continue to move operations to Southeast Asian countries, these countries consequently increase plastic imports and take plastic scraps that China would have otherwise imported directly before the ban. As such, changes in the profile of trade partners and the size of plastic waste trade among them—occurring independently from economic development—were captured by the variation of the centrality measure. Indeed, eigenvector centrality showed to be the most important determinant of plastic imports. Overall, the positive effect of eigenvector centrality indicated that countries that trade with top importers are more likely to import plastic waste as well.

This study was also intended to provide a more in-depth investigation of the drastic and rapid changes experienced by countries in the global plastic waste trade network after National Sword's implementation in 2018. Our analyses revealed that the Southeast Asian countries that have historically played the role of pre-processers and intermediaries for plastic scraps and pairings, as well as European top-trading countries, were most significantly affected by National Sword. While the European nations are generally better equipped to process plastic, other countries in Southeast Asia were not adequately prepared for the influx of waste, resulting in overfilling landfills, plastics contamination in oceans and waterways, and both air pollution and excess GHG emissions.

There are several limitations in this study worth mentioning. Although the environmental performance measure used in this study is not granular enough to capture the specific effect of waste management policy, even this macrolevel indicator suggests that countries with better climate change performance, environmental health, and proximity to achieving their environmental policy targets had the ability to prevent other countries from redirecting their plastic waste to them after China's plastic ban was implemented. However, the lack of environmental performance indicators available for longer periods that exclusively capture policy and performance on plastic waste management prevents us from drawing specific inferences regarding plastic policy.

Indeed, the environmental performance index is based on 40+ indicators including climate change mitigation, air quality, and biodiversity and habitat protection. Among the 11 main issue categories, waste management performance has a weight of 2% in the overall score. As such, instead of using aggregations of multi-issue evaluations regarding the environment, future research will benefit from using indices that capture legislation and policy that are more specifically related to plastic and other types of waste. Also important to mention, is that EPI is not comparable over time. This is because the aggregation methodology varies on an annual basis. The lack of comparability does not only emerge from measuring different aspects of policy at different levels and with different weighting, but also the insertion of measurement error varies. Accordingly, within-country comparisons are not possible. And, as such, our inferences were carried out with caution. Our models nevertheless controlled for time fixed effects, which could remove part of time-related heterogeneity in the measure.

Overall, other challenges and limitations of this research are primarily related to data quality and availability. For instance, although plastic exports and imports are by definition symmetrical, plastic scraps trade data is self-reported by nations, often being underreported or missing. A direct result of this, is that less information on country exports was available. Not only are values often missing, but the inability to distinguish between transit countries and final destinations of plastic conditions the type of inferences that can be drawn from our findings.

Ideally, future research could benefit from using a better categorization of plastic imports—i.e., one enabling the separation of low-density PE (LDPE) from high-density (HDPE) and PET imports. Considering the low profitability of recycling LDPE products, such as plastic bags, this type of scrap would ideally be excluded from the "ethylene polymers" model estimation, which is assumed to be the most desirable plastic in the market. However, the available data are not as granular, with LDPE being included in the same commodity code as HDPE and PET. Our current inferences therefore are agnostic to the type of plastic, which are known to have different trade, environmental, and policy properties and implications.

As for measures of other relevant factors discussed in the literature, the percentage of employed population in the production of plastic and rubber products, available from the International Labor Organization (ILO), was available only for 2009 and for a limited number of countries. This situation brings to light the need of plastic-relevant confounders that future research should incorporate in their models. This is especially true as researchers would be interested in developing and testing connectivity models that can be operationalized differently from traditional macroeconomic models of trade.

Given that plastic scraps are not individually tracked, it is not possible to determine whether plastic that is imported is processed domestically or if it is re-exported to other countries. In the same way, without data on the generation of plastic waste, it is difficult to distinguish between plastic waste that is produced in the country from which it is being imported and waste produced in a different country. Accordingly, our estimates do not distinguish between, for example, intraregional trade and trade to “intermediary” countries. Again, our measures are, therefore, a crude quantification of the size of trade and the direction of it without distinguishing what happens in-between processes and paths of the traded plastic. Future research should explore within-country changes in plastic waste policy and the production, origin, and paths of it. By observing how changes in waste affect different countries and in different forms—e.g., countries that account for large portions of global trade, and, equally important, those that operate in the periphery of the plastic market. Furthermore, a closer look at the behavior of highly central countries can provide a more detailed understanding of the regions in which plastic waste has accumulated, such as the descriptions included in chapter 3 of this study.

Another limitation of the study is that one of our main independent variables of interest—i.e., eigenvector centrality—is the product of an estimation process—namely, a social network analysis. In this case, the SNA incorporated some of the variation in trade that may also be part of the dependent variable. To be precise, whereas eigenvector centrality incorporates variation from country-dyads of bilateral imports of all types of plastic, our dependent variables in the regression models are both total imports and total exports of specific types of plastic. Yet, connectivity—in the way that has been conceptualized and operationalized here—is a measure that assesses the degree to which a country trades plastic with other countries accounting for the fact that those nations have in turn other plastic trading partners. That is, imports and exports of specific plastics—i.e., our dependent variables—may be an indirect function of the strength of plastic trading networks. This situation increases the risk of invalidly testing a null hypothesis on the basis of shared-variance at both sides of the equation.

Two strategies were applied to increase our confidence that our estimates were not the product of this situation. Firstly, as a robustness check and risking for overcontrol, we included in the right side of the equation total plastic imports as a control in models of total exports, and *vice versa* (i.e., we controlled for total exports in models of total imports). Our estimates showed to be robust to the inclusion of such controls (see tables 2 and 3). A second strategy comes from our SGMM estimation (estimates retrieved from these analyses are the ones we interpreted in this study), which accounts for endogenous processes in the model. In our particular case, we control—depending on the model—for 1- and 2-year lagged versions of the dependent variable, which in turn are instrumented by deeper lags of themselves. Our estimates for eigenvector centrality are therefore free of time-dependent variation of the dependent variable—i.e., independent from an important fraction of the variation it presumably shares with the dependent variable.

This study examined a short span of plastic scraps trade data, covering up to 2020. Yet, the COVID-19 pandemic—which started on the last year of our data series—represents a shock wave affecting supply chains, macroeconomic indicators and policy, manufacturing and plastic trade. Drastic changes are rapidly being incorporated to the new plastic trade landscape that could not be estimated with our data. For example, by 2021, the effects of the amendments to the Basel convention—which established more strict regulations on the international trade of plastic—were left out of the scope of this study. Future research should incorporate post-amendment data to quantify an evaluate the effects of this international policy, which is paramount as it can settle a long-lasting debate about the effectiveness of environmental international agreements.

We also believe that improving the quality, coverage, and availability of the data would enable researchers to make use of other relevant methodologies. For instance, we experimented with Latent Class Analysis (LCA) and Latent Transition Analysis (LTA), which are two classification methods that benefit from large sample sizes. Classification methodologies like these would provide valuable insights into the latent plastic trade proclivities of countries, how unobservable heterogeneity operates in the background of the associations of interest in typical regression analyses, as well as how they have changed over time and which factors primarily drive changes (preliminary analyses implementing these methodologies are included Section 2 of the Appendix).

Future research can also further explore the role of relational characteristics in a country's plastic waste trade. Although affected by high-leverage observations, the eigenvector centrality measure showed to be an important determinant of imports of polyethylene and other plastic scraps, suggesting that countries' roles within the global plastic trade context may be influenced by factors beyond macroeconomic ones. This approach would also inform dimensions of policy according to relational country characteristics. This is because plastic waste trade policy is a multilateral issue that requires action from both producers and recipients of plastic waste, and many times governments act on the basis of their own interests—which are better captured by country-specific characteristics in a modeling setting.

Overall, the results of this analysis highlight the importance of countries' relational context over macroeconomic indicators as determinants of plastic scraps trade. Although large manufacturers were found to be more likely to import more plastic scraps with high recycling potential (i.e., polyethylene waste) and more mixed scraps (though to a lesser extent), it was those with higher eigenvector centrality instead (i.e., those importing from top plastic waste traders) who reported the largest plastic scraps imports—especially after the implementation of ONS. Similarly, while wealthier countries were found to import and export more plastic waste (including Western European countries), highly connected countries in Southeast Asia are the ones that have accumulated plastic waste from other regions, being the largest receptors of Chinese and American exports after the ban.

These findings have important implications: namely, that plastic waste accumulation is an environmental, socioeconomic, and public health burden borne mostly by poorer and less-resourced nations across Southeast Asia. For instance, plastic scraps are often contaminated in commingled and single-stream recycling processes, and as a result a substantial amount of the incoming plastic will continue to accumulate in landfills of countries without neither the technology nor the infrastructure to properly recycle it. Furthermore, open dumping and waste burning prevails in these countries, which have recycling sectors that mostly consist of informal workers without proper physical and labor protections. Consequently, it is they who will remain at greater risk of exposure to toxic pollutants and carcinogens from decomposing or burning plastic. These implications thus reinforce the notion that the plastic waste trade is not solely an economic issue, but also an environmental justice issue.

Appendix

Section 1: Supplementary Figures and Tables

Figure A. Eigenvector Centrality and Plastic Imports (Logged Kilograms) for Other Countries (1999-2020)

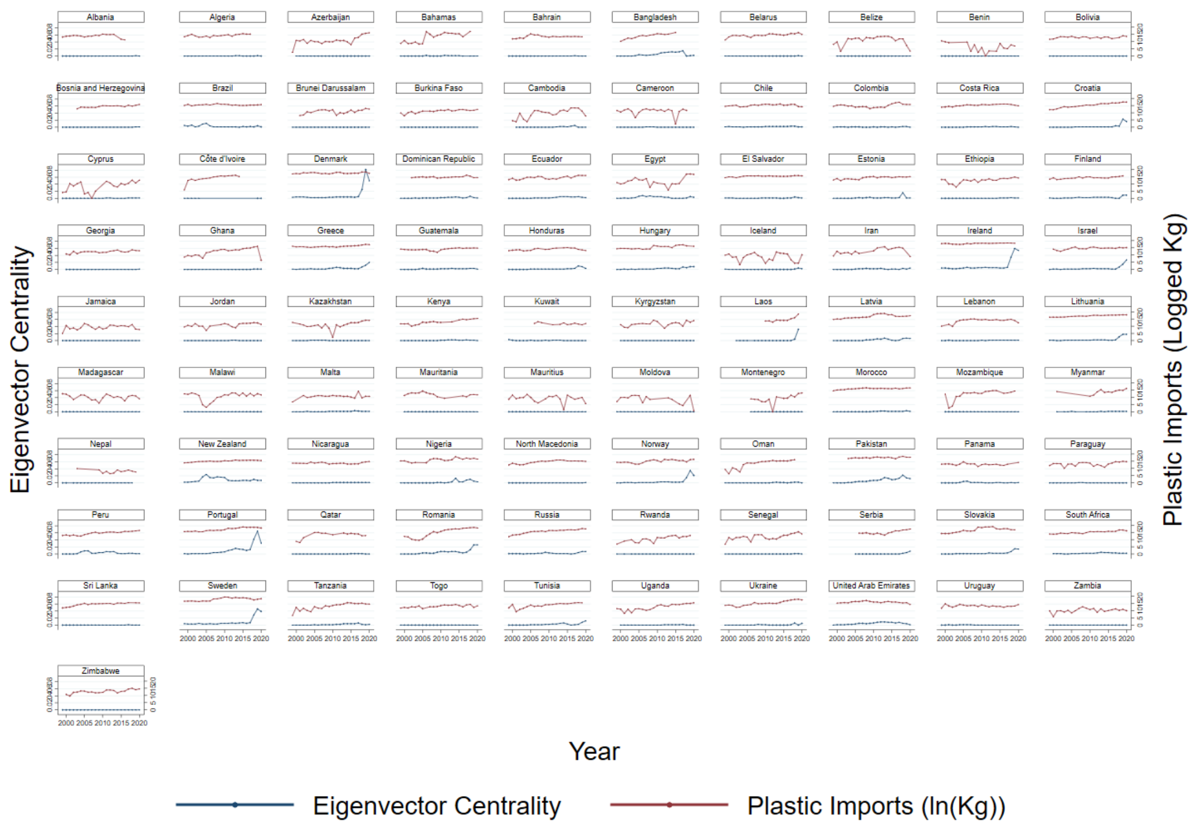


Figure B. Clustering Coefficient and Plastic Imports (Logged Kg) for Select Countries

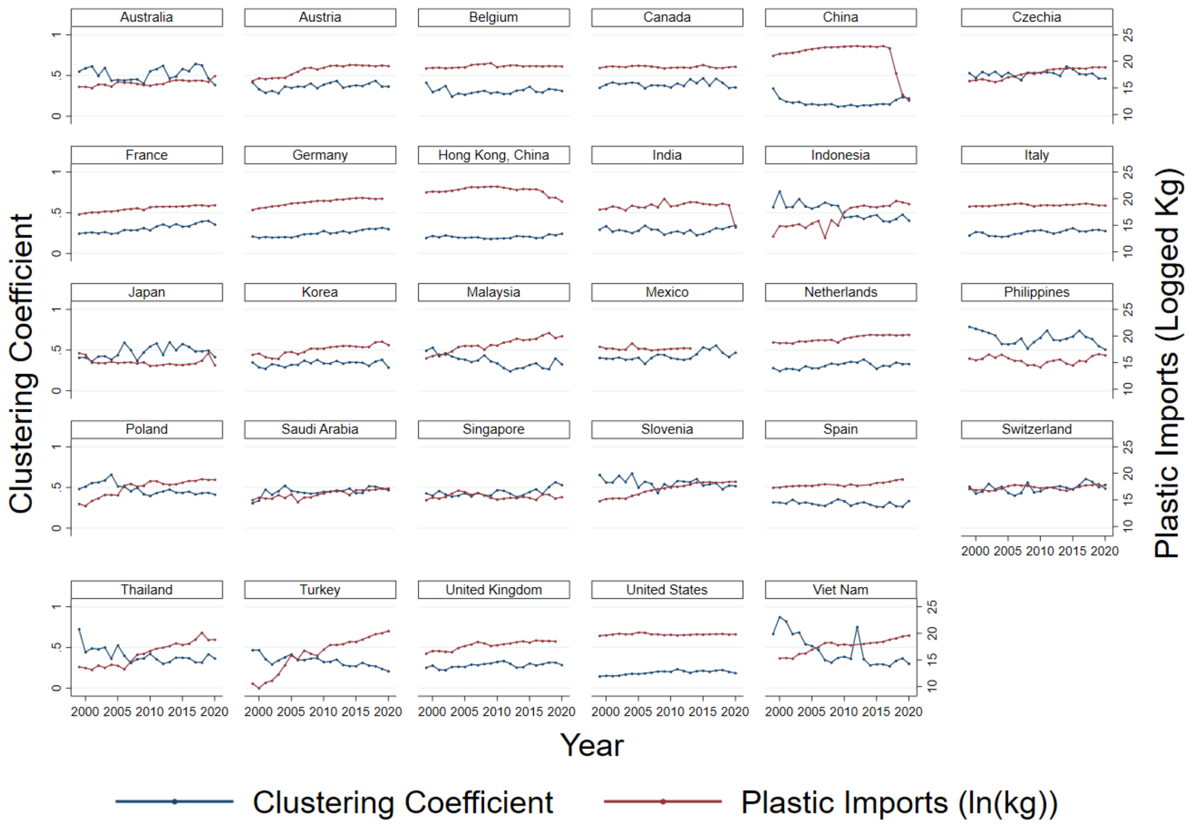


Table A. Sargan-Hansen (difference) test of overidentifying restrictions

		Excluding			Difference		
	Moment conditions	chi2	df	p-value	chi2	df	p-value
Ethylene Imports	Diff. Model (Autoregressive Term L3 and L4)	6.9436	11	0.8036	0.7306	2	0.6940
	Diff. Model (Covariates L2 and L3)	0.5048	1	0.4774	7.1694	12	0.8462
	Level Model (L1 Differences)	.	-15	.	.	.	.
	Difference Model	.	-1	.	.	.	.
Ethylene Exports	Diff. Model (Autoregressive Term L3 and L4)	12.8989	11	0.3000	2.2261	2	0.3286
	Diff. Model (Covariates L2 and L3)	1.1858	1	0.2762	13.9392	12	0.3046
	Level Model (L1 Differences)	.	-15	.	.	.	.
	Difference Model	.	-1	.	.	.	.
Other Plastic Imports	Diff. Model (Autoregressive Term L3 and L4)	15.7943	18	0.6069	0.5585	2	0.7564
	Diff. Model (Covariates L2 and L3)	0.5000	2	0.7788	15.8528	18	0.6028
	Level Model (L1 Differences)	.	-8	.	.	.	.
	Difference Model	0	0	.	16.3528	20	0.6945
Other Plastic Exports	Diff. Model (Autoregressive Term L3 and L4)	24.3990	18	0.1424	0.2473	2	0.8837
	Diff. Model (Covariates L2 and L3)	0.3664	2	0.8326	24.2799	18	0.1461
	Level Model (L1 Differences)	.	-8	.	.	.	.
	Difference Model	0.6467	0	.	23.9996	20	0.2424

Table B. Arellano-Bond test for autocorrelation of the first-differenced residuals

	Z	p-value
Ethylene Imports	-0.4837	0.6286
Ethylene Exports	-1.7150	0.0862
Other Plastic Imports	-0.1319	0.8950
Other Plastic Exports	0.4382	0.6612

Table C. SGMM Parameter Estimates, Plastic Imports and Exports by Type (with interaction term)

VARIABLES	Model 1 Logged Imports Ethylene	Model 2 Logged Exports Ethylene	Model 3 Logged Imports Other	Model 4 Logged Exports Other
Logged Plastic Imports (Type for given model) (t-1)	0.370***		0.249***	
	(0.0572)		(0.0874)	
Logged Plastic Imports (Type for given model) (t-2)	0.181***		-0.0174	
	(0.0480)		(0.0903)	
EPI	-0.0121	0.00912	0.0184	-0.0108
	(0.0403)	(0.0582)	(0.0219)	(0.0161)
Logged Plastic Exports (Type for given model)	0.184**		-0.144**	
	(0.0717)		(0.0729)	
Logged GDPpc (constant 2010 USD)	0.0148	0.182	0.293	0.767***
	(0.531)	(0.717)	(0.350)	(0.274)
Manufacturing (% GDP)	0.169	0.0895	0.0800	0.0198
	(0.116)	(0.107)	(0.0778)	(0.0402)
Eigenvector Centrality	10.78**	-4.950	8.926**	1.410
	(4.687)	(4.478)	(3.622)	(2.138)
Before ONS Dummy	0.558	-0.558	-0.0109	0.411**
	(0.513)	(0.732)	(0.380)	(0.176)
Eigenvector * Before ONS	-3.017	2.212	1.660	-1.141
	(3.896)	(4.727)	(3.701)	(2.474)
Logged Population	-0.912*	0.581	-0.297	0.322
	(0.468)	(0.613)	(0.332)	(0.217)
Weighted Average Distance to Top 5 Exporters	7.26e-05		-0.000298*	
	(0.000224)		(0.000154)	
Logged Plastic Exports (Type for given model) (t-1)		0.603***		0.524***
		(0.0768)		(0.0871)
Logged Plastic Exports (Type for given model) (t-2)		0.210***		
		(0.0575)		
Logged Plastic Imports (Type for given model)		0.233*		0.0250
		(0.141)		(0.0663)
Average Distance to Top 5 Importers		0.000230		5.76e-05
		(0.000214)		(8.53e-05)
Time Fixed Effects	Yes	Yes	Yes	Yes
Constant	15.68*	-14.85	15.47***	-5.380
	(8.810)	(10.01)	(5.849)	(4.220)
Observations	1,895	1,895	1,873	1,893
Number of countries	119	119	119	119

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table D. SGMM Parameter Estimates, Plastic Imports and Exports All Types

VARIABLES	Model 1 Logged Plastic Imports	Model 2 Logged Plastic Imports	Model 3 Logged Plastic Imports	Model 4 Logged Plastic Exports	Model 5 Logged Plastic Exports	Model 6 Logged Plastic Exports
Logged Plastic Imports (t-1)	0.802***	0.729***	0.770***			
	(0.125)	(0.105)	(0.110)			
Logged Plastic Exports (t-1)				0.920***	0.872***	0.848***
				(0.098)	(0.099)	(0.094)
EPI	0.021**	0.0058		0.0067	0.0023	
	(0.009)	(0.014)		(0.010)	(0.014)	
Logged Exports of Plastic for Packaging		0.026	-0.018			
		(0.159)	(0.170)			
Logged GDPpc (constant 2010 USD)		0.253	0.307		0.176	0.172
		(0.339)	(0.352)		(0.182)	(0.151)
Manufacturing (% GDP)		0.0339	0.029		0.041	0.0425
		(0.039)	(0.040)		(0.049)	(0.046)
Weighted Average Distance to Top 5 Exporters		-0.00013	-0.00013			
		(0.000)	(0.0001)			
Logged Population		0.269	0.319		-0.008	-0.0357
		(0.270)	(0.379)		(0.155)	(0.140)
Logged Plastic Imports					0.009	0.009
					(0.064)	(0.055)
Average Distance to Top 5 Importers					0.00007	0.00004
					(0.00001)	(0.00008)
Constant		-2.992	-		-	-
		(6.056)	-		-	-
Observations	2,058	2,058	2,058	2,107	2,017	2,017
Number of countries	127	127	127	122	122	122

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table E. SGMM Parameter Estimates, Plastic Imports and Exports by Type with Eigenvector Centrality

VARIABLES	Model 1 Logged Imports Ethylene	Model 2 Logged Exports Ethylene	Model 3 Logged Imports Other	Model 4 Logged Exports Other
Logged Plastic Imports (Type for given model) (t-1)	0.367***		0.303***	
	(0.060)		(0.067)	
Logged Plastic Imports (Type for given model) (t-2)	0.189***			
	(0.051)			
EPI	-0.0190	-0.027	0.004	-0.008
	(0.039)	(0.040)	(0.019)	(0.017)
Logged Plastic Exports (Type for given model)	0.154*		-0.156*	
	(0.079)		(0.088)	
Logged GDPpc (constant 2010 USD)	0.288	0.389	0.578**	0.704**
	(0.558)	(0.551)	(0.288)	(0.316)
Manufacturing (% GDP)	0.210*	0.010	0.106	0.015
	(0.118)	(0.093)	(0.071)	(0.049)
Eigenvector Centrality	11.92**	0.732	8.660**	1.981
	(4.968)	(2.628)	(4.411)	(1.527)
Logged Population	-0.474	-0.271	-0.122	0.245
	(0.871)	(1.128)	(0.612)	(0.263)
Weighted Average Distance to Top 5 Exporters	-0.00011		-0.0002*	
	(0.00025)		(0.0001)	
Logged Plastic Exports (Type for given model) (t-1)		0.587***		0.527***
		(0.074)		(0.103)
Logged Plastic Exports (Type for given model) (t-2)		0.231***		
		(0.046)		
Logged Plastic Imports (Type for given model)		0.147		0.034
		(0.114)		(0.080)
Average Distance to Top 5 Importers		0.00015		0.00005
		(0.0002)		(0.0001)
Time Fixed Effects	Yes	Yes	Yes	Yes
Constant	5.69	0.759	8.853	-4.036
	(17.95)	(21.60)	(11.25)	(5.13)
Observations	1,895	1,895	1,893	1,893
Number of countries	119	119	119	119

Table F. SGMM Parameter Estimates, Plastic Imports and Exports by Type with Limited Sample

VARIABLES	Model 1 Logged Imports Ethylene	Model 3 Logged Imports Other
Logged Plastic Imports (Type for given model) (t-1)	0.280*	0.796***
	(0.160)	(0.173)
Logged Plastic Imports (Type for given model) (t-2)	0.088	
	(0.198)	
EPI	-0.009	0.007
	(0.030)	(0.019)
Logged Plastic Exports (Type for given model)	0.203	-0.034
	(0.192)	(0.044)
Logged GDPpc (constant 2010 USD)	-0.551	-0.146**
	(0.777)	(0.435)
Manufacturing (% GDP)	-0.020	-0.040
	(0.053)	(0.055)
Eigenvector Centrality	6.97**	3.93*
	(2.762)	(2.38)
Logged Population	-0.268	-0.3187
	(0.227)	(0.228)
Weighted Average Distance to Top 5 Exporters	-0.00014	0.0000
	(0.00025)	(0.0001)
Logged Plastic Exports (Type for given model) (t-1)		
Logged Plastic Exports (Type for given model) (t-2)		
Logged Plastic Imports (Type for given model)		
Average Distance to Top 5 Importers		
Time Fixed Effects	Yes	Yes
Constant	18.20***	10.62*
	(6.36)	(5.64)
Observations	460	448
Number of countries	44	44

Table G. Multinomial Logistic Regression Parameter Estimates, Status 2016 and 2018 Including Population Size

	(1) Net importer both years	(2) Net importer only 2016	(4) Net importer only 2018
Logged GDPpc (constant 2010 USD) (2016)	0.689	0.321**	1.445
	(0.295)	(0.173)	(0.545)
EPI (2016)	1.063	1.269***	0.951
	(0.052)	(0.142)	(0.040)
Manufacturing (% GDP) (2016)	1.059	1.113	1.059
	(0.064)	(0.072)	(0.054)
Logged Population	1.246	1.811	1.408*
	(0.283)	(0.765)	(0.270)
Constant	0.001	0.000	0.001
	(0.005)	(0.000)	(0.002)
Observations	102	102	102
Pseudo R^2	0.089	0.089	0.089
Wald Chi^2	19.20**	19.20**	19.20**

Note: standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table H. Hausman McFadden Tests

	Removing Class 1 Base outcome: Class 4	Removing Class 2 Base outcome: Class 4	Removing Class 3 Base outcome: Class 4	Removing Class 4 Base outcome: Class 3
Chi2	2.40	-0.24	6.69	0.78
Prob > Chi2	0.9662	.	0.4621	0.998

Table I. Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
EPI	102	71.87	13.73	37.1	90.68
Log GDP pc	102	8.87	1.40	5.94	11.36
Manufacturing	102	12.91	5.15	2.99	33.35

Section 2: Latent Class Analysis Preliminary Findings

Through Latent Class Analysis (LCA) countries can be categorized in "latent classes" of plastic trade tendencies based on their given characteristics (e.g., level of development and environmental performance). Since LCA takes each value of a variable as a category, all variables were recoded as categorical variables, using quintiles as levels, to facilitate the classification process. In other words, each variable was recoded into 5 levels, one per quintile. LCA fits the number of classes specified prior to estimation and output conditional probabilities of observing each category-value of each covariate in a given class, (i.e., it estimates the probability for countries in each class to exhibit a specific characteristic).

Countries' class membership (in the generated latent classes) can be estimated with or without the inclusion of covariates. The basic model with no covariates assumes that countries' prior probabilities of class membership are the same, whereas including covariates allows the prior probabilities to vary for each country according to the observed values of the covariates. If the first approach is implemented, one can also estimate the effect of the covariates on class membership by predicting posterior class membership probabilities and using them as the dependent variable in a regression with the covariates of interest.

I start by fitting a basic latent class model for 127 countries based on levels of plastic imports, exports, and the difference between them (exports(kg)-imports (kg)). The difference measure is introduced to identify top net importers and net exporters, which are countries that import more than they export and vice versa. Accordingly, net importer countries, would be identified as potential waste havens. Table J shows conditional category response probabilities (i.e., the probability of observing each category value in a given class) for the year 2010. The year 2010 was selected as a representative year before the implementation of the ban since regulatory measures in China were launched in the early 2010s and started being implemented as early as 2013. Only 114 countries were fitted since the remaining did not have complete data. Three classes are selected as the number of classes producing the best fit. Each class was assigned an identifying name according to the probabilities in each category. Countries in class 2, for example, are characterized by being either top net importers or top exporters, but nothing in between. This means that class 2 countries either import substantially more plastic than they export, or they export substantially more than they import. Countries in class 1 are those that trade the least plastic and those in Class 3 have medium-high levels of trade. 40.7% of countries are assigned to class 1, 31% to class 2, and 28.3% to class 3.

Table J. 2010 LCA Conditional Probabilities

Plastic Imports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.4622	0.3182	0.2195	0.0000	0.0000
Class 2 – Polarized Diff	0.0000	0.0000	0.0908	0.2853	0.6238
Class 3 – Higher Levels	0.0797	0.2529	0.3783	0.3783	0.0000
Plastic Exports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.5249	0.4751	0.0000	0.0000	0.0000
Class 2 – Polarized Diff	0.0308	0.0596	0.0400	0.2722	0.5975
Class 3 – Higher Levels	0.0000	0.0000	0.6499	0.3501	0.0000
Difference (1 High imports relative to exports – 5 High exports relative to imports)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.1367	0.5180	0.3453	0.0000	0.0000
Class 2 – Polarized Diff	0.3916	0.0000	0.0000	0.0324	0.5760
Class 3 – Higher Levels	0.0542	0.0597	0.2386	0.6475	0.0000

To evaluate more immediate trade behaviors before and after the enactment of the National Sword Policy, the year 2016 is compared to 2010 and 2018. Table K shows the posterior probabilities of the 2016 LCA model, showing similar patterns to 2010. 36% of countries are assigned to class 1, 41% to class 2, and 23% to class 3. Compared to 2010, class 2 membership increased by 10%. Similarly, the posterior probability of observing a value of 1 in the difference between exports and imports (signaling greater imports compared to exports) increased to 49% from 39% in 2010. This indicates that even before the ban implementation, top plastic trading countries (those in class 2) were experiencing a more rapid increase of their imports relative to their exports.

The output of a latent class model for the year 2018, the year the ban went into effect, is reported in Table L. 35.2% of countries were assigned to class 1, 35.6% to class 2, and 29.2% to class 3. One of the most evident differences to the previous years is seen in the “polarized differences” class (i.e., class 2). Whereas in 2016 49% of countries in this class were countries with the largest imports relative to their exports (category 1), this percentage increased to 58% in 2018. While this is a similar increase from 2010 to 2016, that 10% increase happened over a period of six years, whereas the same increase was observed in 2018 just after 2 years. Membership in class 2 decreased from 41% of countries in 2016 to about 36% in 2018. These results suggest that immediately after the ban went into effect, some countries (~5%) with the highest levels of both imports and exports reduced their overall trade. However, countries who stayed in the top of plastic scrap traders, saw an increase in their imports relative to their exports of plastic scraps.

Table K. 2016 LCA Conditional Probabilities

Plastic Imports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.4970	0.4362	0.0669	0.0000	0.0000
Class 2 – Polarized Diff	0.0000	0.0000	0.1364	0.3834	0.4803
Class 3 – Higher Levels	0.1273	0.1867	0.5125	0.1735	0.0000
Plastic Exports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.5273	0.4727	0.0000	0.0000	0.0000
Class 2 – Polarized Diff	0.0422	0.0880	0.0639	0.3210	0.4849
Class 3 – Higher Levels	0.0000	0.0000	0.7197	0.2803	0.0000
Difference (1 High imports relative to exports – 5 High exports relative to imports)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.0000	0.5385	0.4615	0.0000	0.0000
Class 2 – Polarized Diff	0.4867	0.0000	0.0000	0.0266	0.4867
Class 3 – Higher Levels	0.0000	0.0721	0.1442	0.7837	0.0000

As aforementioned, to estimate the effect of the covariates on class membership, I take the posterior probabilities of the yearly models and calculate their differences to use as dependent variables. Specifically, I subtract 2016's posterior probability of belonging to class 2 (i.e., the class of interest) from 2018's. This difference is then a measure of the change in countries' probability of being a top net exporter or importer before and after the ban implementation. Estimates from an OLS linear regression with robust standard errors are reported in Table M for the difference between 2016 and 2018. The geographical distance variable is not included since this does not vary over time. Additionally, given the size of the sample, the included covariates are limited to the baseline values (values in 2016) GDP per capita, environmental performance, size of manufacturing sector, and population size. The direction of the difference (2018 – 2016) means that positive values represent a higher probability of membership in 2018 and negative values mean that the probability was greater in 2016. The baseline GDP per capita estimate has a robust positive effect on the difference in the probability of class 2 membership between 2016 and 2018. This means that the greater the level of development in 2016, the greater the difference, hence the higher the probability of class 2 membership in 2018. The coefficient for environmental performance is negative, reducing the probability of belonging to class 2 in 2018. However, its effect is small and only statistically significant in the presence of other controls.

Table L. 2018 LCA Conditional Probabilities

Plastic Imports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.5226	0.3015	0.1759	0.0000	0.0000
Class 2 – Polarized Diff	0.0000	0.0000	0.0346	0.4003	0.5651
Class 3 – Higher Levels	0.0632	0.3189	0.4232	0.1947	0.0000
Plastic Exports Levels (1 Lowest - 5 Highest)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.5263	0.4737	0.0000	0.0000	0.0000
Class 2 – Polarized Diff	0.0510	0.1020	0.0489	0.2366	0.5615
Class 3 – Higher Levels	0.0000	0.0000	0.6120	0.3880	0.0000
Difference (1 High imports relative to exports – 5 High exports relative to imports)					
	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
Class 1 – Lower Levels	0.0000	0.4474	0.4474	0.1053	0.0000
Class 2 – Polarized Diff	0.5795	0.0000	0.0000	0.0274	0.3932
Class 3 – Higher Levels	0.0000	0.1457	0.1457	0.4930	0.2156

Table M. OLS Estimates – Differences in Posterior Probabilities

	Model 1	Model 2	Model 3
Logged GDPpc (constant 2010 USD) (2016)	0.072**	0.086***	0.105***
	(0.037)	(0.037)	(0.038)
EPI (2016)	-0.005	-0.006**	-0.004
	(0.004)	(0.004)	(0.004)
Manufacturing (% GDP) (2016)		0.011***	0.008
		(0.006)	(0.006)
Logged Population (number of people)			0.048***
			(0.022)
Posterior Probability Class 2 - 2016	-0.378***	-0.440***	-0.543***
	(0.071)	(0.077)	(0.089)
Constant	-0.170	-0.334*	-1.316***
	(0.207)	(0.221)	(0.502)
Observations	127	126	126
R^2	0.234	0.261	0.289
Adjusted R^2	0.215	0.237	0.260
Residual Std. Error	0.326	0.323	0.318
F Statistic	12.509***	10.700***	9.765***
Note:	Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1	

List of References

Abdollahian, M. & Yang, Z. (2013). Toward Trade Equalisation: A Network Perspective on Trade and Income Convergence Across the Twentieth Century. New Political Economy. 19. 601-627. 10.1080/13563467.2013.796450.

Alabi OA, Ologbonjaye KI, Awosolu O, Alalade OE (2019) Public and Environmental Health Effects of Plastic Wastes Disposal: A Review. J Toxicol Risk Assess 5:021. doi.org/10.23937/2572-4061.151002

Ananthalakshmi, A. (2018, October 26). Malaysia to curb imports of plastic waste – minister. *Reuters.* Retrieved from https://www.reuters.com/article/us-malaysia-waste-imports/malaysia-to-curb-imports-of-plastic-waste-minister-idUSKCN1N028P

Anderson, T. W. & Hsiao, Cheng (1982). Formulation and estimation of dynamic models using panel data. Journal of Econometrics, Elsevier, vol. 18(1), pages 47-82, January.

Andrews, Donald W. K. & Lu, Biao (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. Journal of Econometrics, Elsevier, vol. 101(1), pages 123-164, March.

Arellano, M. (2003) Panel Data Econometrics, Oxford University Press, Oxford.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, Elsevier, vol. 68(1), pages 29-51, July.

Baggs J. (2009). International trade in hazardous waste. Review of International Economics 17(1) 1–16

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of econometrics 87, no. 1: 115-143.

Borgatti, S.P., Everett, M.G. and Freeman, L.C: Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies (2002).

Brooks, A., Wang S., Jambeck, J. (2018). The Chinese import ban and its impact on global plastic waste trade. Science Advances, vol. 4, no. 6.

Brown, A., Laubinger F., Börkey, P. (2022). Monitoring trade in plastic waste and scrap. OECD Environment Working Papers No. 194.

Campbell, M, (2022, November 11). Thailand Is Tired of the Noxious Fumes From Recycling Your Trash. *Bloomberg*. https://www.bloomberg.com/features/2022-thailand-plastic-waste-recycling-import-ban/?leadSource=uverify%20wall

Clapp, J. (1994). The toxic waste trade with less-industrialised countries: Economic linkages and political alliances. Third World Quarterly, 15(3), 505-518.

Clark, X., Dollar, D. and Micco, A. (2004). Port efficiency, maritime transport costs, and bilateral trade. Journal of Development Economics, 75: 417–450.

Commission on Growth and Development and International Bank for Reconstruction and Development (2008). The growth report: strategies for sustained and inclusive development. Retrieved from: https://digitallibrary.un.org/record/640214?ln=en

D'Amato, A., Iozzi A., Trovato, G. (2012). "The trade of polyethylene waste: prices or policies?," Environmental Economics and Policy Studies, Society for Environmental Economics and Policy Studies - SEEPS, vol. 14(4), pages 341-356

European Union: European Commission, Communication from the Commission to the European Parliament, the European Council and the Council, The European Economic and Social Committee and the Committee of the Regions: A European Strategy for Plastics in a Circular Economy, 16 January 2018, COM(2018) 28 final, available at: https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018DC0028&from=PT

Federal Statistical Office of Germany (Destatis). Genesis-Online. Waste Balance 2020. Retrieved from: https://www.destatis.de/EN/Themes/Society-Environment/Environment/Waste-Management/Tables/waste-balance-brief-overview-2020.html

Frankel, J. A., and Romer, D. (1999). Does Trade Cause Growth? The American Economic Review, 89(3), 379–399. http://www.jstor.org/stable/117025

Gardiner, B. (2021, April 1). *In Europe, a Backlash Is Growing Over Incinerating Garbage.* YaleEnvironment360. https://e360.yale.edu/features/in-europe-a-backlash-is-growing-over-incinerating-garbage

Geyer, R., Jambeck, J., Lavender Law, K: Production, use, and fate of all plastics ever made. Science Advances, vol. 3, no. 7 (2017).

Government of the Netherlands. (2020, April 4). Deposit on small plastic bottles to reduce street litter. https://www.government.nl/latest/news/2020/04/30/deposit-on-small-plastic-bottles-to-reduce-street-litter

Grigore, Mădălina E. (2017). "Methods of Recycling, Properties and Applications of Recycled Thermoplastic Polymers" Recycling 2, no. 4: 24. https://doi.org/10.3390/recycling2040024

Hausman, J. and McFadden, D. (1984) Specification Tests for the Multinomial Logit Model. Econometrica, 52, 1219-1240. http://dx.doi.org/10.2307/1910997

Higashida K, Managi S. (2014). Determinants of trade in recyclable wastes: evidence from commodity-based trade of waste and scrap. Environ. Dev. Econ. 19(2):250–70

Huang, Q., Chen G., Wang Y., Chen S., Xu L., Wang R. (2020). Modelling the global impact of China's ban on plastic waste imports. Resources, Conservation & Recycling 154 Article 104607 https://doi.org/10.1016/j.resconrec.2019.104607

Human Rights Watch. (2022). "It's As If They're Poisoning Us" The Health Impacts of Plastic Recycling in Turkey. Retrieved from https://www.hrw.org/report/2022/09/21/its-if-theyre-poisoning-us/health-impacts-plastic-recycling-turkey

Jain, A. (2017). Waste Management in ASEAN Countries: Summary Report. United Nations Environment Programme. https://www.unep.org/resources/report/waste-management-asean-countries-summary-report

Jambeck, J., Geyer, R., Wilcox, C., Siegler, T., Perryman, M., Andrady, A., Narayan, R., Lavender Law, K.(2015) Plastic waste inputs from land into the ocean. Science Advances, vol. 347, Issue 6223, pp. 768-771.

Joltreau, E. (2022). "Five Years after China's Plastic Import Ban: Have European Taken Responsibility?" Briefings de l'Ifri. French Institute of International Relations. Retrieved September 21, 2022. From https://www.ifri.org/en/publications/briefings-de-lifri/five-years-after-chinas-plastic-import-ban-have-europeans-taken

Kellenberg D. (2012). Trading wastes. J. Environ. Econ. Manag. 64(1):68–87

Kellenberg, D. (2015) The Economics of the International Trade of Waste (October 2015). Annual Review of Resource Economics, Vol. 7, Issue 1, pp. 109-125. http://dx.doi.org/10.1146/annurev-resource-100913-012639

Lai, O. (2022, November 26). China's Plastic Pollution Crisis: Causes and Solutions. POLICY & ECONOMICS POLLUTION – Earth.org. https://earth.org/china-plastic-pollution/

Lanza ST, Collins LM, Lemmon DR, Schafer JL. (2007). PROC LCA: A SAS Procedure for Latent Class Analysis. Struct Equ Modeling. 14(4):671-694. doi: 10.1080/10705510701575602 PMID: 19953201; PMCID: PMC2785099.

Lebreton, L., Andrady, A. (2019) Future scenarios of global plastic waste generation and disposal. Palgrave Commun 5, 6. https://doi.org/10.1057/s41599-018-0212-7

Lee, C. (2022). Plastic Atlas Japan Special Edition: A Closer Look at Japan's Plastic Waste Management. Heinrich Böll Stiftung. Retrieved from https://hk.boell.org/en/2022/05/30/plastic-atlas-japan-special-edition-closer-look-japans-plastic-waste-management

Mohamed. S. (2021) Use. Recycle. Repeat. The Peninsula. Retrieved from https://thepeninsulaqatar.com/article/05/12/2021/use-recycle-repeat

Nerland, I. L., Halsband, C., Allan, I., & Thomas, K. V. (2014). Microplastics in Marine Environments: Occurrence, distribution and effects. Retrieved November 23, 2021, from https://www.miljodirektoratet.no/globalassets/publikasjoner/M319/M319.pdf.

New South Wales Government (2018, November 28). *Response to the enforcement of the China National Sword Policy.* https://www.epa.nsw.gov.au/your-environment/recycling-and-reuse/response-to-china-national-sword

Nishio, A. (2021). When poverty meets climate change: A critical challenge that demands cross-cutting solutions. Development and a Changing Climate, World Bank Blogs. Retrieved from: https://blogs.worldbank.org/climatechange/when-poverty-meets-climate-change-critical-challenge-demands-cross-cutting-solutions

North Carolina Department of Environmental Quality (DEQ) (n.d.). Differences in Recyclability and Recycling of Common Consumer Plastic Resins. Retrieved December 12, 2021, from https://deq.nc.gov/conservation/recycling/plastic-bottles/additional-plastic-bottle-resources

Organization for Economic Co-operation and Development (OECD). (2018). Improving Plastics Management: Trends, policy responses, and the role of international co-operation and trade. Policy Perspectives. OECD Environment Policy Papers.

Organization for Economic Co-operation and Development (OECD). (2022). Global Plastics Outlook: Economic Drivers, Environmental Impacts and Policy Options, OECD Publishing, Paris, https://doi.org/10.1787/de747aef-en.

Pacini, H., Shi, G., Sanches-Pereira, A., da Silva Filho, A. (2021). Network analysis of international trade in plastic scrap. Sustainable Production and Consumption. 27: 203-217. https://doi.org/10.1016/j.spc.2020.10.027

Posnack, N. G. (2021). Plastics and cardiovascular disease. Nature Reviews. Cardiology, 18(2), 69–70. https://doi.org/10.1038/s41569-020-00474-4

Quinn, M. (2022, June 10). EPA aims to disburse $375M in waste and recycling funds from infrastructure bill by spring 2023. *Waste Dive.*

Resource Recycling. (2020). From Green Fence to red alert: A China timeline - resource recycling. Resource Recycling News. Retrieved November 23, 2021, from https://resource-recycling.com/recycling/2018/02/13/green-fence-red-alert-china-timeline/.

Sánchez, R. J. (2003). Port efficiency and international trade. Maritime Economics and Logistics, 5: 199–218

Secretariat of the Basel Convention. Basel Convention Plastic Waste amendments. Basel Convention. Retrieved November 23, 2021, from http://www.basel.int/Implementation/Plasticwaste/Amendments/Overview/tabid/8426/Default.aspx

Strohm, L. A. (1993). The Environmental Politics of the International Waste Trade. The Journal of Environment & Development, 2(2), 129–153. https://doi.org/10.1177/107049659300200209

The Nation (2022). Thai plastic pellet exporters “to gain” after Philippines halts safeguard probe. Retrieved November 30, 2022, from https://www.nationthailand.com/business/40016907

United States Environmental Protection Agency. (2022, November 15). Solid Waste Infrastructure for Recycling Grant Program. https://www.epa.gov/rcra/solid-waste-infrastructure-recycling-grant-program

Verma, R., Vinoda, K. S., Papireddy, M., & Gowda, A. N. S. (2016). Toxic pollutants from plastic waste- a review. Procedia Environmental Sciences, 35, 701–708. https://doi.org/10.1016/j.proenv.2016.07.069

Waldeck, S. (2022, September 19). Thailand announces total ban on plastic waste imports by 2025 to “protect country.” *Packaging Insights.* Retrieved from https://pi.cnsmedia.com/a/zCYt__UJKRs=

Wang, Chao, et al. "Structure of the global plastic waste trade network and the impact of China's import Ban." Resources, Conservation and Recycling 153 (2020): 104591. https://dx.doi.org/10.1016/j.resconrec.2019.104591

Wen, Z., Xie, Y., Chen, M. et al. (2021) China's plastic import ban increases prospects of environmental impact mitigation of plastic waste trade flow worldwide. Nat Commun 12, 425. https://doi.org/10.1038/s41467-020-20741-9

Wolf, M. J., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al. (2022). 2022 Environmental Performance Index. New Haven, CT: Yale Center for Environmental Law & Policy. epi.yale.edu

World Bank: GDP per capita (constant 2010 US$). World Development Indicators. https://data.worldbank.org/indicator/NY.GDP.PCAP.KD

World Bank: Trade (% of GDP). World Development Indicators. https://data.worldbank.org/indicator/ne.trd.gnfs.zs

World Bank: GDP Per Capita Growth (Annual %) - China, India, World. World Development Indicators. https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?locations=CN-IN-1W

World Bank. (2022). Solid Waste Management. The World Bank Brief. Retrieved from: https://www.worldbank.org/en/topic/urbandevelopment/brief/solid-waste-management

World Trade Organization (2017, October 3). *China's import ban on solid waste queried at import licensing meeting.* https://www.wto.org/english/news_e/news17_e/impl_03oct17_e.htm

Yoshida, A. (2021). China's ban of imported recyclable waste and its impact on the waste plastic recycling industry in China and Taiwan. J Mater Cycles Waste Manag 24, 73–82. https://doi.org/10.1007/s10163-021-01297-2

Zhao, C.; Liu, M.; Du, H.; Gong, Y. The Evolutionary Trend and Impact of Global Plastic Waste Trade Network. Sustainability 2021, 13, 3662. https://doi.org/10.3390/su13073662