PLASTIC TURKEY: INTERNATIONAL IMPACTS OF CHINA'S WASTE IMPORT BAN

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Abstract. Trade and environmental policies of large economies can have significant effects on the level and incidence of pollution and economic activity around the world. This paper studies the environmental and economic effects of China's ban on plastic waste imports. In recent decades, high-income countries have reduced their plastic waste burden by exporting it to lower-income countries, primarily China, often raising concerns over creation of waste havens in parts of the world where environmental regulation is weaker. Following environmental concerns at home, China banned key plastic waste imports in 2017. This paper shows that China's policy led to a diversion of trade that had repercussions for countries across the world. Turkey emerged as a major importer of plastic waste from high-income countries. We provide direct evidence that importers in Turkey gained economically from better access to plastic waste that could be recycled and re-used as inputs in production. But their gains did not outweigh the losses of domestic firms that generated plastic waste and were displaced by import competition after China's ban. These domestic waste generators became more likely to mismanage their plastic waste, including through burning or dumping in water bodies. Air pollution increased more in Turkish regions where they were located. We model the channels of waste recycling and virgin resource use in a gravity model of trade and the environment to quantify the global spillovers of environmental externalities and the welfare impacts of China's unilateral import ban policy. The ban generated aggregate emission savings through trade destruction effects in the world plastic waste market, but the economic and environmental burden was unequally distributed across countries.

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1. Introduction

Trade and environmental policies of large economies can have significant effects on the level and incidence of pollution and economic activity around the world. The relationship between environmental policy and globalisation has been a controversial subject, with concerns over a race to the bottom in environmental outcomes and policies as developing countries integrate with the world economy. Emerging markets, including China and India, that have integrated with the world economy have seen substantial increases in incomes as well as pollution levels in recent decades, and are enacting more stringent environmental policies to address domestic concerns over pollution. Being major players in the world economy, their policies have environmental and economic impacts across the world, and are more complex than the earlier lens of North-South trade. To understand these international spillovers, this paper examines the ban on plastic waste imports imposed by China in 2017 that led to a reorganisation of the world plastic waste market.

Global plastic production has increased dramatically since the 1950s, and it has generated large volumes of plastic waste.[1] Most plastic waste poses pollution problems that persist for a long time due to the slow rate of natural removal of plastic (Brooks, Wang, and Jambeck (2018), Geyer, Jambeck, and Law (2017), MacLeod, Arp, Tekman, and Jahnke (2021), Worm, Lotze, Jubinville, Wilcox, and Jambeck (2017)). The global challenges posed by various types of plastic waste to the environment, human health and biodiversity have led to their inclusion in the materials covered by the Basel Convention since 2019.[2]

High-income countries reduce their plastic waste burden by exporting it to developing countries. The ability to export waste to countries with cheaper, but often poorer waste disposal practices, has been a source of controversy and research at least as far back as the

[1]From 2 million metric tons (MMT) in 1950 to 322 MMT in 2015.

[2]https://www.basel.int/Portals/4/download.aspx?d=UNEP-CHW-PUB-Factsheets-Actions-PlasticWaste-2020.English.pdf. For example, UN Environment (2018) estimates that 99 percent of seabirds would have ingested plastic waste by 2050. New plastic material makes up 20 percent of virgin petroleum consumption and is expected to contribute 15 percent to global greenhouse gas emissions by 2050 (Ellen MacArthur Foundation 2016; Walker and McKay (2021)).

1980s when news hit of garbage ships from OECD ports attempting to dump their unapproved cargo in various low-income countries (Copeland (1991), Baggs (2009), Kellenberg (2012)). Since then, cheaper processing fees in emerging markets have led to a staggering rise in global waste trade.

Global exports of plastic waste increased by 817 percent between 1993 and 2016, and 87 percent of all exports have been shipped from high-income countries to developing countries (Brooks, Wang, and Jambeck (2018)). This has raised concerns over creation of waste havens in parts of the world where environmental regulations are weaker. The concerns have been exacerbated by the recent reorganisation of the world market in plastic waste, that has resulted in the plastic waste amendment to the Basel Convention.

In the 1990s, emerging markets, particularly China, found that ships could efficiently deliver waste from developed economies and that material could be drawn from this waste to be used for further production (Lee, Wei, and Xu (2020), Brooks, Wang, and Jambeck (2018)). Between 2010 and 2016, China had amassed an additional 10 to 13 percent of plastic waste through imports. While recyclable material could be drawn from the imported waste, unused material added to China's already burgeoning problem of managing domestically-generated waste. Environmental and health concerns over processing and disposal became more salient in China over time, particularly after its winter haze in 2013. The Chinese government tightened a number of air pollution regulations including permits and targets for activities emitting volatile organic compounds (Li and Takeuchi (2023)). In 2017, it enacted a far-reaching policy to only allow waste imports that passed very stringent contamination criteria into the country. This policy, known as "Operation National Sword" (ONS), led to a collapse in waste imports into China, and immediately led to calls for global action to prevent the displaced waste from potentially finding its way to nations with weaker regulations (Brooks, Wang, and Jambeck (2018)).

The ONS policy presents a stark test case to understand the relocation of economic activity and pollution arising from unilateral policy action. The policy clearly had bite - it amounted to a complete collapse of waste imports into China which made up more than half of all world imports (Brooks, Wang, and Jambeck (2018)). The shakeup of the global market that resulted could have improved global waste management had the displaced imports stayed back in their source countries or moved to third countries with more stringent environmental regulations. Or, it could have resulted in a deterioration, had the displaced waste got diverted to third countries that mismanaged it more. As it turned out, the displaced waste imports did find their way to other emerging market destinations (Martin, Oliveira, Oliveira, and Bezerra (2021), Wen, Zou, Liu, Huang, Evrendilek, Yan, Li, and Liu (2021)). But we know little about the economic and environmental effects from the trade diversion that resulted from China's ban.

Research on these effects has been limited by the paucity of direct evidence, both in trade in waste and more generally in the literature on pollution-generating activities. While trade data provides granular information on international flows, it is often hard to measure domestic responses in pollution-generating activities and the overall consequences for social welfare (Kellenberg (2015)). To make progress, we focus on Turkey which emerged as a key "dumping ground" for waste generated in advanced economies after the China ban (Interpol (2020), Human Rights Watch (2022)).[3] A first observation is that despite the sharp bite of the policy, the pollution haven hypothesis finds little support because Turkey was not amongst countries with the highest shares of mismanaged waste globally. This turns out to be a summary observation because with multiple countries in an integrated global economy, the pollution haven hypothesis is more subtle. Under the pollution haven hypothesis, tightening environmental policy in one country causes production of the polluting activity to relocate to other countries with weaker environmental policy.[4] Polluting activities leaving one country may not move to a country with the weakest environmental policy. And in the current context, Turkey was not the worst but it mismanaged more of its waste than China before

[3]See hrw.org/report/2022/09/21. Also see Liu (2021), deframedia.blog.gov.uk/2020/06/26, theguardian.com/global-development/2022/sep/21 and greenpeace.org.uk/news/wasteminster-downing-street-disaster.

[4]This definition is taken from Brian Copeland's 2013 lecture notes on the pollution haven hypothesis in a multi-country setting.

the policy - 47 percent of plastic waste was mismanaged in Turkey compared to 25 percent in China in 2016 (Law, Starr, Siegler, Jambeck, Mallos, and Leonard (2020)).

Firm-level customs data show a notable increase in Turkish imports of plastic waste banned by China after 2017 (relative to similar products not subject to the ban). The vast majority of importers were manufacturing firms that recycled the plastic waste as inputs in their production process. These firms gained access to cheaper imported plastic waste material which enabled them to reduce their production costs and to increase their sales and domestic market share. As importers gained access to better quality plastic waste from abroad, they no longer wanted to buy as much of it from domestic firms that generated the plastic waste products banned by China. These domestic plastic waste suppliers experienced a decline in their sales (relative to other firms).

Trade data records plastic waste at a finely disaggregated product level, but domestic waste generation and management are rarely observable. Utilizing unique data on waste disposal of Turkish firms, we provide direct evidence that China's waste ban hampered domestic waste management by generating firms, leading to elevated pollution levels in Turkish regions where they are concentrated. After the China ban, domestic firms in Turkey that generated ONS-affected plastic by-products faced greater competition from waste imports. These domestic firms became less likely to recycle their waste. In fact, they became more likely to mismanage it by burning or dumping it in water bodies. And regions in Turkey that were more exposed to these domestic plastic waste generators experienced higher pollution levels after the China policy, relative to less exposed regions.

Building on the empirical findings, we generalise the workhorse model of trade and the environment to externalities from waste generation and management (see Shapiro (2016) and Shapiro and Walker (2018)). The model conceptualises the distinction between waste and other pollution-generating activities through the ability to recycle waste. In line with a gravity model of trade, it provides a mapping between trade outcomes and welfare, with the addition of recycling among the sufficient statistics to infer welfare. Along with changes in waste trade, global and national welfare impacts depend on three statistics: (i) the change in mismanagement of locally produced waste, (ii) the change in the usage of virgin resources that are replaced through recycling waste, and (iii) the degree of pollution generated from waste recycling, waste mismanagement and virgin resource extraction. The first channel is similar to the choice of installing abatement technology in the trade and environment literature. Our analysis enables its direct estimation for waste-generating firms in Turkey, and its inference from satellite data for other countries. The second channel makes waste different from pollution-generating activities, such as transport, that emit pollutants which cannot be recycled to conserve virgin resources. We infer this from substitutability between primary plastic production and waste imports. The third channel is the relative degree of externalities generated from each waste activity and these are calibrated to emission factors from the natural sciences literature.

The model enables an examination of welfare effects through economic and environmental channels. Importantly, it provides market clearing conditions to pin down aggregate effects from estimates of relative effects in the causal difference-in-differences analysis of revenues, waste imports and virgin resource use. The main finding is that China's unilateral ban had a substantial trade destruction effect that reduced emissions from waste mismanagement in China, and resulted in global emission savings. But the economic and environmental burden was unequally distributed across countries. For Turkey, we find that total incomes fell because domestic plastic waste suppliers lost out to import competition, and waste mismanagement increased. Turkey experienced negative economic and environmental consequences from the China ban. More generally, exporters and third countries that received the displaced waste imports after the China ban had worse environmental outcomes that were not fully offset by savings from reduced virgin resource use.

Related Literature.

Our paper makes contributions to four key areas of existing literature. We build on recent advances combining trade with environmental externalities to examine the welfare impacts of a large unilateral policy (e.g. Shapiro (2016), Shapiro and Walker (2018)). Within this literature, a number of studies provide empirical support for pollution haven effects arising from differences in environmental policy stringency across countries, but the pollution haven hypothesis, of environmental policy differences determining the location of pollution-generating activities, has been empirically elusive because of various factors such as capital abundance that are correlated with environmental stringency and trade flows. In early work, Copeland and Taylor (2003, 2004) argue that pollution haven effects could be more precisely measured in a multi-country setting, and we exploit such variation of a more stringent environmental policy in one country to determine shifts in pollution-generating activities to third countries.

A multi-country setting provides new insights into the global effects of unilateral policy. We find the channel of reduced domestic abatement in third countries to be empirically relevant, and the model suggests that it is the main driver of the increased environmental burden faced by Turkey after the ban. Previous work has mostly focused on the exporting channel of firm emissions and the more limited evidence on importing has typically suggested increase abatement through access to intermediate imports or escape competition effects from technology upgrading under increased importing (see Cherniwchan, Copeland, and Taylor (2017) for a review, and Barrows and Ollivier (2018), Gutiérrez and Teshima (2018) for importing). We instead find evidence for the "distressed and dirty industry hypothesis" of reduced abatement expenditures among firms that are negatively affected by imports (Cherniwchan, Copeland, and Taylor (2017), also see Forslid, Okubo, and Ulltveit-Moe (2018)).

Waste trade has a long tradition of research and several papers consider its welfare consequences theoretically (e.g. Copeland (1991), Levinson (1999), Lee, Wei, and Xu (2020)). Prior empirical studies, such as Bunn and Blaney (1997), Baggs (2009), Kellenberg and Levinson (2014) and Thakur (2022), highlight patterns in waste trade, particularly the tendency for waste to flow from nations with more stringent environmental regulations to those with more lenient ones (Pollution Haven effects and hypothesis in waste). We confirm the finding of waste exports by advanced nations to more environmentally lax destinations in our setting. In light of the comprehensive review of Kellenberg (2015), we advance the literature in key dimensions identified as avenues for future research - the microeconomic upstream-downstream relations (that we pin down with Turkish data), substitutability between virgin resources and recyclables (that are important for the welfare calculation in our study), and direct evidence of social welfare effects of waste trade (that we explore through pollution and incomes). The review notes the stark conclusion of Ray (2008) that the environmental costs associated with international trade in waste has outweighed any potential economic benefits for Asia and points to the need for evidence to examine this more thoroughly. We make progress on this front by evaluating the economic and environmental effects of a large policy change. This is closest in spirit to Tanaka, Teshima, and Verhoogen (2022) which also focuses on the welfare consequences of an international environmental policy - birth outcomes in Mexico after the tightening of US air quality standards for lead.

The paper is also related to a large literature on the economics of waste that has studied a number of issues such as optimal recycling policy and impacts of cleanup of waste sites, primarily in developed countries (see Kinnaman (2006), Fullerton (2024) for reviews, and Viscusi, Huber, and Bell (2011), Currie, Greenstone, and Moretti (2011) for examples). Research on emerging and developing economies is a recent but growing literature that has examined the rise in waste and domestic waste management solutions (see The World Bank (2018) for a review, Chong, Karlan, Shapiro, and Zinman (2015), Dhingra and Machin (2024) for examples).

Finally, our study contributes to an emerging literature on China's pollution policies (e.g. Greenstone, He, Li, and Zou (2021)) and specifically to new work on China's ONS policy, that we discuss in more detail in relevant sections later. Previous research on China's waste import ban has provided evidence for better environmental and health outcomes within China, demonstrating notable improvements in air quality in coastal areas (Li and Takeuchi (2023); Shi and Zhang (2023); Unfried and Wang (2022)). We account for these in our global assessment, and show that the ban had the opposite consequences in some other parts of the world.

The rest of the paper is structured as follows. Section 2 describes China's ONS policy and its trade diversion impacts. Section 3 presents empirical findings at the microeconomic level of importing and waste-generating firms in Turkey, along with regional evidence on pollution. Section 4 introduces a theoretical framework to explain key findings and enable calibration of aggregate welfare impacts of the policy. Section 5 quantifies the economic and environemental impacts of the policy. Section 6 concludes.

2. Policy Background: Operation National Sword

In the 1990s, China's booming manufacturing sector led to a high demand for scrap materials as feedstock for its industries. As a result, many developed countries, especially in North America and Europe, began exporting large quantities of waste materials of paper, plastics and metals to China for recycling. These materials were often considered low-value or difficult to process domestically.

China's role as a global recycling hub led to the establishment of informal recycling and processing facilities, where imported waste materials were sorted, processed, and the residuals were disposed of. Over time, however, concerns grew about the environmental and health impacts of these practices. Many recycling operations lacked proper regulations and infrastructure, leading to pollution, groundwater contamination, and health hazards for workers.

The majority of these concerns were around the substantial influx of waste into China, often contaminated with food, garbage, and other pollutants. While paper, plastic, and metal were valuable to China, their recyclability was compromised if they arrived mixed with contaminants. To address this, China initiated "Operation Green Fence" in February 2013, a stringent inspection effort aimed at reducing contaminated waste imports. While the value of plastic waste trade did not recover to levels seen before Green Fence in China, it remained significant in 2016. China imported 56% of the world's plastic waste in 2016 and the inspection policy gave way to a more comprehensive step after 2016, which affected the entire world market in waste (Brooks, Wang, and Jambeck (2018), Tran, Goto, and Matsuda (2021).

In July 2017, China implemented "Operation National Sword". This policy banned 24 types of solid waste imports, including certain plastics and paper, while imposing strict quality standards on others. China ceased imports of banned products as illustrated in Panel A of Figure 2.1. The figure shows China's annual imports of plastic scrap and waste products that were banned by China (referred to as "treated" products) in 2017. The imports of these banned products are represented in red, while the trajectory of China's imports of other products falling within the same 2-digit HS code is shown in blue. To provide clarity, both flows have been normalized to their respective levels in 2013. Notably, after 2017, there is a significant decline in the imports of treated products, in stark contrast to the relatively stable import pattern observed for other products within the same 2-digit HS code.[5]

After China's waste import ban, Turkey became one of the main destinations for plastic scrap and waste products that were subject to the ONS policy. Panel B of Figure 2.1 illustrates the evolution of the (normalized) value of Turkish imports for treated products in red, plotted against that of other products within the same 2-digit HS code as the treated ones in blue. The pattern observed for treated products aligns with the hypothesis that China's ban on scrap and waste products might have prompted exports of such products to shift to other emerging markets.

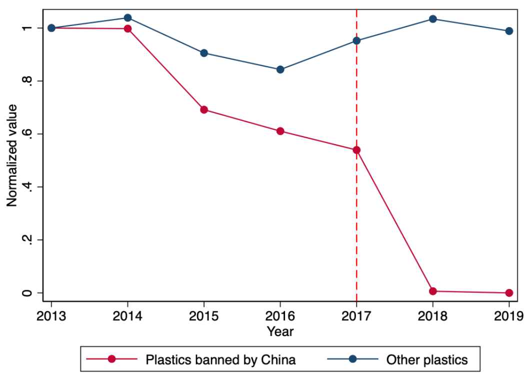
To examine this more systematically, we conduct a difference-in-differences analysis in Figure 2.1. We estimate the following equation:

$$
\begin{aligned}
(2.1) \qquad \frac{Trade_{podt}}{\sum_{d'} Trade_{pod't}} &= \beta_1 Post_t * \text{Banned}_{po} * \text{CHN}_d + \beta_2 Post_t * \text{Banned}_{po} \\
&+ \alpha_{pod} + \alpha_{odt} + \alpha_{pdt} + e_{podt},
\end{aligned}
$$

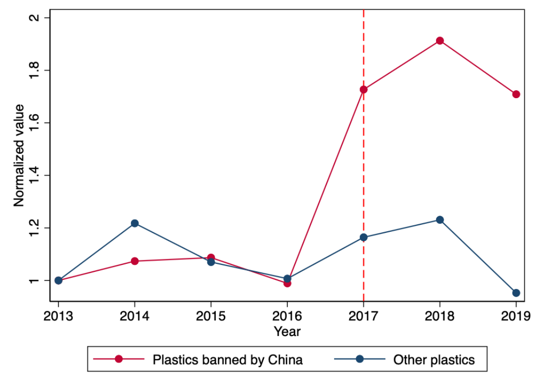
where the dependent variable is the share of exports of product p by origin country o to destination country d in year t. Banned_{po} indicates the set of China-banned plastic waste products and origin countries which had exported such products to China in 2015/2016,

[5]Subsequent to July 2017, China progressively introduced additional restrictions on waste trade. Notably, by December 31, 2017, a new contamination standard was set, rejecting waste imports with contamination rates exceeding 0.5%. China also successively banned 16 categories of waste products by the end of 2018, with plans to ban another 16 by the close of 2019.

Figure 2.1. Imports of plastic scrap and waste products banned by China



(A) China (HS6 product level)



(B) Turkey (HS8 product level)

i.e. before the implementation of ONS. The sample covers the years between 2013 to 2019. $Post_t$ takes on the value one for years after 2017, and zero otherwise. With the inclusion of product-origin-destination fixed effects (α_{pod}), we exploit variation within a triplet over time arising from the implementation of China's policy in 2017. We further account for time-varying factors at the level of product-destination pairs with the inclusion of α_{pdt}, and time-varying factors that affect trade from country o to country d. If the ONS policy was binding, then we would expect a negative estimate of β_1 because imports of banned plastic waste products to China would fall. Similarly, a positive estimate for β_2 would show that the policy led to the diversion of plastic waste trade to countries other than China.

Results obtained from estimating equation (2.1) are presented in the first column of Table 1. The coefficient on the triple interaction term, which indicates whether the Chinese policy was binding, is estimated to be negative and statistically significant. Accordingly, existing exporters of plastic waste products subject to the ONS policy reduced their exports to China by 16 percent after 2017, relative to other products and origin countries. Evidence presented in the table also points to trade diversion: existing exporters of plastic waste products to China diverted their exports to other destinations after the introduction of the ONS policy, relative to other products and origin countries. The second column presents results obtained from a more stringent specification which also controls for time-varying origin-product level

TABLE 1. Change in Trade in Plastic Waste:

Dependent Variable: $\frac{Trade_{podt}}{\sum_{d'} Trade_{pod't}}$	(1)	(2)
$Post_t * \text{Banned}_{po} * \text{CHN}_d$	-0.173a	-0.173a
	(0.014)	(0.014)
$Post_t * \text{Banned}_{po}$	0.0011c	
	(0.00007)	
R^2	0.692	0.692
# observations	9689965	9689965
Fixed Effects:		
Destination×Product×Time	Yes	Yes
Origin×Destination×Time	Yes	Yes
Destination×Origin×Product	Yes	Yes
Origin×Product×Time	No	Yes

Note: This table shows the results from estimating equation 2.1, where the dependent variable is the share of exports of product p by origin o to destination d at year t. The coefficient of interest is on the triple interaction term: $Post_t$*$Banned_{po}$*CHN_d. Where $Post_t$ is a dummy variable indicating 1 if year is greater than 2017, $Banned_{po}$ indicates the set of China-banned plastic waste products from initial exporter o, and CHN_d takes a value of 1 if the destination country is China. The sample covers the years 2013-2019. Letters indicate statistical significance: a indicates p<0.01, b indicates p<0.05, and c indicates p<0.10.

factors. The estimated coefficient on the triple interaction $Post_t * \text{Treat}_{po} * \text{CHN}_d$ remains robust to the inclusion of these additional fixed effects, providing further confidence in the effectiveness of the Chinese waste ban.[6]

China's decision to restrict waste imports had wide-ranging effects, including changes in waste management strategies in exporting countries, as discussed above. It highlighted the need for more sustainable waste management practices, improved recycling technologies, and international cooperation to address the challenges posed by waste trade. In the next section, we delve deeper into understanding how this policy change affected firm-level decisions in a third country. We focus on Turkey as a case study for two reasons. First, Turkey became one of the main destinations for plastic waste as illustrated in Figure 2.1. Second, comprehensive imports and waste data from Turkey allow us to directly examine the economic

[6]Figure A2 in Appendix shows no evidence of pre-trends in exports of treated products to China.

and environmental effects on firm-level production, input sourcing, and waste management practices.

3. Empirical Analysis

We start our analysis by examining whether China's ban on the import of specific plastic waste products resulted in a redirection of these waste products to Turkey using detailed customs data. We index these importing firms with i. This is followed by an examination of the effects of the policy ban on domestic generators of plastic waste in Turkey. To distinguish these firms from importing firms, we index them with k. And we also examine the performance of importers and domestic generators after the ban, followed by air pollution in ban-exposed regions of Turkey.

In the empirical analysis, we rely on three rich micro-level datasets from Turkey. Turkish Customs data provides information on annual exports and imports, disaggregated by firm, (destination/origin) country, and 8-digit Harmonized System (HS) product code. These are utilised to examine the diversion of waste trade to Turkey after the ONS policy. Firm registry and corporate financial statements contain firms' annual gross sales, material costs, and wage costs, as well as their employment, location (province), and industry of operation (4-digit NACE (the Statistical Classification of Economic Activities in the European Community) code). These enable a study of the economic effects of the policy on waste importers and the indirect effects on firms that use plastic waste as an input. The final data on the production and management of domestically produced waste in Turkey is derived from the Manufacturing Industry Waste Statistics survey. This survey, conducted biennially, covers every formal firm with more than 50 employees, along with a representative sample of smaller firms. These firms are asked to report their annual waste production and the disposal methods employed (such as selling, reusing, dumping, burning, etc.), all categorized by waste type, defined by the European Waste Classification for Statistics (EWC-Stat). We then classify these waste products as banned from China or not by concording EWC-Stat and HS6.

3.1. **Importing Firms' Responses to ONS in Turkey.** The trends depicted in Figure 2.1 indicate a substantial increase in Turkish imports of scrap and waste products banned by China after 2017. But they do not account for time invariant factors at the product-origin level or changes in time varying country-specific factors that could correlate with the ban. To address this concern, we conduct a standard event study using the following specification:

$$\ln \text{Imports}_{pot} = \sum_{l=2013}^{2019} \beta_l D_t^l * \text{Banned}_p + \alpha_{po} + \alpha_{ot} + e_{pot}, \tag{3.1}$$

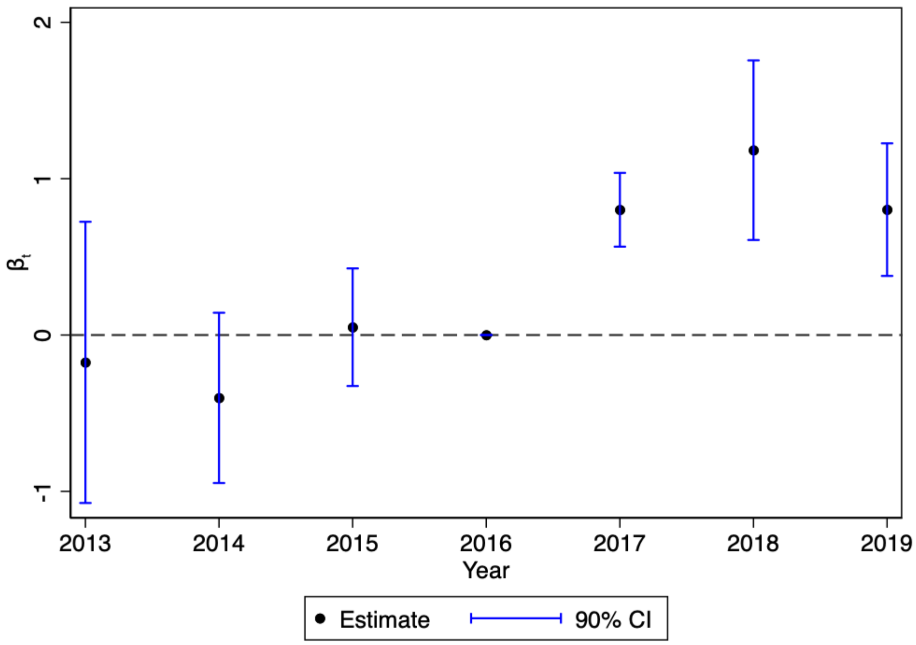
where Imports_{pot} denotes the value of imports of 8-digit HS product p from country o in year t. The sample covers the years from 2013 to 2019. We are interested in the estimates of β_l which measure the annual change in the imports of plastic waste products subject to the ONS policy in year l relative to the sample average at the level of product-origin country and controlling for time-varying factors affecting imports at the level of origin countries. Figure 3.1 presents point estimates for β_l, along with their 90% confidence intervals. The year preceding the Chinese ban on scrap and waste products, 2016, is excluded and serves as the reference year. In line with the pattern observed in Figure 2.1, Turkish imports of products banned under the ONS in 2017 significantly increased after 2016 and remained high until 2019.

Figure A3 in the Appendix conducts the same analysis at a finer level of firm-product-origin-time import changes to account for firm-specific demand shifts and finds that firms increased their imports of banned products after the ONS policy. Furthermore, Figure A4 in the Appendix decomposes the observed change in the value of imports into quantities and unit values and finds that the quantity of treated products rose (Panel A) after 2017 while their unit prices declined (Panel B).[7] The ONS policy reduced global demand for the banned products. Prices for the banned products fell in international markets, making them more attractive to Turkish firms that increased their imports of the products banned by China.[8]

[7] In Figure A5, we present evidence indicating a downward trend in quality-adjusted prices. This observation implies that the observed decrease in unit prices cannot be attributed to a reduction in quality.

[8] We also test whether Turkey only redirects these plastic waste products to other countries. As presented in Figure A6. the results indicate no discernible increase in the exports of the China-banned plastic products.

Figure 3.1. Event Study: Value of Imports



Note: The figure plots the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in B.1 in addition to the 90% confidence intervals. The dependent variable is the (log) value of imports of Turkish firm f of product p from origin o at year t. The coefficient of interest is on an interaction term of year dummies D_t^l and $Treat_p$. Where $Treat_p$ indicates the set of China-banned plastic waste products. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

To mitigate potential errors in our findings stemming from the misclassification of products, we randomly allocate treatment status to 8-digit HS products within their corresponding 4-digit HS codes and then re-estimate Equation B.1. This procedure is replicated 250 times. The outcomes of this robustness check, depicted in Figure A7, reveal that the distribution of estimates from the 250 simulations are clustered around zero, whereas our primary estimate is slightly larger than unity. This reinforces the reliability of the main findings and shows that results are not driven by product misclassification following the ban.

3.1.1. *Waste management by domestic firms.* In the previous section we showed that following China's ban in 2017, firms in Turkey gained access to lower cost imports of plastic waste. Firms that incorporate recyclable plastic waste into their production processes face a decision: whether to source the material domestically or import it.

We use firm and product level domestic waste survey data to examine how the China ban affected domestic waste management in Turkey. The survey is conducted every two years. It covers all firms with at least 50 employees, as well as a representative sample of smaller firms. Each participating firm is asked about the annual quantity and type of waste it generates, as categorized by the EWC-Stat classification. Importantly, the survey records the waste management method of each firm, and this includes selling waste, re-using waste or mismanaging waste.[9]

We manually concord the EWC-Stat product codes to 6-digit HS codes to determine which domestic firms generate plastic by-products that were banned under China's ONS policy. We can therefore test whether domestic firms faced more import competition in their waste sales from the policy by estimating the following specification:

$$\mathrm{X}_{kpt} = \sum_{l=2012}^{2020} \beta_l D_t^l * \mathrm{Banned}_p + \alpha_{kt} + \alpha_p + \epsilon_{kpt}. \tag{3.2}$$

The dependent variable is the share of firm k's volume of waste product p that is sold at time t. Banned_p is a dummy variable indicating whether waste product p is banned under China's ONS. We control for time varying firm-specific factors and time invariant product specific factors.

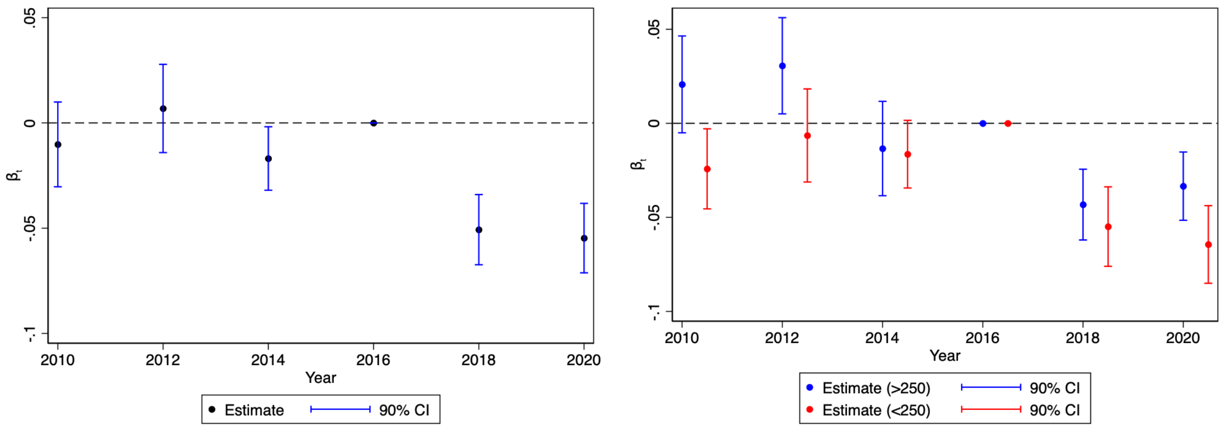
Estimates presented in Panel (A) of Figure 3.2 suggests a reduction in the share of waste banned by China in the total volume of waste sold by the firm. This is consistent with a fall in the demand for domestic waste as Turkey gained access to cheaper imports. Panel (B) of Figure 3.2 shows heterogeneity in sales by firm type. The decline in domestic waste sales occurs among smaller firms (with fewer than 250 employees) but not for larger firms. This suggests that larger firms were more able to compete with the heightened competition in recyclable waste compared to smaller firms.

Domestic firms sold less of their waste products and this raises the question of what happened to the waste that they were unable to sell. To understand this, we change the dependent variable of Equation 3.2 to the share of firm k's volume of waste product p that is

[9] Mismanaged waste is burned in open air, dumped into water bodies (rivers, seas, etc.), or dumped into open land.

Figure 3.2. Event study: Waste Sales of Firms in Turkey

(A) Overall (B) By Size



Note: These figures plot the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.2. Each observation is at the firm-product-year level. The dependent variable is the share of waste that firm k sells of waste product p at year t. Coefficients on the interaction between year dummies D_t^l and an indicator for waste products banned by China $Banned_p$ are plotted in the figure. Panel (A) shows the estimates of the regression on all manufacturing firms, whereas Panel (B) presents the estimates of the same regression on firms greater than 250 employees (blue) and less than 250 employees (red) separately. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

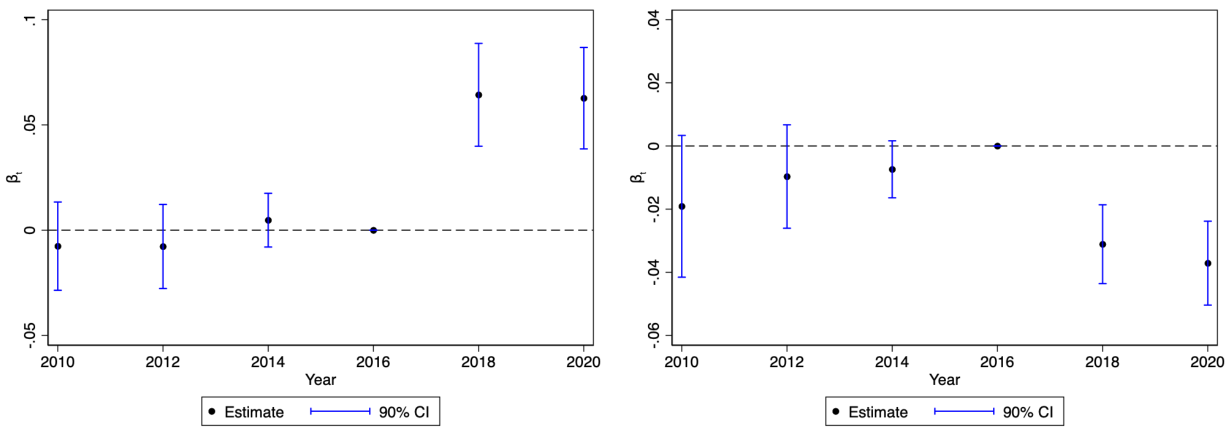
mismanaged or that is not re-used at time t. Mismanaged waste encompasses waste that is either deposited into uninspected storage facilities, discharged into rivers, streams, or lakes, dumped onto open land, or incinerated solely for disposal purposes rather than for energy generation in controlled chambers. Re-used waste, on the other hand, consists of waste that is sold or recycled for the purpose of reuse.[10]

Figure 3.3 shows that following the China ban, waste products banned by China were more likely to be mismanaged and not re-used by Turkish waste generating firms. As before, we also explore firm heterogeneity in the management of waste and find that the increase in mismanaged waste and not re-used waste occurs among smaller firms. Imported waste displaced domestic waste generated by smaller firms. This can be explained by importing firms upgrading to better quality and now cheaper waste from abroad. Waste must undergo

[10] The remainder category includes waste that is neither mismanaged nor reused. For example, plastic waste that is stored in an inspected facility is not categorized as mismanaged waste, and also not categorized as being re-used.

FIGURE 3.3. Event study: Management of Waste by Firms in Turkey

(A) Mismanaged Waste (B) Not re-used Waste



Note: These figures plot the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.2. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. Coefficients on the interaction between year dummies D_t^l and an indicator for waste products banned by China $Banned_p$ are plotted in the figure. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

separation and cleaning for it to be recycled as an input. By international law, imported waste must already have undergone some amount of separation and cleaning before it is exported. It is therefore likely to be a better quality input that displaced lower quality domestic waste but did not have substantive displacements effects on higher quality domestic waste.

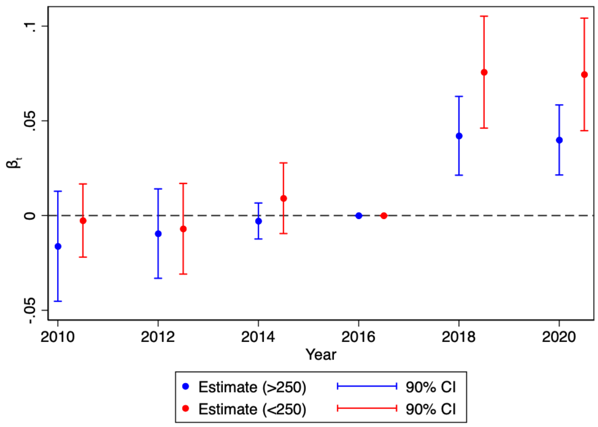
We demonstrated that following the China ban, domestic firms mismanaged a greater share of the waste they generated and re-used a smaller share of their waste. To ensure that these findings are not influenced by any changes in the total waste production (or the scale of waste generation) of these firms, we estimate the following specification:

$$\text{Total waste}_{kt} = \sum_{l=2012}^{2020} \beta_l D_t^l * \text{Exposure}_k + \alpha_k + \alpha_{s(k)t} + \alpha_{r(k)t} + \epsilon_{kt} \tag{3.3}$$

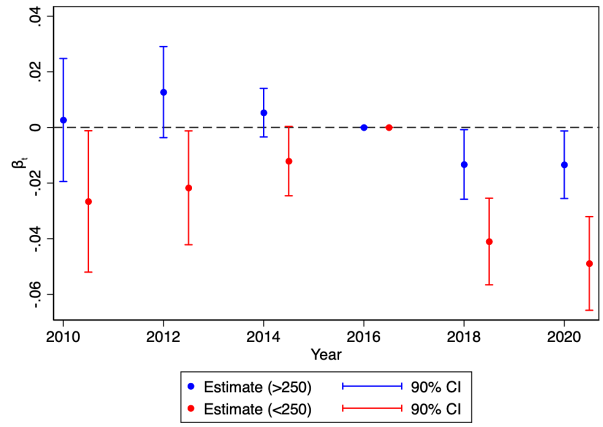
where the dependent variable is the total amount of waste generated by firm k at time t. $Exposure_k$ is the share of China-banned waste products in the total waste generated by

FIGURE 3.4. Event study: Management of Waste by Firms in Turkey, By Firm Size

(A) Mismanaged Waste



(B) Not re-used Waste



Note: These figures plot the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.2. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. Coefficients on the interaction between year dummies D_t^l and an indicator for waste products banned by China $Banned_p$ are plotted in the figure. The results are presented separately for two different samples of the data: (i) sample including firms with greater than 250 employees in blue, and (ii) sample including firms with less than 250 employees in red. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

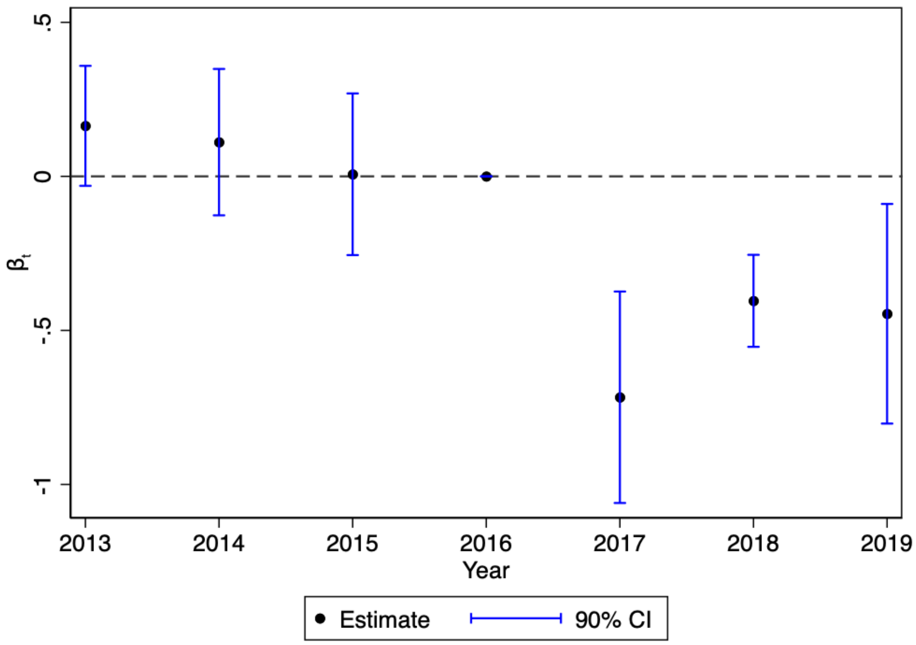
firm k before the ONS policy. $s(k)$ and $r(k)$ denote the sector and region (province) of firm k. Figure A9 plots the estimates, β_l, which do not show any noticeable change in the total waste generated by firms that were more intensive in ONS-banned waste products. Therefore, the main finding is a change in domestic waste mismanagement after the surge in import competition, and not a change in the scale of waste generation that could be driven by upstream plastic product demand.

3.1.2. *Purchases from Domestic Waste Producers.* Leveraging firm-product level waste survey data, we observed a decline in the sales share of domestically-generated waste products that were banned by China, as illustrated in Figure 3.2. We now formally test for reduced sales of domestic waste with firm-to-firm sales data, based on Turkish VAT declarations, by estimating the following specification:

$$
\begin{aligned}
\ln(val_{i(s),s',t}) &= \sum_{l=2013}^{2019} \beta_l D_t^l * \text{Exposure}_i * \text{Exposure}_{s'} + \alpha_{it} + \alpha_{ss't} \\
&+ \alpha_{is'} + e_{i(s),s',t} \qquad (3.4)
\end{aligned}
$$

The dependent variable is the logarithm of purchases by buyer firm i in the 4-digit NACE industry s from industry s' in year t. $Exposure_i$ is a continuous variable indicating the share of firm i's usage of China banned plastic products in its inputs in 2016, it is calculated as the share of ONS-banned plastic imports in total input costs of (wages + domestic purchases + imports). $Exposure_{s'}$ represents the share of plastic waste sold by industry s' in total plastic waste generated in Turkey in 2016. It serves as a continuous metric indicating the likelihood of sector s' engaging in the sale of plastic waste. This measure is derived by aggregating data from the plastic waste survey to determine the percentage of total plastic waste sold by each sector. This industry-level exposure measure is derived from the waste management survey data. We include firm-year fixed effects α_{it} which, among other factors, control for changes in firm scale and thus total input purchases over time. We also include firm-source industry and time-varying source-destination industry fixed effects. Therefore, identification comes from variation across supplying industries within a buyer firm and year cell.

FIGURE 3.5. Purchases from Domestic Waste Producers



Note: The figure plots the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.4. Each observation is at the firm-sector-year level. Coefficients on the interaction between year dummies D_t^l and the product of exposures are plotted in the figure. $Exposure_i$ is a continuous variable indicating the share of firm i's usage of China banned plastic imports in its inputs (wages + domestic purchases + imports) in 2016. $Exposure_{s'}$ represents the share of plastic waste sold by industry s' in total plastic waste generated in Turkey in 2016. The sample covers the years from 2013 to 2019.

The β_l coefficients, along with their 90% confidence intervals estimated from equation (3.4), are illustrated in Figure 3.5. These results demonstrate a significant shift of purchases away from major domestic plastic waste producers following the ONS ban. Therefore Turkish buyers of plastic waste substituted domestic plastic waste inputs with imported varieties.

3.1.3. *Effects on Importing Firms' Performance.* To investigate whether the importers of China-banned products benefited from the surplus supply of global waste, we examine their economic performance after the ban. More than 70 percent of firms importing China-banned products belong to the manufacturing sector, and just 6% are waste management companies.

Notably, only less than 10 percent of the importers of China-banned products are suppliers to waste management companies (see Figure A8). This implies that the majority of imported waste is directly utilized as inputs by manufacturing firms rather than being processed by waste management companies. It might therefore be expected that better access to material inputs would improve the economic performance of manufacturing firms and we estimate the following specification to examine this:

$$X_{it} = \sum_{l=2013}^{2019} \gamma_l D_t^l * \text{Exposure}_i + \sum_{l=2013}^{2019} \delta_l D_t^l * \text{Employment}_i + \alpha_i + \alpha_t + \epsilon_{it} \tag{3.5}$$

where X_{it} is the outcome of interest for firm i at time t such as sales, market share, and firm costs. $Exposure_i$ is a continuous variable indicating the share of firm i's usage of China banned plastic products in its inputs in 2016, and $Employment_i$ is the number of employees in firm i in 2016.[11] The specification controls for firm fixed effects and year fixed effects. The control group consists of importers of other products within the same 4-digit NACE industry as the importers of banned 8-digit HS plastic products.

First, we test whether reduced prices of imported plastic inputs led to a reduction in firms' costs, measured in terms of the ratio of material costs to sales or wages to sales. As illustrated in Figure 3.6, following China's ban, firms that relied more heavily on imports of China-banned products as inputs experienced a reduction in their expenditures on material inputs and wage payments relative to their sales though the estimates are not very precisely estimated. Firms substituted away from relatively costly domestic inputs towards cheaper imported waste inputs. This also resulted in lower labour costs, likely because less sorting and processing was needed for imported plastic waste.[12]

Our next test investigates whether firms that more intensively imported products that were banned by China experienced a differential change in their sales or profit margins. We estimate the specification in equation (3.5) with domestic sales and industry (4-digit NACE

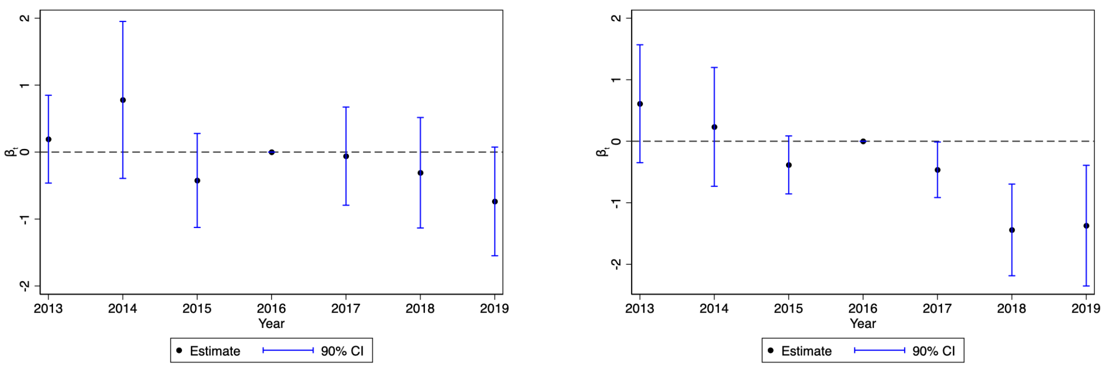
[11]Input costs are constructed as the sum of wage payments, purchases from domestic firms based on the VAT data, and imports.

[12]This result is in line with Castro Vincenzi and Kleinman (2020), where they show causal evidence for the negative effect of materials prices on the labor share. Hummels, Jørgensen, Munch, and Xiang (2014) also shows that offshoring decreases low-skilled wages.

Figure 3.6. Effects of ONS on Importer-level Costs

(A) Material costs over sales

(B) Wages over sales



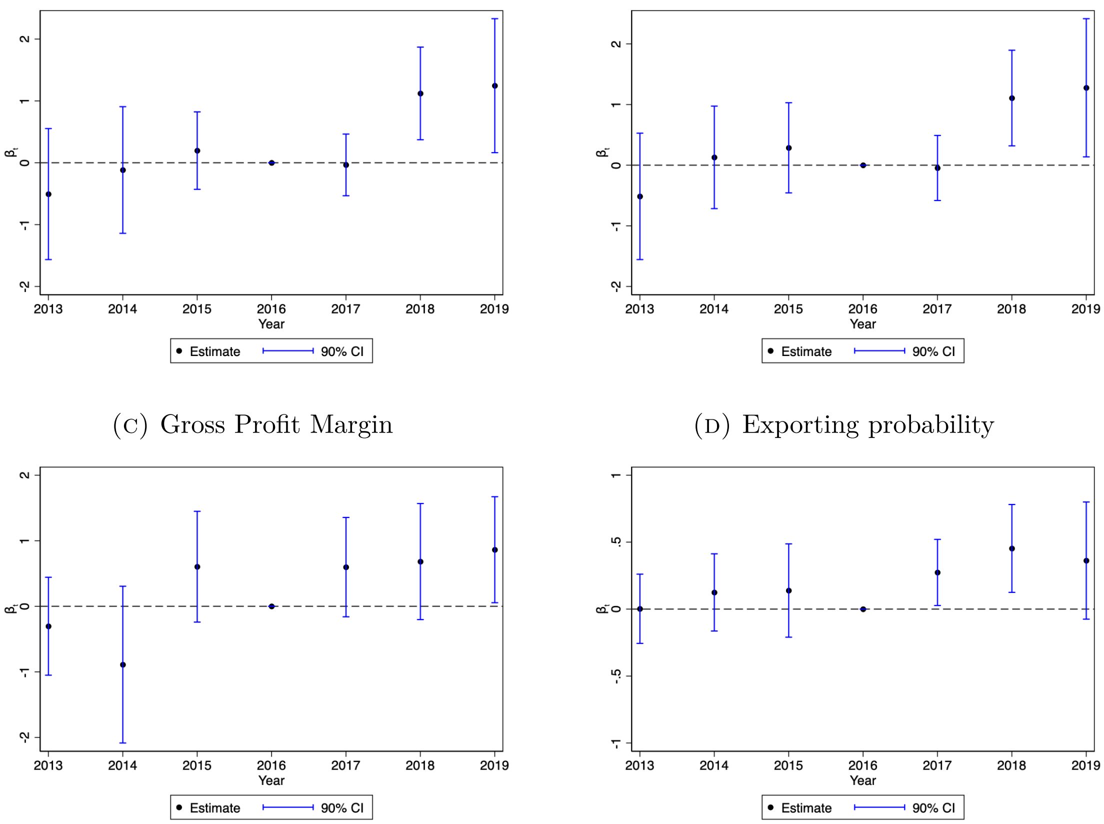
Note: These figures plot the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.5. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. The coefficient of interest is on an interaction term of year dummies D^l_t and $Exposure_i$, where $Exposure_i$ is the share of firm i's usage of banned plastic products in its inputs in year 2016. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

category) market shares as dependent variables.[13] The top panels of Figure A1 plot the coefficients for domestic sales and industry market shares of more exposed firms, and show that they experienced relatively higher growth after the ban. The lower panels of Figure A1 examine their gross profit margins and probability of exporting (as a proxy for international competitiveness of firms). More exposed firms experienced an increase in their gross profit margin and to some degree, their export market participation, but these effects are not precisely estimated. These findings suggest that firms in Turkey benefited from the lower global price of plastic waste inputs from China's ONS policy.

3.2. **Air Quality.** Our results have shown that increased plastic waste imports benefited firms that use them as inputs, but they displaced domestic waste sales of firms that generate plastic waste. Waste generators became more likely to mismanage their waste. We therefore ask the following question: did Turkish provinces with high concentration of local plastic waste generation experience higher pollution after 2016? We focus on inhalable particulate

[13]Market share is defined as the ratio of firm's gross revenues to the sum of revenues in the firm's 4-digit NACE industry.

FIGURE 3.7. Effects of ONS on Importer-level Sales and Profits



(A) Domestic sales

(B) Market share in own industry

(C) Gross Profit Margin

(D) Exporting probability

Note: These figures plot the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.5. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. The coefficient of interest is on an interaction term of year dummies D_t^l and $Exposure_i$. Where $Exposure_i$ is the share of firm i's usage of banned plastic products in its inputs in year 2016. The interaction with year 2016 is removed from the equation to serve as a reference year. The sample covers the years 2013-2019.

matter PM10 as it includes (in addition to combustion of gasoline, oil, and diesel fuel included in PM2.5) dust from landfills and waste burning – which are relevant to our question of interest. The air quality data is from Turkey's Ministry of Environment, Urbanization, and Climate Change based on real-time station level measurements of PM10. We aggregate the data to province-year level by constructing the maximum of all reported measurements for a given province and year. We estimate the following specification:

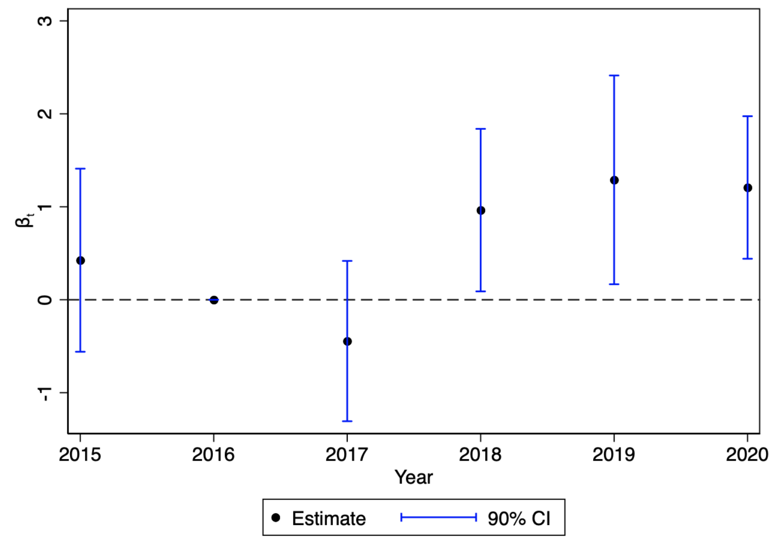
$$\ln PM10_{rt} = \sum_{l=2015}^{2021} \beta_l D_t^l * \text{Exposure}_r + \alpha_r + \alpha_{NUTS2,t} + \epsilon_{ct} \quad (3.6)$$

where $PM10_{rt}$ captures the extreme pollution readings within a province in year t.[14] Exposure_r is measured by the share of plastic waste produced by firms with less than 250 employees in province r. We construct regional exposure based on the size distribution of plastic waste producers as, given the results presented above, these firms are more likely to mismanage unsold plastic waste products. Province fixed effects are included to focus on changes over time in a province and time-varying NUTS2-level fixed effects are included to account for weather fluctuations in broader regions.[15] Figure 3.8 shows the estimated coefficients. There was an increase in PM10 levels after 2017 in regions where the banned waste products were more intensively produced by smaller firms (with less than 250 employees).

[14]We construct this variable using data on daily readings from multiple locations for each province. After adjusting these multiple readings from their month-year, day-month, and province level averages, we use the maximum value over a year for each province.

[15]Provinces in Turkey correspond to NUTS3-level regions.

Figure 3.8. Air Pollution in Areas of Domestic Plastic Waste Generation



Note: This figure plots the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.6. Each observation is at the province-year level. The dependent variable is the (log) pollution readings at province p and year t. The coefficient of interest is on an interaction term of year dummies D_t^l and $Exposure_p$, where $Exposure_p$ is the share of plastic waste generated by firms with less than 250 employees in province p. The interaction with year 2016 is excluded to serve as a reference year. The sample covers the years from 2015 to 2020.

4. Theory

To interpret the main empirical findings in light of the literature on trade and the environment, we generalise the canonical theoretical framework of Shapiro (2016) to waste as a pollutant. We focus on the minimal structure needed to explain the empirical findings and to provide a mapping from observable waste outcomes to an ex-post assessment of the welfare impacts of China's ONS policy in Turkey and globally. The section starts with describing production and waste choices of firms that use and supply waste and those that do neither. It then discusses welfare and environmental externalities from waste activities. Finally, it provides a mapping from waste imports to welfare to define the ONS policy. Details are relegated to the Appendix and the main findings are discussed here.

4.1. **Firms.** There are three types of firms in the economy: plastic waste using firms u, plastic waste supplying firms s and firms that neither use nor supply plastic waste n. To fix ideas, a firm producing plastic traffic cones is a plastic waste-using firm and a firm producing medical syringes is a plastic waste supplying firm. In contrast, a carpentry firm that neither uses nor supplies plastic waste is not exposed through supply and use and denoted by n or referred to as a “neither” firm. They have zero exposure as measured by the exposure variables defined in the empirical section before. In other words, firm types are distinguished by their "netput" of plastic waste - using firms are net buyers of plastic waste, supplying firms are net sellers of plastic waste and non-exposed firms have zero net purchases/sales of plastic waste.

Waste Generation. Firms that use plastic in production of their main outputs generate plastic by-products, that can be treated to generate "managed" plastic waste. When the managed plastic waste is supplied to waste using firms, they can recycle it for use as an input into final production. For example, the plastic waste generated by the medical syringe producer is sold to the plastic cone producer to use as an input in cone production. Let a denote the waste treatment technology, that is familiar from the literature on pollution abatement. If a firm treats its by-products, it generates $\chi(x, a)$ units of managed waste per unit of virgin resource used in its main production process. We assume $\chi(x, a) = xa$ so that $0 \leq a \leq 1$ can be interpreted as the share of waste that is managed and has recyclable value. Treating waste requires workers to sort the by-products to separate out recyclable plastics and costs $w\gamma(a)$ where w is the wage rate and γ is an increasing and convex function. Better abatement technology costs more, and extracting more and more recyclables out of a given by-product requires more labour. Here we assume economies of scale in pollution abatement, but it is not necessary for the main results.

By-products that are mismanaged, such as through burning or open dumping, are more polluting than managed waste with emission rates $\xi^b > \xi^x$, that we will explain in more detail later in the context of the consumers’ welfare function that is defined over consumption goods produced by all firms, as usual, and over environmental externalities from waste and virgin resource use. International law forbids sales of by-products, but allows trade in managed waste material. Therefore, by-products stay in their own country while managed waste can be traded across countries.

Waste Recycling. Production in u needs labour and plastic which could be virgin material v or recycled plastic χ. Let m denote the amount of material used in production in u. Then $m = m(v, \chi)$ and we assume that v and χ are partly substitutable. This distinguishes waste from some other pollutants because recycling has an offsetting effect on pollution through conservation of virgin resources, that would otherwise need to be exploited and would contribute to environmental degradation.

Firm Decisions. Firms maximise profits, taking wages w_d and input prices as given. We begin with the decisions of supplying firms and then proceed to using firms and those neither supplying nor using plastic waste. The subscripts u, s, n denote the firm type and the subscripts d, d' denote countries.

Supplying firms s in country d use virgin plastic to earn revenues $R_{sd}(v_{sd})$. Virgin material costs z_{od} and this can be interpreted as the units of a freely traded world commodity, such as oil and natural gas, needed to produce virgin plastic in country d. Then $z_{od} = z_d = \tau_d z$ where z is the world price of virgin resources and $\tau_d \geq 1$ is the iceberg transport cost in shipping from the world market to destination d.

Use of virgin material generates by-products. Management of these by-products results in recyclable waste that provides the supplying firms with revenues worth $\sum_{d'} r(\chi_{sdd'}) / \tau_{dd'}$ when sold to firms in country d' (where $\tau_{dd'} > 1$ is the usual iceberg transport cost that is set to 1 when $d' = d$). Firm choose whether to pay $w_d \gamma(a_{sd})$ for the waste management technology. Having paid this, $x_{sd} a_{sd}$ units of managed waste are available to be recycled. λ_{sd} is the Lagrange multiplier on the constraint that recyclable waste demand cannot exceed the supply of managed waste.

Using firms u in country d choose labour and material (that could be virgin and/or recyclable). Plastic waste from origin country o used by u is denoted by χ_{uod}, and it comes at a market price of p_{od}. Other firms n that neither buy nor sell plastic waste produce final products with labour, taking wages as given.

The profit maximisation problems of each firm is summarised below:

$$\begin{aligned}
\max_{l,v,\chi} \Pi_{ud} =& R_u\left(l_{ud}, m_{ud}\right) - w_d l_{ud} - \sum_o z_{od} v_{uod} - \sum_o p_{od}\chi_{uod} + \lambda_{ud}\left(m\left(v_{uod}, \chi_{uod}\right) - m_{ud}\right) \\
\max_{a,v} \Pi_{sd} =& R_s\left(v_{sod}\right) - \sum_o z_{od} v_{sod} + \sum_{d'} r_{dd'}\left(\chi_{sdd'}\right)/\tau_{dd'} - w_d\gamma\left(a_{sd}\right)\sum_o v_{sod} \\
&+ \lambda_{sd}\left(x_{sd}a_{sd}\sum_o v_{sod} - \sum_{d'}\chi_{sdd'}\right) \\
\max_{l} \Pi_{nd} =& R_n\left(l_{nd}\right) - w_d l_{nd}
\end{aligned}$$

Solving for the choice of waste management, a first observation is that waste management rises with waste generation and falls with the sorting costs. This follows directly from the second order condition for profit maximisation in the s sector, and we summarize it below.

Remark 1. *When $\gamma'' > 0$ and given all else equal, the share of waste that is managed and can be recycled, a_{sd}, rises with the scale of waste generated x_{sd} and falls with waste sorting costs w_d.*

The theoretical framework is consistent with gravity in waste trade, as documented in the literature and in our empirical specification earlier. Details are in the Appendix and the key observation is summarized below.

Remark 2. *Let g_{od} denote the inverse of geographical distance between o and d. Under a distance elasticity of -1 and a power function for marginal revenue $r'(x)$, waste imports into destination d take a gravity form:*

$$x_d = \sum_o r'^{-1}\left(\frac{\tau_{od}}{\tau_{oc}} r'\left(x_{soc}\right)\right) = \sum_o \frac{g_{od}}{g_{oc}} x_{soc}.$$

The main insight of the gravity relationship is that China's import ban would have larger impacts in third country destinations that are relatively closer to countries that initially exported larger volumes to China. We later use this as a first stage to determine which countries received more of the displaced waste imports after the ban, and how that affected the environmental burden of waste across different destinations.

Before proceeding to the welfare analysis, it is also worth noting that the revenue functions above are defined over factors of production that appear in the empirical findings, but they can be generalised to make them symmetric across supplying, using and doing neither firms. This will add more factor choices without changing the mapping to moments that we need to calibrate the ex post assessment, as discussed in the Appendix. We show moreover that the economies of scale over by-products in abatement technologies is not necessary for the quantification exercise and can be altered to the context under consideration.

4.2. **Consumption and Welfare.** Welfare is generalised from its usual formulation in the trade and environment literature to account for waste instead of other pollution-generating activities.

How does waste trade affect pollution, domestically and globally? We consider three channels here:

(A) **Waste mismanagement** externality from waste generators' choices at home (e.g. Turkish firms dump or burn their own waste),

(B) **Waste recycling** externality from more processing of waste in the country (e.g. Turkey and China import waste that gets recycled within the country and produces emissions during processing or landfilling of the remainder)

(C) Offsetting **virgin resource** externality from less virgin material being used when waste is recycled (e.g. Turkey gets access to cheaper plastic waste imports and does not need as much virgin plastic for industrial production).

A key feature of this formulation is that recycling reduces the use of virgin materials, which would otherwise generate pollution, such as emissions from resource extraction and use. Waste therefore differs from other pollution-generating activities that cannot be recycled for further production. For example, shipping emissions generated during transport cannot typically be recycled to offset virgin energy use.

To formalise these features, a representative consumer in country d gets utility from consumption of goods produced by each firm. She faces externalities from pollution that lower her utility through extraction of virgin resources (such as fossil fuel pollution that generates disutility at a rate ξ^v) and from pollution generated by plastic waste (such as through marine pollution and greenhouse gas emissions that generates disutility at a rate ξ^x).

It will be convenient to refer to products, indexed by h, because the China ban applies to specific products h within plastic that are more polluting or contaminated. Assume without loss of generality that ξ_h^x is increasing in h. China's ONS policy bans imports of $h > \bar{h}$ and therefore removes higher disutility imported waste destined for recycling in China.

Under linear utility, welfare can be summarised in Welfare W1 below:

Welfare W1.

$$\begin{aligned} W_d \equiv & W\left(U_d, S_d, N_d, -V_d - Z_d\right) \\ V_d \equiv & \sum_h \xi_h^v \sum_{d'} \left(v_{hudd'} + v_{hsdd'}\right) \\ Z_d \equiv & \sum_h \left(\xi_h^b \left(1 - a_{hsd}\right) x_{hsd} + \sum_o \xi_h^x \chi_{huod}\right) \end{aligned}$$

where W is increasing in final consumption of goods U, S, N produced by firms u, s and n, and welfare maximisation generates demand relationships that firms take as given. W is decreasing in virgin resource extraction V and waste pollution Z. Only virgin resources that are extracted within the country directly feature in the welfare function, though this can be extended to account for global virgin resource extraction in welfare. Waste pollution arises from waste mismanagement at home and from waste recycling operations at home. By definition, mismanaged waste generates more disutility than managed waste $\xi_h^b > \xi_h^x$ as explained before.

4.3. **China ONS Policy.** China's ONS policy bans imports of $h > \bar{h}$ and therefore removes higher disutility imported waste destined for recycling in China. Let $\Delta\chi_{huoc} \equiv \chi_{huoc}\left(\tau_{hoc}^{ONS}\right) - \chi_{huoc}\left(\tau_{hoc}\right)$ denote the change in imports into China, indexed by c. Then τ_{hoc}^{ONS} is prohibitively high for $h > \bar{h}$ and for all $o \neq c$ after the ONS policy in 2017. Imports are zero under a prohibitive tariff, and the ban is defined as a shift to an equilibrium with a prohibitive price for the banned waste imports, $\Delta\chi_{huoc} = -\chi_{huoc}$.

5. Quantification

This section provides an ex-post evaluation of the economic and environmental effects of China's waste import ban. We start with the effects in Turkey where we have the finest data on waste and other economic outcomes. We then deploy market clearing conditions from the model and estimates of environmental impacts from the literature to arrive at regional and global emission impacts of the policy.

For Turkey, firm-level difference-in-differences estimates of the revenue and employment impacts on firms exposed through supply or use of plastic waste provides the economic effects, relative to non-exposed firms in the same industry. Labour market clearing pins down the effects on non-exposed firms, that enables inference of the absolute revenue impacts on non-exposed and exposed firms under standard production theory assumptions.

For global trade, product-country-level difference-in-differences estimates of trade impacts are estimated for Exporters, China, Turkey, and the Rest of the World. The estimates are obtained for both banned products and products similar to the banned products, relative to other products. These estimates, together with balanced trade conditions and firm-level estimates from Turkey, pin down the missing intercept of trade effects on other products.

The difference-in-differences estimates and the market clearing conditions enable inference of the absolute impacts on trade across banned and other products, as well as for different regions of the world. To arrive at welfare impacts, we need estimates of waste mismanagement impacts, virgin resource use impacts, together with the relative disutility arising from environmental externalities of waste recycling, waste mismanagement and virgin resource use.

Mismanagement impacts for Turkey are from our estimation of firm-level data that provide direct observation of waste outcomes. These are not available in most countries across the world, and corresponding estimates for China are taken from the literature (that examines satellite data to determine waste pollution and plastic production data to determine substitution between virgin and recyclable plastic from the policy). We calibrate the waste management impact in regions (other than Turkey and China) to the elasticity of waste emissions with respect to waste imports obtained from satellite data and trade data respectively. Virgin resource impacts of the policy are similarly calibrated to the elasticity of primary plastic production and waste imports. These are combined with emission factors from the United States Environmental Protection Agency (US EPA) to calibrate the relative disutility rates ξ. The regional and global estimates enable an ex-post assessment of the aggregate environmental impacts of the ONS policy.

We present the three sets of results – revenue impacts in Turkey, trade impacts across regions and environmental impacts across regions and globally - in turn below.

5.1. **Revenue Impacts in Turkey.** Utilising firm-level data, we employ a difference-in-differences specification to analyze how the policy affected revenues among firms using plastic waste, u; firms supplying plastic waste, s; and firms that neither supply nor use plastic waste, n. The specification takes non-exposed firms as the reference category and estimates the following equation:

$$\text{(5.1)} \quad \ln(Revenue_{f(j)t}) = \alpha + \beta_u^R Post_t * Exposure_f^u + \beta_s^R Post_t * Exposure_f^s + \gamma_{jt} + \gamma_f + \epsilon_{ft},$$

where $Exposure_f^u$ captures firm f's exposure to the China policy through its use of plastic waste u, measured as the share of plastic waste imports in total input costs in 2016. Similarly, $Exposure_f^s$ captures the firm's exposure through its supply of plastic waste s, measured as the share of plastic waste sales in total sales in 2016. Results are presented in Table 2.

As earlier, we find exposure through use of waste raises output sales of using firms while exposure through waste supply reduces sales of supplying firms. The findings from our difference-in-difference analysis, presented in Table 2, should be interpreted relative to firms classified as "neither using nor supplying" plastic, denoted as n. It is important to consider that firms in the n category could also be affected by the policy through indirect general equilibrium effects. To assess these potential general equilibrium (GE) effects, we utilise the labour market clearing condition. In contrast to the revenue effects, the sum of the labour market effects will be zero across all firms under a fixed labour supply in the economy. We

TABLE 2. Effects on Revenues

	(1)	(2)
	ln($Sales$)	ln($Employment$)
$Post_t * Exposure^u_f$	0.170a	0.107a
	(0.0238)	(0.0106)
$Post_t * Exposure^s_f$	-0.132b	0.00579
	(0.0551)	(0.0444)
$Post_t *$ Initial Employment$_f$	0.122a	0.0727a
	(0.00357)	(0.00171)
N	618907	662989
R^2	0.803	0.881
Fixed Effects:		
Firm	Yes	Yes
Industry × Time	Yes	Yes

Note: This table shows the results from estimating equation (5.1), where the dependent variable for the first column is the log sales in dollars of firm f, and the dependent variable for the second column is the log employment of firm f. $Exposure^u_f$ is the share of waste imports in the total input cost of firm f (wages + domestic purchases + imports), $Exposure^s_f$ is the share of waste sales in total sales of firm f, and $Post_t$ is a dummy variable indicating 1 if year is greater than 2017. The sample covers the years between 2013 to 2019. Letters indicate statistical significance: a indicates p<0.01, b indicates p<0.05, and c indicates p<0.10.

estimate the difference-in-differences (equation(5.1)) with employment as the depenedent variable instead in Table 2. The effects are positive through exposure in the use of plastic waste and negligible through supply exposure, relative to the non-exposed firms that form the reference group. The labour market impact of these "neither using nor supplying" firms, denoted as β_{ln}, can be inferred from the labour market clearing condition evaluated at the mean exposure and initial labor shares in the economy.

The labor market clearing condition in changes gives:

$$\begin{aligned} 0 &= \Delta l_u^{TR} + \Delta l_s^{TR} + \Delta l_n^{TR} \\ &= (\beta_{lu} \cdot Exposure_u + \beta_{ln}) \left(\frac{l_{ud}}{L_d}\right) + (\beta_{ls} \cdot Exposure_s + \beta_{ln}) \left(\frac{l_{sd}}{L_d}\right) + \beta_{ln} \left(\frac{l_n}{L}\right) \\ &= \beta_{lu} \cdot Exposure_u \left(\frac{l_u}{L}\right) + \beta_{ls} \cdot Exposure_s \left(\frac{l_s}{L}\right) + \beta_{ln} \end{aligned}$$

$$= 0.107 \times 0.008 \times 0.0429 + 0 \times 0.064 \times 0.2194 + \beta_{ln}$$

$$= 0.0008\% + \beta_{ln}.$$

Labour costs for firms in n make up 21 percent of total costs. Under standard assumptions of Cobb-Douglas production (or a first order approximation to production changes) and constant markups, revenues therefore change by $\Delta R_n = 0.21 \times \Delta l_n \approx 0$. This generally implies that domestic sales of non-exposed firms are not affected by China's ban. We have therefore pinned down the revenue effect of n firms as negligible. We can now go back to the DiD specification to determine the revenue effects of u and s firms. Let β_u, β_s denote the DiD coefficients on $Exposure_u$ and $Exposure_s$. Then the aggregate revenue changes are:

$$\begin{aligned}
\Delta R =& \Delta R_u + \Delta R_s + \Delta R_n \\
=& \beta_u Exposure_u \left(R_u/R\right) R + \beta_s Exposure_s \left(R_s/R\right) R + \beta_n R \\
=& \left(0.170 \times 0.0002 \times 0.0048 - 0.132 \times 0.0045 \times 0.4085 + 0\right) R_d \\
=& - 0.02\% \times \$437.9 \text{ bn.} = -\$106.18 \text{ mn.}
\end{aligned}$$

where the second line follows from non-exposed firms by definition having zero exposure directly to the ban. We find that using firms gain from the ban. Their revenues rise as they gain access to cheaper imported inputs, but they account for a small share of the Turkish economy, and thus the displacement of domestic waste generated by supplying firms instead dominates. They lose their waste income to import competition, leading to revenue losses in the aggregate. While their revenue from waste falls, supplying firms do not cut back on overall employment. This is because by-products are not their main source of economic activity, and their main output is not substantially affected by reorganisation in the world plastic waste market. In other words, medical syringe producers in Turkey lose some income from sales of plastic waste to plastic cone producers but their syringe business is not much affected by the ban.

To sum up, using a difference-in-differences specification, and recovering the missing intercept from labor market clearing, we infer that the ONS policy decreased aggregate revenues by \$106.18 million in Turkey. This number can be contextualised by comparing it with the influx of imports after China's ban. After 2017, Turkey received an extra \$205 to \$295 million of plastic waste imports annually, implying less than full displacement of domestic sales from import competition.[16]

5.2. **Trade Impacts Across Regions.** To quantify the changes in plastic waste imports across different country groups, we employ a difference-in-differences specification to isolate the effect of the ONS policy by comparing the changes over time between products that were affected by the policy and those that were not. The estimating equation is:

$$\begin{aligned} \ln x_{pct} &= \sum_{c \in D} \beta_x^c \mathbb{1}\{t \geq 2017\} * \mathbb{1}\{c = D\} * \mathbb{1}\{Banned_p^{HS6}\} \\ &+ \sum_{c \in D} \beta_x^{c,HS2} \mathbb{1}\{t \geq 2017\} * \mathbb{1}\{c = D\} * \mathbb{1}\{Banned_p^{HS2}\} \\ &+ \mathbb{1}\{t \geq 2017\} * \text{Tariff Rate}_{pc,t=2016} + \alpha_c + \alpha_t + \alpha_{pc} + \epsilon_{pct}, \end{aligned} \tag{5.2}$$

where the set of destination countries is $D = \{\text{China}, \text{Exporters}, \text{Turkey}, \text{Rest of the World}\}$. To account for potential spillover effects over similar products, we control for treatment status at the 2-digit HS product level. The results are shown in Table A2.

The results in columns (1) and (3) of Table A2 indicate that China's imports of banned plastic waste products declined by approximately 99%, while its exports of these products remained unchanged. Turkey's imports of banned plastic waste products increased by 202%, whereas its exports did not change. Countries that heavily exported banned products to China before the ONS policy (such as the USA, Canada, and the UK) did not increase their imports of banned products but reduced their exports by 51%. Lastly, the rest of the

[16]Import values refer to the difference between the annual averages for 2012-2016 and 2018-2021. \$205 million is the difference in actual trade values while \$295 million refers to actual trade volumes evaluated at 2016 unit values to account for underestimation due to the drop in prices from the ban.

world increased their imports of banned products by 21% and reduced their exports by 35%.[17]

All changes should be interpreted relative to the changes in global imports and exports of non-plastic products. Naturally, imports of non-plastic products could also change due to the ONS policy through general equilibrium effects. To capture these effects, we rely on Balance of Trade (BoT) identities for each country group. Under the assumption of balanced trade, changes in total demand cannot exceed changes in total supply in any country and globally. This enables us to infer the missing piece of changes in imports of non-plastic products because this market must clear globally and any country-specific trade imbalance in these products must exactly equal the opposing trade imbalance in plastic products, as detailed in Appendix D.1.

After accounting for the missing intercept problem in the difference-in-differences analysis under the balanced trade assumption, changes in ONS-banned plastic imports and exports for each country are as estimated in Table 3.

Table 3. Change in ONS-Banned Products

Country Group	$\Delta \ln(Imports)$	$\Delta \ln(Exports)$
China	-4.27	0
Turkey	1.105	0
Exporters	0.002	-0.71
RoW	0.19	-0.44

Note: This table indicates the total log changes in imports and exports for ONS-Banned products for each country-group (China, Turkey, Exporters, and RoW). The total log changes are calculated by the adding the estimates of Equation (D.1) shown in Table A2 with the missing intercept calculated using Balance of Trade conditions as detailed in Appendix D.1

5.3. **Environmental Impacts.** For each country-group we estimate the environmental burden from the mismanagement and management of waste and virgin plastic consumption, and then convert them to comparable environmental impacts. These estimates are discussed in turn.

[17] Log changes are converted into percentage changes by taking the exponential of the coefficient and deducting 1: $e^{\beta_x^c} - 1$

To estimate the impact of the ONS policy, we need information on the level of and changes in mismanagement for each country-group. In Turkey, we assessed levels and changes in mismanagement using detailed data on waste management practices, which showed that the share of firms that mismanage their waste increased from 45 percent to 52 percent following the surge in imports from the ONS ban.

Since comparable granular data on waste management are not available for other countries, we rely on OECD plastic waste and satellite data to fill the gap. The OECD Global Plastic Outlook provides the share of plastic waste that is mismanaged for broad country groups, including China, Exporters (United States and OECD European Union) and the Rest of the World (RoW). To estimate the change in waste management following ONS in China, Shi and Zhang (2023) examine satellite data on open burning and estimate a 14 percent decline in such episodes in areas that were more exposed to the ONS policy. At a mean exposure of 38 percent, this amounts to a 5.3 percent reduction in mismanagement of waste in China. One caveat is that any burning episode will be recorded in satellite data but these are minimised through institutional knowledge of the seasons and regions where these are likely to be driven by other factors such as farming.

For Exporters and the Rest of the World (RoW), we calibrate waste mismanagement impacts with the elasticity of waste emissions with respect to waste imports. Waste emissions for countries are from Climate Trace. They draw on emissions from satellite data and have the advantage of capturing formal and informal waste mismanagement but they apply to all waste and not just plastic waste. Waste imports of destinations are instrumented with the destination's proximity to countries that initially exported more of the banned plastic waste products to China. Following gravity in waste trade, the reasoning is that destinations that are closer to origin countries that exported more to China will be more likely to receive the displaced waste imports after China's ban. We find that a 1 percent higher gravity measure for a destination is associated with a 0.652 percent higher increase in waste imports after the ban. A 1 percent increase in ONS-banned plastic waste imports in turn translates into a 0.04 percent increase in emissions from waste in the destination. This emission elasticity is multiplied by the drop in waste exports for Exporters and the rise in waste imports for the RoW to arrive at the baseline values for the change in waste mismanagement.

Table 4 contains results for waste mismanagement levels before and after the ban. As mentioned earlier, Turkey has high mismanagement shares than China and this difference widens after the ban. The RoW also experiences a rise but the rise for Exporters is very small and their mismanagement share remains much smaller than that of other regions.

Table 4. Plastic Mismanagement by Region

Region	**Share of Mismanaged Plastic Pre-2017**	**Share of Mismanaged Plastic Post-2017**	**Change in Percentage Points**
China	32%	30%	-2 pp
Turkey	45%	52%	+7 pp
Exporters	4%	5%	+0 pp
RoW	34%	35%	+1 pp

Notes: Data for mismanaged plastic waste are obtained from firm-level survey data in Turkey and from OECD for other country groups. Changes in mismanaged waste are from firm-level estimated for Turkey and derived from satellite data on waste emissions for China, Exporters and the Rest of the World (RoW). The changes in mismanagement levels are described in Appendix D.3.

The waste management burden across countries varies by how much they import of plastic waste and hence how much has to be processed at home. This is readily obtained from our quantification exercise that has already determined the aggregate effects on plastic waste imports and exports for each country group. Appendix D.3 contains details of the estimation for imports and exports separately and also contains step-by-step details of the derivations of aggregate impacts based on balanced trade.

Impacts on virgin plastic usage would change after the ban if recycled plastic waste imports substitute for virgin plastic in production. Following the implementation of the ONS policy, Sun and Tabata (2021) estimate that China reduced its plastic waste imports by 99.8 percent but increased its production of virgin resin by 10 percent. This relationship suggests that a 1 percent decrease in plastic waste imports corresponds to a 0.1 percent increase in the demand for virgin resin. This can be multiplied with the aggregate trade impacts for each destination to arrive at changes in the environmental burden from virgin plastic use. Levels of virgin plastic usage are available by country in the EXIOBASE data.[18]

Finally, we need to calibrate the relative environmental burdens or disutility rates ξ for all three types of waste activities - waste mismanagement, waste recycling and virgin resource use - to arrive at their net effects. To do so, we take greenhouse gas emission factors from the natural science literature that are available from the United States Environmental Protection Agency. The mismanagement/combustion of one ton of plastic waste results in the emission of approximately 2.40 tons of carbon dioxide equivalent greenhouse gases CO_2e. In contrast, waste recycling produces 0.02 tons while the production of one ton of virgin plastic emits an average of 1.39 tons of CO_2e. These are multiplied by the initial values of plastic waste managed/mismanaged/virgin resources and the percentage changes in them to arrive at the environmental burden of each activity in comparable units of millions of metric tonnes of CO_2e emissions. Table A1 in the Appendix presents the figures broken down by different plastic types.

Table 5 shows results for CO_2e emissions from each activity across country groups and the detailed steps are provided in Appendix D.3. The findings show a mixed picture of environmental burden by region and activity. Specifically, the ban directly reduced China's environmental burden from waste management and this dominated the increase from greater virgin plastic production. It also experienced better waste management at home. Conversely, Turkey's burden of waste management increased with imports, despite some offsetting effects from reduced virgin plastic production. The main finding though is of a large increase in environmental degradation from increased waste mismanagement in Turkey. If this had not occurred, estimated emissions from Turkey would have been just 16 percent of those reported in the Table. Therefore, the bulk of the environmental burden came from reduced abatement in the face of greater import competition in the country. Exporters experienced

[18]When we follow the gravity instrumental variable approach that we used for calibrating waste mismanagement and estimate a virgin plastic production elasticity with EXIOBASE, we find a highly similar substitution elasticity estimate. A 1 percent increase in waste imports, instrumented with a gravity measure after the ban, translates into a 0.11 percent decrease in primary production of plastic. Results are detailed in Appendix D.2.

greater emissions, net of savings from reduced virgin resource use, and the Rest of the World saw negligible changes in its environmental burden.

TABLE 5. Welfare Estimations

Region	Waste Imports ΔX_d (%)	Waste Emissions ΔZ_d (CO2e mmt)	Virgin Consumption Δy_d^v (CO2e mmt)
China	-98.8%	-20.53	12.99
Turkey	201.9%	1.83	-0.64
Exporters	0.2%	1.59	-0.05
Rest of the World	20.9%	6.20	-5.44
Global	-56.8%	-10.91	6.85

Note: This table displays the percentage decline in banned plastic waste imports for China, Turkey, Exporters and the Rest of the World in the first column. The second column presents the CO_2e emissions resulting from both waste management and mismanagement for each country group. The final column provides the estimated CO_2e emissions from virgin plastic consumption. Detailed calculations for these emissions can be found in Appendix. D.3.

Overall, the analysis suggests that global emissions associated with plastic waste declined after China's ONS policy. The decrease in emissions from waste management in China overshadowed increases from other sources, such as trade diversion and virgin plastic production. In other words, the trade destruction effect of the ban was far greater than its trade diversion effect. This finding underscores the complex and varied environmental impacts of the ONS policy across different country groups. Strikingly, Turkey loses out both economically and environmentally from the influx of imports that resulted after China banned the most polluting waste imports. Evaluated at the price of carbon credits in the European Union, Turkey's 1.83 mmt rise amounts to a loss of about €140 million, which more than doubles the economic burden from waste revenue losses.

5.4. **Sensitivity Analysis.** To evaluate alternative scenarios in global trade and waste management, we conducted two hypothetical analyses concerning CO_2e emissions:

Scenario 1: No Trade Destruction and All Diversion to Turkey. We examine the environmental implications of no trade destruction. Under this scenario, all waste that would have been imported by China is redirected to Turkey. This reallocation would have resulted in Turkey's waste imports increasing by 5600%, rather than the observed 200%.

Consequently, such a significant shift would have led to an increase in global CO_2e emissions by approximately 14.08 million tons.

TABLE 6. Welfare Estimations with No Trade Destruction and All Diversion to Turkey

Region	Waste Imports ΔX_d (%)	Waste Emissions ΔZ_d (CO2e mmt)	Virgin Consumption Δy_d^v (CO2e mmt)
China	-98.8%	-20.53	12.99
Turkey	5900%	23.33	-3.17[a]
Exporters	0.2%	1.45	-0.05
Rest of the World	20.9%	5.53	-5.44
Global	0%	9.75	4.33

Note: The first column of this table displays the percentage change in banned plastic waste imports for each country group in the case that all plastic waste was diverted from China to Turkey. The second column presents the CO_2e emissions resulting from both waste management and mismanagement for each country group. The final column provides the estimated CO_2e emissions from virgin plastic consumption.

[a]We estimated that a 1% increase in plastic waste imports leads to a 0.1% decrease in the demand for virgin plastic. Extrapolating this relationship, a 5900% increase in plastic waste imports would imply an unrealistic 590% decrease in virgin plastic demand. Since a reduction in demand exceeding 100% is not economically feasible, we have capped the decrease in virgin plastic consumption at 100% in our estimates.

Scenario 2: No Country Composition Effect. Additionally, we assess the potential impact on global emissions if Turkey and the Rest of the World (RoW) adhered to the waste mismanagement levels observed in major exporting countries (primarily, the US and the EU). Under this scenario, if mismanagement practices were aligned, global CO_2e emissions from waste would have decreased by 10.53 million tons, which is a further 6.47 million tons compared with what occurred.

Finally, we conduct two more robustness checks. First, we examine sensitivity of the main findings to alternative parameter values of mismanagement impacts in Exporters and the Rest of the World. We follow the gravity instrumental variables procedure for inferring mismanagement impacts in Turkey from satellite data. We can compare this with the actual mismanagement change in Turkey to obtain a scaling factor for how much emission elasticities translate into actual mismanagement elasticities. Scaling the mismanagement changes for Exporters and the RoW with this factor of 1.6 does not alter the main finding, but the global

Table 7. Welfare Estimations with Turkey and the Rest of the World at the Mismanagement Levels of Exporters

Region	Waste Imports ΔX_d (%)	Waste Emissions ΔZ_d (CO2e mmt)	Virgin Consumption Δy_d^v (CO2e mmt)
China	-98.8%	-20.53	12.99
Turkey	201.9%	0.11	-0.64
Exporters	0.2%	1.59	-0.05
Rest of the World	20.9%	1.45	-5.44
Global	-56.8%	-17.38	6.85

Note: The first column of this table displays the percentage change in banned plastic waste imports for each country group. The second column presents the CO_2e emissions resulting from both waste management and mismanagement for each country group provided that waste mismanagement levels in Turkey and the Rest of the World (RoW) are the same as the mismanagement levels of Exporters. The final column provides the estimated CO_2e emissions from virgin plastic consumption.

emission savings are reduced to -4 mmt CO_2e. Exporters and the RoW are estimated to have an increased environmental burden, with the latter of about 1MMT of CO_2e. A second point of robustness is that the increased environmental burden of some Exporters within the group may be larger. For the United States, Sigman and Strow (2024) find that landfilling of waste increased while employment in recycling facilities temporarily declined in US states that were more exposed to the ONS ban, relative to those that were less exposed. But the estimates are relative and also apply to all waste (and not just plastic waste).

6. Conclusion

This paper highlights the international spillover effects of trade and environmental policy, focusing on China's waste import ban. The policy led to a large displacement of waste exports from advanced economies to China, a substantial part of which then got diverted to Turkey. We find that plastic using firms in Turkey gained access to cheaper inputs due to China's policy, and experienced better outcomes such as increased sales and profitability. However, demand for locally generated waste in Turkey dropped, resulting in higher levels of waste mismanagement by domestic firms that experienced reduced sales as a result of increased import competition. Air pollution increased in regions where these firms were concentrated, despite offsetting effects from reduced virgin plastic production in Turkey.

We incorporate waste trade in a gravity model of trade and the environment and study the effects of the import ban. In addition to the usual economic gains from trade, the model suggests that changes in global and national welfare depend on three main environmental effects: changes in waste mismanagement of domestic firms, changes in the environmental burden from recycling waste, and substitution possibilties between virgin resources and recyclables. The model provides market clearing conditions that enable a quantification of the aggregate national and global welfare impacts.

Combining labour market clearing and balanced trade with firm-level difference-in-differences analysis, we find that Turkey lost economically and environmentally. Heightened import competition led to a fall in domestic waste sales and these firms became more likely to mismanage their plastic waste by-products.

To study the global effects of the ban, the model is calibrated to balanced trade conditions for different regions. Together with estimates of waste emissions from satellite data and virgin plastic production, the model quantifies the environmental burden resulting from the ban across regions. The unilateral ban led to global emission savings due to the large trade destruction effect that reduced the environmental burden of waste management in China. But the burden of the ban was borne unequally across the world. Other countries experienced greater waste mismanagement and in the case of emerging markets, such as Turkey, the economic gains from cheap imports were too small to offset the losses from displaced earnings of domestic waste suppliers. And the environmental losses more than doubled the aggregate economic burden.

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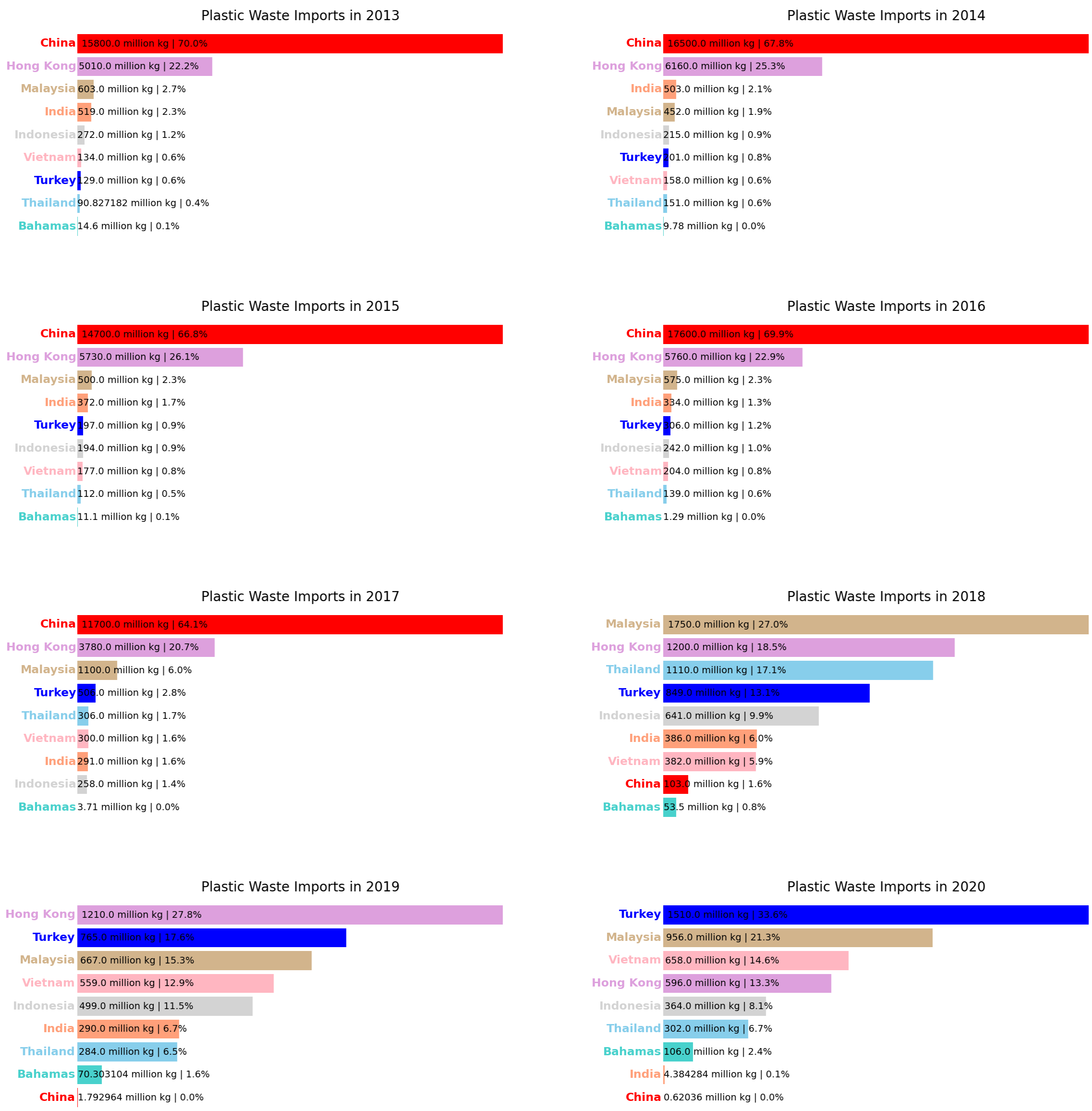
Appendix A. Additional Figures and Tables

Figure A1. Imports of Plastic Waste

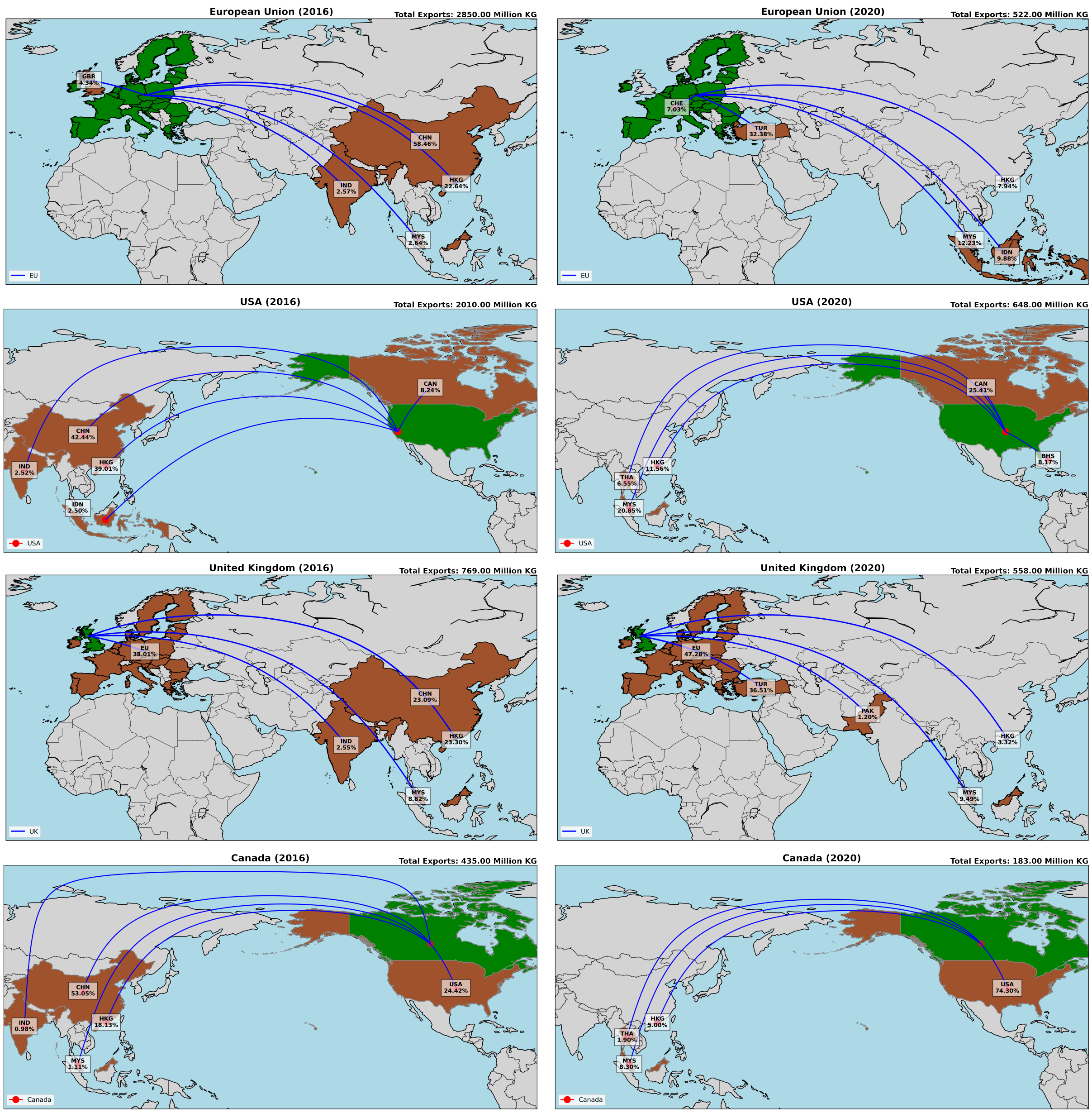


Note: Each bar represents the percentage imports (in kg) of plastic waste by country in a given year.

Appendix B. Additional Figures and Tables

Figure A3 estimates a firm-product-origin-time specification for imports:

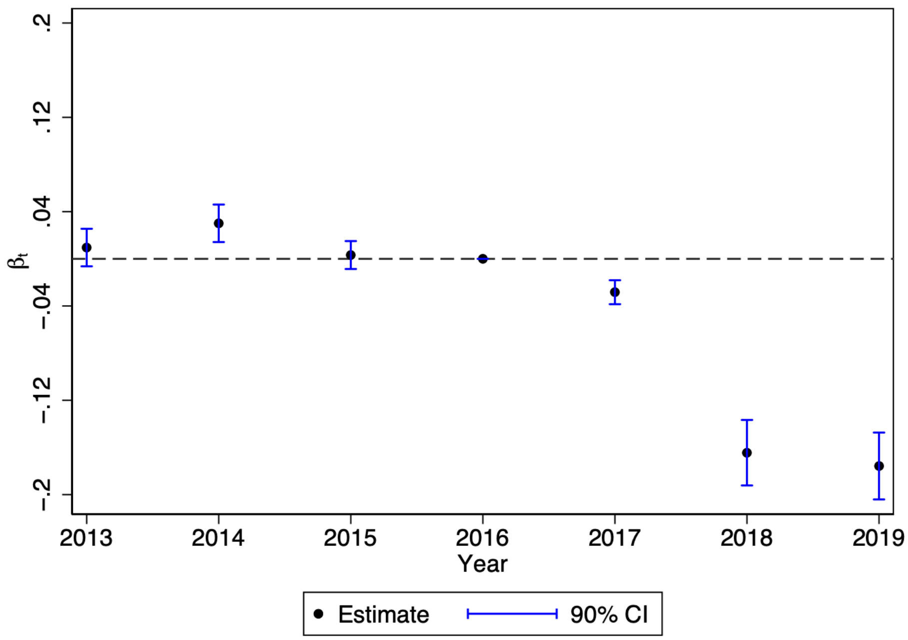
Figure A1. Plastic Waste Exports by Major Exporting Country



*Note:*Each map displays the top five plastic waste exporting destinations for different countries. The first row illustrates the European Unionâs major destinations in 2016 (right panel) and 2020 (left panel). The second row depicts the United States' top five exporting destinations for plastic waste for the same years, 2016 on the right and 2020 on the left. The third row presents data from the United Kingdom, while the final row focuses on Canada's main exporting destinations.

$$\ln \text{Imports}_{ipot} = \sum_{l=2013}^{2019} \beta_l D_t^l * \text{Banned}_p + \alpha_{ipo} + \alpha_{ot} + e_{ipot}, \tag{B.1}$$

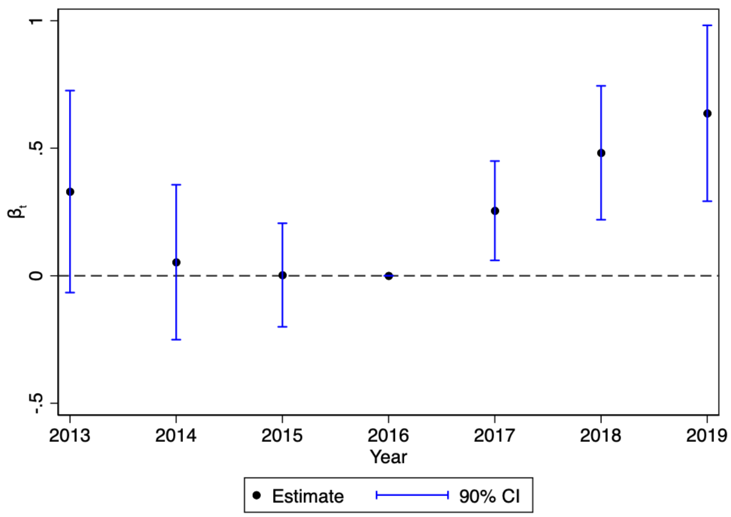
Figure A2. Event Study: Global Trade after the Operation National Sword Policy



Note: This figure plots the estimates, together with 90% confidence intervals, obtained from an event study where the global trade of 6-digit HS products are regressed on an interaction of two dummy variables, $Treat_{HS6}$ and $Post_t$. $Treat_{HS6}$ is a dummy variable indicating whether that 6-digit HS product was banned by China through the ONS, and $Post_t$ is a dummy variable taking a value of 1 post 2017. The sample covers the years from 2013-2019.

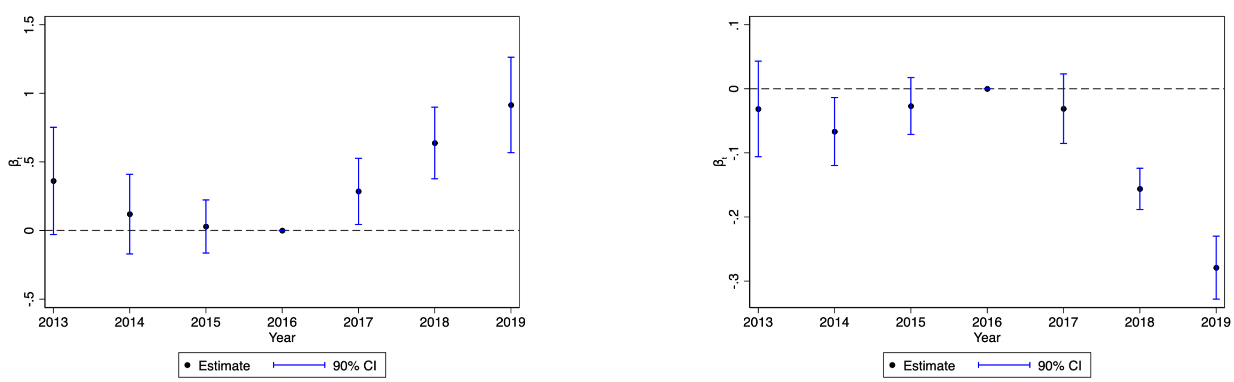
where Imports_{ipot} denotes the value of imports of 8-digit HS product p by Turkish firm i from country o in year t, D_t^l are year dummies and $Treat_p$ indicates the set of China-banned plastic waste products.

Figure A3. Event Study: Firm-level Value of Imports



Note: The figure plots the estimates of β_l, together with 90% confidence intervals, obtained from equation B.1. The interaction with year 2016 is removed from the equation to serve as a reference year. The sample covers the years from 2013 to 2019.

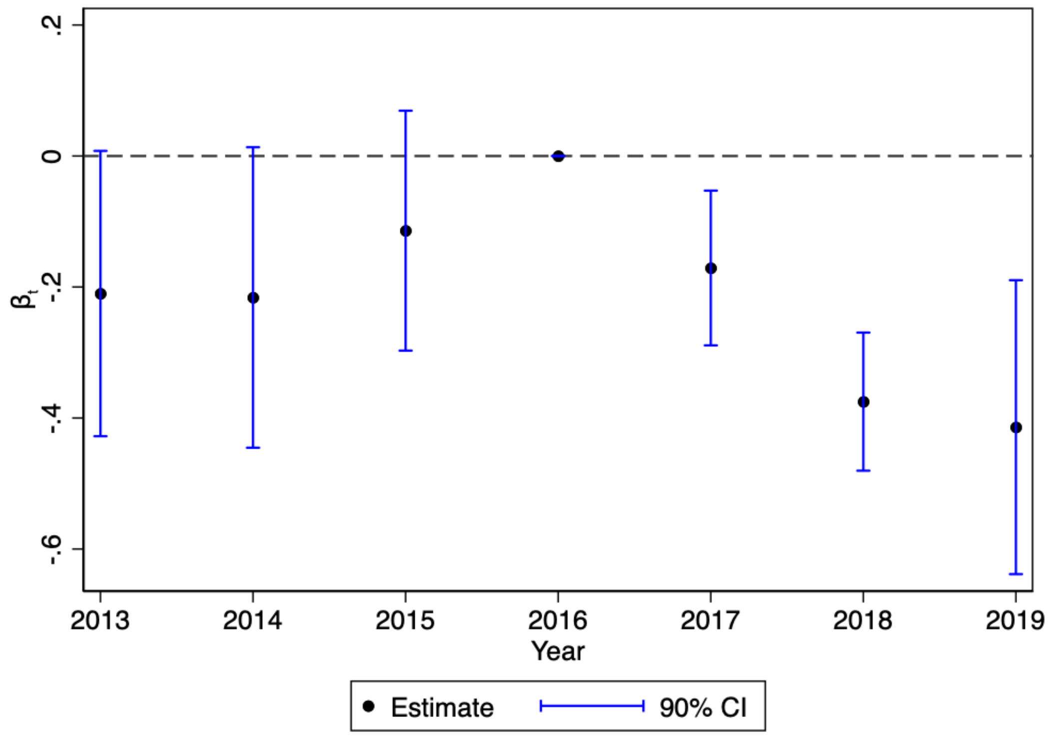
Figure A4. Event Study: Decomposition of Turkish Imports into Prices and Quantities



(A) Quantity (B) Unit prices

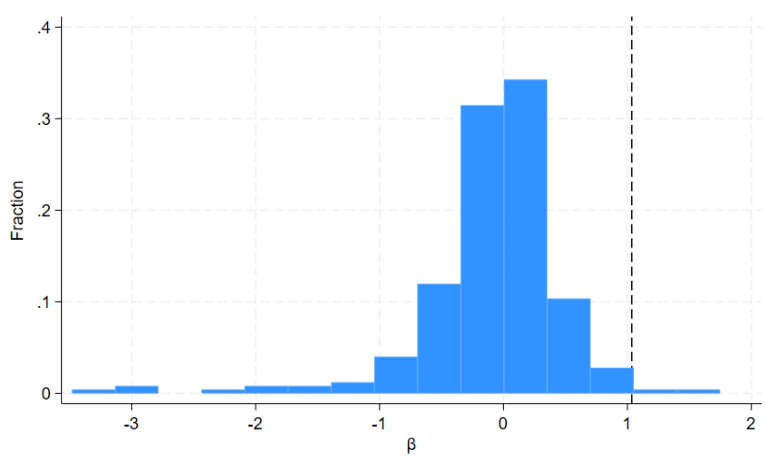
Note: The figure plots the estimates of β_l, together with 90% confidence intervals, obtained from equation B.1, where the dependent variable in Panel (A) is quantity (measured in kg) of Turkish imports at the 8-digit HS level and in Panel (B) is the unit price (measured in dollars per kg) of Turkish imports at the 8-digit HS level. The interaction with year 2016 is removed from the equation to serve as a reference year. The sample covers the years from 2013 to 2019.

Figure A5. Event Study: Quality Adjusted Import Prices



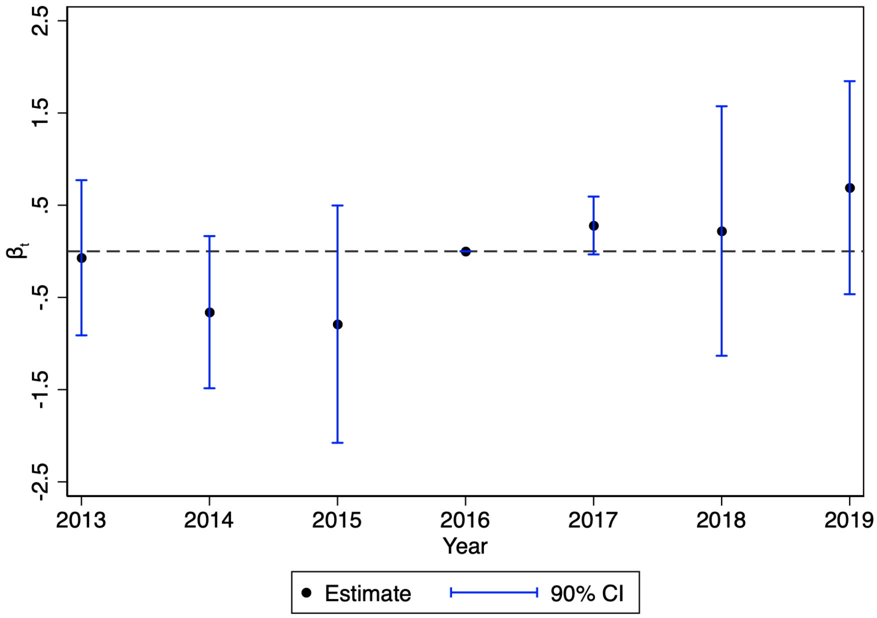
Note: This figure plots the estimates of β_l, together with the 90% confidence intervals, obtained from Equation B.1, where the dependent variable is the quality adjusted price. Quality of a particular 8-digit HS product is the residual from regressing the log quantity + 5*log unit value on country-year, product-year, and firm-year fixed effects. The quality adjusted price is therefore simply the log unit price - log quality. The sample covers the years from 2013 to 2019.

Figure A7. Imports of Plastic Products Randomly Assigned Treatment



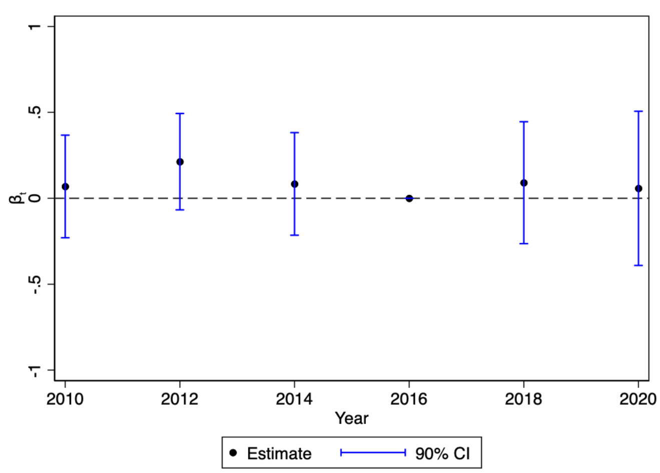
Note: This figure plots the β coefficients of Equation Equation B.1. The treatment variable is randomly allocated treatment status to 8-digit HS products within their corresponding 4-digit HS codes and then re-estimated. This procedure is replicated 250 times. This is used as a robustness check.

Figure A6. Event Study: Exports



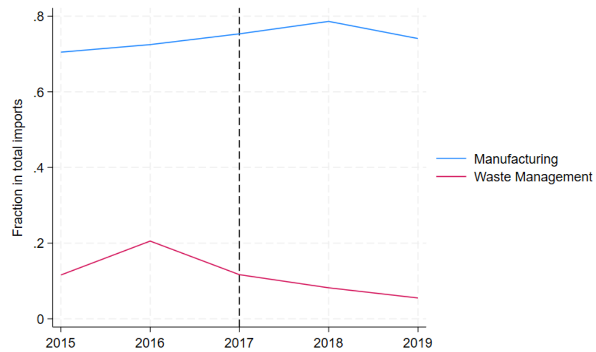
Note: The figure plots the estimates of β_l, together with 90% confidence intervals, obtained from equation B.1, where the dependent variable is the quantity of Turkish exports at the 8-digit HS level. The interaction with year 2016 is removed from the equation to serve as a reference year. The sample covers the years from 2013 to 2019.

Figure A9. Total Waste Production of Domestic Waste Generators

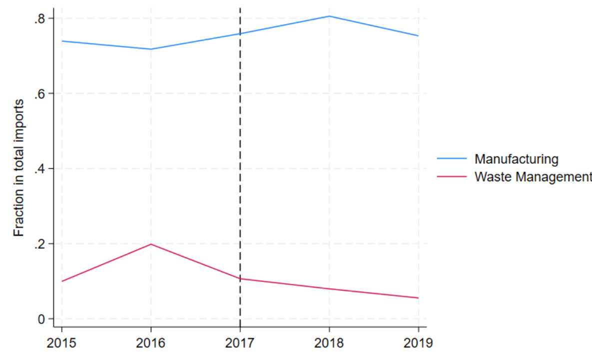


Note: This figure plots the estimates of β_l, together with 90% confidence intervals, obtained from estimating the specification in 3.3. Each observation is at the firm-year level. The dependent variable is the amount of waste that firm k produces at year t. The coefficient of interest is on an interaction term of year dummies D_t^l and $Exposure_k$. Where $Exposure_k$ is the share of firm k's production of China banned waste in its total waste. The interaction with year 2016 is removed from the equation to serve as a reference year. The sample covers the years 2013-2019.

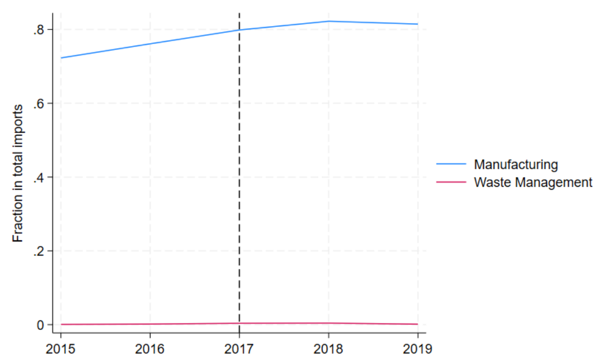
Figure A8. Share of Manufacturing Firms in Imports



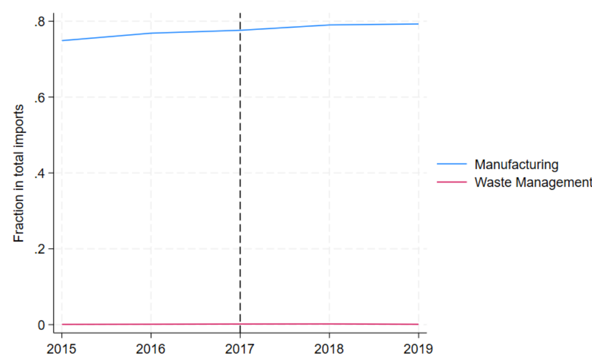
(a) Share of Imports by Quantity: Plastic Waste



(b) Share of Imports by Value: Plastic Waste



(c) Share of Imports by Value: Other Goods



(d) Share of Imports by Value: Other Goods

Note: These graphs show the share of imports of plastic waste and other goods by quantity and value over the years by manufacturing firms and waste management firms.

Appendix C. Theory

C.1. **Firm Choices.** Firms maximise profits and let λ denote the Lagrange multipliers on the production constraints:

$$\max_{l,m,v,x} \Pi_{ud} = R_u\left(l_{ud}, m_{ud}\right) - w_d l_{ud} - \sum_h \sum_o z_d v_{huod} - \sum_h \sum_o p_{hod} x_{huod} + \lambda_{ud}\left(m\left(v_{huod}, x_{huod}\right) - m_{ud}\right)$$

$$\begin{aligned} \max_{a,v,x} \Pi_{sd} = & R_s\left(v_{hsod}\right) - \sum_h \sum_o z_d v_{hsod} + \sum_h \sum_{d'} r_{sdd'}\left(x_{hsdd'}\right) / \tau_{hdd'} - \sum_h w_d \gamma\left(a_{hsd}\right) \sum_o v_{hsod} \\ & + \sum_h \lambda_{hsd}\left(x_{hsd} a_{hsd} \sum_o v_{hsod} - \sum_{d'} x_{hsdd'}\right) \end{aligned}$$

$$\max_{l} \Pi_{nd} = R_n\left(l_{nd}\right) - w_d l_{nd}$$

TABLE A1. Emissions by Plastic Type

Plastic Type	2016 Global Production (million t)	Share Global Production (%)	Mis- management/ Combustion ($MTCO_2E$ per Short Ton)	Managed ($MTCO_2E$ per Short Ton)	Raw Material Acquisition and Manufacturing Emission $MTCO_2E$ per Short Ton)
HDPE	50.81	12.10	2.80	0.02	1.10
LLDPE/ LDPE	49.34	11.74	2.80	0.02	1.27
PET	22.99	0.05	2.05	0.02	1.75
PP	66.63	15.87	2.80	0.02	1.17
PS	19.23	0.05	3.02	0.02	1.87
PVC	46.09	10.97	1.26	0.02	1.69
Other	206.31	49.22	2.34	0.02	1.49
TOTAL	419.17	100	2.40	0.02	1.39

Notes: The global production of plastic in 2016 by plastic type is provided by Our World in Data: https://ourworldindata.org/grapher/plastic-production-polymer?time=2013..latest. Shares are calculated using the global production. The CO_2 emissions of mismanagement/combustion are taken from EPA's GHG emission hub. Similarly, the emissions from the raw material acquisition and manufacturing are obtained by US EPA: https://archive.epa.gov/epawaste/conserve/tools/warm/pdfs/Plastics.pdf

Optimal choices are given by the FOCs below:

$$(1) R_{lu}\left(l_{ud}, m\left(v_{huod}, x_{huod}\right)\right) - w_d = 0$$

$$(2) R_{mu}\left(l_{ud}, m\left(v_{huod}, x_{huod}\right)\right) m_{v_{huod}}\left(v_{huod}, x_{huod}\right) - z_d = 0$$

$$(3) R_{mu}\left(l_{ud}, m\left(v_{huod}, x_{huod}\right)\right) m_{x_{huod}}\left(v_{huod}, x_{huod}\right) - p_{hod} = 0$$

$$(4) r'_{sdd'}\left(\bar{x}_{hsd}\right) x_{hsd} - w_d \gamma'\left(a_{hsd}\right) = 0$$

$$(5) R_{v_h s}\left(v_{hsod}\right) - z_d + r'\left(\bar{x}_{hsd}\right) x_{hsd} a_{hsd} - w_d \gamma\left(a_{hsd}\right) = 0$$

$$(6) r'\left(x_{hsdd'}\right) / \tau_{hdd'} = \lambda_{hsd} \equiv r'_{sdd'}\left(\bar{x}_{hsd}\right)$$

$$(7) R_{ln}\left(l_{nd}\right) - w_d = 0$$

$$(8) x_{hsd} a_{hsd} \sum_o v_{hsod} - \sum_{d'} x_{hsdd'} = 0$$

For a strictly concave maximisation problem, we must assume $R'', m'', r'', -\gamma'' < 0$ and $\gamma' > 0$. Given all else equal, equation (4) implies a is a decreasing function of $w/r'x$ because $\gamma'' > 0$. We have implicitly assumed r to be symmetric in all its arguments but this is not necessary.

C.2. **Market Equilibrium.** Give revenues and input prices$(z_d, w_d, p_{hod}, R_{ud}, R_{sd}, R_{nd})$, equations (1) to (8) have 8 unknowns $(l_{ud}, v_{huod}, x_{huod}, a_{hsd}, v_{hsod}, x_{hsdd'}, \bar{x}_{hsd}, l_{nd})$. The market equilibrium is determined by demand for labour and materials determined by the profit maximisation FOCs (1)-(3), given factor prices and revenue functions. Waste management is determined from the abatement FOC (4) and the virgin material choice of supplying firms in FOC (5), given factor prices, revenue functions and the by-product function. Waste demand and supply x is given by FOC (6) and the supply constraint (8). Labour choice of non-exposed firms is given by FOC (7).

In a market equilibrium, virgin resource prices are fixed by arbitrage and free trade. Let z denote the global energy price and τ_d denote the cost of shipping energy from a Walrasian global market to d. Because virgin resources are traded in a global market, the price of shipping it from o to d is $z_{od} = z_d = \tau_d z$, shown below as equation (9). Wages w are determined by labour market clearing in equation (10) below and waste prices p_{iod} are determined by market clearing of demand and supply in equation (11).

$$(9) z_d = \tau_d z$$

$$(10) L_d = l_{ud} + l_{nd} + l_{sd}, l_{sd} \equiv \sum_h \gamma\left(a_{hsd}\right) \sum_o v_{hsod}$$

$$(11) x_{hsod} = x_{huod}$$

Finally, factor incomes I equal expenditures Y on final consumption in the economy. And, these in turn, equal the profits and earnings of all agents (where domestic transfers such as wages get cancelled out). Let $\bar{V}_d$ denote the country's endowment of virgin resources (such as oil or natural gas) that can be directly converted to plastic. The national income identities are summarised in equation (12) below.

$$
\begin{aligned}
(12) I_d =& Y_{sd} + Y_{ud} + Y_{nd} \\
=& R_{sd} + R_{ud} + R_{nd} + z\bar{V}_d \\
&+ \sum_h \left(\sum_{d' \neq d} p_{hdd'} x_{hsdd'} - \sum_{o \neq d} z_d v_{huod} - \sum_{o \neq d} z_d v_{hsod} - \sum_{o \neq d} p_{hod} x_{huod} \right)
\end{aligned}
$$

Together, (1) to (12) provide solutions to the 8 unknowns in production, the 3 factor prices and the income of the representative consumer, given demand for domestic and imported outputs summarised by R and Y.

C.3. **Gravity Trade.** To show that the model is consistent with gravity in waste trade, equations (4) and (6) show waste supply from o to d is

$$r'\left(x_{hsod}\right) = \tau_{hod} w_o \gamma'\left(a_{hso}\right) / x_{hso}$$

Dividing by exports to China gives a form similar to gravity when τ is interpreted as a measure of distance:

$$\frac{r'\left(x_{hsod}\right)}{r'\left(x_{hsoc}\right)} = \frac{\tau_{hod}}{\tau_{hoc}}.$$

Summing across origins and products, waste imports of banned products into destination d are

$$x_d \equiv \sum_{h > \bar{h}} \sum_o x_{hsod} = \sum_{h > \bar{h}} \sum_o r'^{-1}\left(\frac{\tau_{hod}}{\tau_{hoc}} r'\left(x_{hsoc}\right)\right)$$

Let g_{od} denote the inverse of geographical distance between o and d and assume an elasticity of trade to distance of -1. Assuming a power function for marginal revenue $r'(x) \propto x^{\eta}$ (for $\eta < 1$), we get the gravity relationship:

$$x_d = \sum_o r'^{-1}\left(\frac{\tau_{od}}{\tau_{oc}} r'\left(x_{soc}\right)\right) = \sum_o \frac{g_{od}}{g_{oc}} x_{soc}.$$

In logs, this can be written accounting for zero waste imports into China after ONS as:

$$\Delta \ln x_d = - \ln \sum_{h>\bar{h}} \sum_o \frac{g_{od}}{g_{oc}} x_{hsoc}.$$

De-meaning by all exports to China, banned waste imports are

$$\Delta \ln x_d = - \ln \sum_{h>\bar{h}} \sum_o x_{hsoc} - \ln \sum_{h>\bar{h}} \sum_o \frac{g_{od}}{g_{oc}} \frac{x_{hsoc}}{\sum_{h>\bar{h}} \sum_o x_{hsoc}}$$

This is operationalized empirically as

$$\ln x_{dt} \equiv \alpha_d + \alpha_t + \beta_x \cdot \ln \sum_{h>\bar{h}} \sum_o \frac{g_{od}}{g_{oc}} \frac{x_{hsoc}}{\sum_{h>\bar{h}} \sum_o x_{hsoc}} \cdot Post_t$$

C.4. **Extension to Symmetric Revenue Functions.** To examine robustness to symmetry in revenue functions, we harmonize the arguments in the revenue function R_{jd}. We still maintain well-defined firm types and therefore the revenue functions will not be completely symmetric. In particular, the revenue functions are defined in terms of netput vectors - using firms u are net buyers of plastic waste and supplying firms s are net sellers of plastic waste while neither firms n have zero net sales or purchases of plastic waste. The profit functions are now re-written as:

$$\begin{aligned}
\max_{l,m,v,x} \Pi_{ud} =& R_u \left(l_{ud}, m_{ud} \right) - w_d l_{ud} - \sum_h \sum_o z_d v_{huod} - \sum_h \sum_o p_{hod} x_{huod} + \lambda_{ud} \left(m \left(v_{huod}, x_{huod} \right) - m_{ud} \right) \\
\max_{a,v,x} \Pi_{sd} =& R_s \left(l_{sd}, v_{sd} \right) - \sum_h \sum_o z_d v_{hsod} + \sum_h \sum_{d'} r_{sdd'} \left(x_{hsdd'} \right) / \tau_{hdd'} - \sum_h w_d \gamma \left(a_{hsd} \right) \sum_o v_{hsod} - w_d l_{sd} \\
& + \sum_h \lambda_{hsd} \left(x_{hsd} a_{hsd} \sum_o v_{hsod} - \sum_{d'} x_{hsdd'} \right) \\
\max_{l} \Pi_{nd} =& R_n \left(l_{nd}, v_{nd} \right) - w_d l_{nd} - \sum_h \sum_o z_d v_{hnod}
\end{aligned}$$

We get 2 additional FOCs but the other FOCs (1) to (8) are not affected, except through additional arguments implicitly in the revnue functions:

$$(5)'' R_{ls}\left(l_{sd}, v_{sd}\right) - w_d = 0$$

$$(7)'' R_{v_{hnod}n}\left(l_{nd}, v_{nd}\right) - z_d = 0$$

The new FOCs will alter labour market clearing and virgin resource clearing to

$$(10)' L_d = l_{ud} + l_{nd} + l_{sd} + \sum_h \gamma\left(a_{hsd}\right) \sum_o v_{hsod}$$

$$\begin{aligned}(12)' I_d =& Y_{sd} + Y_{ud} + Y_{nd} \\ =& R_{sd} + R_{ud} + R_{nd} + z\bar{V}_d \\ &+ \sum_h \left(\sum_{d' \neq d} p_{hdd'} x_{hsdd'} - \sum_{o \neq d} z_d v_{huod} - \sum_{o \neq d} z_d v_{hsod} - \sum_{o \neq d} z_d v_{hnod} - \sum_{o \neq d} p_{hod} x_{huod} \right)\end{aligned}$$

where l_{sd} appears on the RHS of (10)' additionally and $\sum_{o \neq d} z_d v_{hnod}$ in (12)'. Because we are already including all labour and virgin resources used in the economy (as we cannot distinguish the purpose for which they are used within a firm), this does not alter the quantification.

C.5. **Extension to Per Unit Abatement Costs.** To examine robustness to constant return to scale in abatement, we re-define the abatement costs to $\sum_h w_d \gamma\left(a_{hsd}\right) x_{hsd} \sum_o v_{hsod}$ where the appearance of x_{hsd} implies that abatement costs are per unit of by-products, rather than amortized across them. Profit functions and optimal choices for u and n are the same as before. But the profit function and FOCs for s change and are shown below:

$$\begin{aligned}\max_{a,v,x} \Pi_{sd} =& R_s\left(v_{hsod}\right) - \sum_h \sum_o z_d v_{hsod} + \sum_h \sum_{d'} r_{sdd'}\left(x_{hsdd'}\right) / \tau_{hdd'} - \sum_i w_d \gamma\left(a_{hsd}\right) x_{hsd} \sum_o v_{hsod} \\ &+ \sum_h \lambda_{hsd} \left(x_{hsd} a_{hsd} \sum_o v_{hsod} - \sum_{d'} x_{hsdd'} \right)\end{aligned}$$

$$(4)'\lambda_{hsd} - w_d \gamma' \left(a_{hsd}\right) = 0$$

$$(5)' R_{v_{hsod}s} \left(v_{hsod}\right) - z_d + \lambda_{hsd} x_{hsd} a_{hsd} - w_d \gamma \left(a_{hsd}\right) x_{hsd} = 0$$

$$(6) r'_{sdd'} \left(x_{hsdd'}\right) / \tau_{hdd'} = \lambda_{hsd} \equiv r' \left(\bar{x}_{hsd}\right)$$

$$(8) x_{hsd} a_{hsd} \sum_o v_{hsod} - \sum_{d'} x_{hsdd'} = 0$$

Substituting for (6) in (4)' and (5)', we arrive at the following FOCs:

$$(4)' r' \left(\bar{x}_{hsd}\right) - w_d \gamma' \left(a_{hsd}\right) = 0$$

$$(5)' R_{v_{hsod}s} \left(v_{hsod}\right) - z_d + r' \left(\bar{x}_{hsd}\right) x_{hsd} a_{hsd} - w_d \gamma \left(a_{hsd}\right) x_{hsd} = 0$$

The forms of (4)' and (5)' are changed slightly from

$$(4) r' \left(\bar{x}_{hsd}\right) x_{hsd} - w_d \gamma' \left(a_{hsd}\right) = 0$$

$$(5) R_{v_{hsod}s} \left(v_{hsod}\right) - z_d + r' \left(\bar{x}_{hsd}\right) x_{hsd} a_{hsd} - w_d \gamma \left(a_{hsd}\right) = 0$$

but the main point of a being a decreasing function of w/r' is still true (under $\gamma'' > 0$), and (6) and (8) FOCs for s remain exactly as before. The key change is that the wage cost is no longer divided by x because it cannot be amortized across by-products. Accordingly, the labour market clearing condition is also altered to

$$(10)' L_d = l_{ud} + l_{nd} + l_{sd}, l_{sd} \equiv \sum_h \gamma \left(a_{hsd}\right) x_{hsd} \sum_o v_{hsod}$$

to account for the per unit nature of abatement costs through x_{hsd}.

Appendix D. Quantification

D.1. **Derivations of Trade Impacts.** To be able to estimate the effect of the ONS on imports and exports, we run the following regression.

$$
\begin{aligned}
\ln x_{pct} &= \sum_{c \in D} \beta_x^c \mathbb{1}\{t \geq 2017\} * \mathbb{1}\{c = D\} * \mathbb{1}\{Banned_p^{HS6}\} \\
&+ \sum_{c \in D} \beta_x^{c,HS2} \mathbb{1}\{t \geq 2017\} * \mathbb{1}\{c = D\} * \mathbb{1}\{Banned_p^{HS2}\} \\
&+ \mathbb{1}\{t \geq 2017\} * \text{Tariff Rate}_{pc,t=2016} + \alpha_{ct} + \alpha_{pc} + \epsilon_{pct},
\end{aligned} \tag{D.1}
$$

where the set of destination countries is $D = \{\text{China}, \text{Exporters}, \text{Turkey}, \text{Rest of the World}\}$. To account for potential spillover effects over similar products, we control for treatment status at the 2-digit HS product level. The results are shown in Table A2.

Table A2. Effect on Imports

	IMPORTS		EXPORTS	
	(1)	(2)	(3)	(4)
	$\ln(val_{pct})$	$\ln(val_{pct})$	$\ln(val_{pct})$	$\ln(val_{pct})$
$\mathbb{1}\{Banned_p^{HS6}\} * \mathbb{1}\{China_c\} * \mathbb{1}\{t \geq 2017\}$	-4.246a	-4.244a	-0.0782	-0.0791
	(0.588)	(0.589)	(0.351)	(0.351)
$\mathbb{1}\{Banned_p^{HS6}\} * \mathbb{1}\{HeavyExporters_c\} * \mathbb{1}\{t \geq 2017\}$	0.137	0.137	-0.713a	-0.714a
	(0.108)	(0.108)	(0.107)	(0.107)
$\mathbb{1}\{Banned_p^{HS6}\} * \mathbb{1}\{Turkey_c\} * \mathbb{1}\{t \geq 2017\}$	1.104a	1.104a	0.360	0.359
	(0.0898)	(0.0898)	(0.938)	(0.937)
$\mathbb{1}\{Banned_p^{HS6}\} * \mathbb{1}\{ROW_c\} * \mathbb{1}\{t \geq 2017\}$	0.192c	0.190c	-0.438a	-0.439a
	(0.0982)	(0.100)	(0.0761)	(0.0781)
$\mathbb{1}\{Banned_p^{HS2}\} * \mathbb{1}\{China_c\} * \mathbb{1}\{t \geq 2017\}$	-0.0254	-0.0255	0.129a	0.129a
	(0.0303)	(0.0303)	(0.0347)	(0.0347)
$\mathbb{1}\{Banned_p^{HS2}\} * \mathbb{1}\{HeavyExporters_c\} * \mathbb{1}\{t \geq 2017\}$	0.0367c	0.0396b	0.0543a	0.0582a
	(0.0196)	(0.0196)	(0.0207)	(0.0208)
$\mathbb{1}\{Banned_p^{HS2}\} * \mathbb{1}\{Turkey_c\} * \mathbb{1}\{t \geq 2017\}$	0.121a	0.121a	-0.0186	-0.0184
	(0.0404)	(0.0404)	(0.0625)	(0.0625)
$\mathbb{1}\{Banned_p^{HS2}\} * \mathbb{1}\{ROW_c\} * \mathbb{1}\{t \geq 2017\}$	0.0481a	0.0466a	0.0750a	0.0778a
	(0.0108)	(0.0106)	(0.0156)	(0.0156)
$\mathbb{1}\{China_c\} * \mathbb{1}\{t \geq 2017\}$	0.0422a		0.00862	
	(0.0126)		(0.0119)	
$\mathbb{1}\{HeavyExporters_c\} * \mathbb{1}\{t \geq 2017\}$	-0.0736a		-0.102a	
	(0.00432)		(0.00530)	
$\mathbb{1}\{Turkey_c\} * \mathbb{1}\{t \geq 2017\}$	-0.214a		0.0266c	
	(0.0120)		(0.0138)	
Tariff Percentage Points$_{pc2016} * \mathbb{1}\{t \geq 2017\}$	0.0798b	0.0984a	0.124a	0.0292
	(0.0327)	(0.0346)	(0.0472)	(0.0493)
# Observations	2,926,379	2,926,379	2,371,529	2,371,529
R^2	0.933	0.935	0.907	0.909
Fixed Effects:				
Year	Yes	No	Yes	No
Country x Year	No	Yes	No	Yes
Product x Country	Yes	Yes	Yes	Yes

Note: This table shows the β coefficient of the regression estimated by Eq. D.1. The sample period is between 2013-2019, and includes all 6-digit HS products. The data for this estimation is obtained from the UN Comtrade. Letters indicate statistical significance: a indicates p<0.01, b indicates p<0.05, and c indicates p<0.10.

The difference-in-difference coefficients should be interpreted in comparison to the growth rate of imports/exports of non-plastic products. We allow for the ONS policy to have affected the non-plastic products through general equilibrium (GE). To estimate the GE effects, we rely on balance of trade for all countries.

For Turkey, the BoT is as follows:

$$0 = \Delta E^{TR}_{HS6} + \Delta E^{TR}_{HS2} + \Delta E^{TR}_{n}$$

where E^{TR}_{HS6} is Turkey's net exports of the 6-digit plastic waste products banned by China, E^{TR}_{HS2} is Turkey's net exports of plastic products, and E^{TR}_{n} is Turkey's net exports of all other products.

We can rewrite the BoT for Turkey in terms of the diff-in-diff coefficients we obtained from Table A2.

$$\begin{aligned}
0 =& \Delta E^{TR}_{HS6} + \Delta E^{TR}_{HS2} + \Delta E^{TR}_{n} \\
=& \underbrace{\left((e^{\beta_x^{TR}} - 1) + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right)}_{\text{\% change banned exports}} Export^{TR}_{HS6} - \underbrace{\left((e^{\beta_m^{TR}} - 1) + \frac{\Delta Import^{All}_n}{Import^{All}_n} \right)}_{\text{\% change banned imports}} Import^{TR}_{HS6} \\
&+ \underbrace{\left((e^{\beta_x^{TR,HS2}} - 1) + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right)}_{\text{\% change plastic exports}} Export^{TR}_{HS2} - \underbrace{\left((e^{\beta_m^{TR,HS2}} - 1) + \frac{\Delta Import^{All}_n}{Import^{All}_n} \right)}_{\text{\% change plastic imports}} Import^{TR}_{HS2} \\
&+ \Delta E^{TR}_{n}
\end{aligned}$$

where $Export^{All}_n$ and $Import^{All}_n$ is the global export and import of non-plastic products.

The three unknowns in the BoT equation are $\Delta Export^{All}_n$, $\Delta Import^{All}_n$, and ΔE^{TR}_{n}. To reduce the number of unknowns, we use our findings from the firm-level regressions in Turkey. That is, the change in Turkish exports due to ONS that we estimate using firm-level data should be equal to the change in Turkish exports due to ONS that we estimate using aggregate trade data.

Using firm-level data, we showed in Table 2 that the change in revenue for firms *using* and *supplying* banned plastic waste products is 17% and -13%, respectively.[19] We convert our firm-level results on revenue to exports by assuming a constant share of exports to revenue. We use a share of 10%, which corresponds to the ratio of exports to income in the manufacturing sector in Turkey.

Using the firm-level results depicted in Table 2, we can calculate the total change in exports in Turkey due to ONS as:

$$
\begin{aligned}
&\Delta Export_u^{TR} + \Delta Export_s^{TR} \\
=&((e^{\beta_u^R} - 1) * Exposure_u^{TR} * Revenue_u^{TR} + (e^{\beta_s^R} - 1) * Exposure_s^{TR} * Revenue_s^{TR}) * \text{Export Share}^{TR} \\
=&(0.170 * 0.0002 * \$2.1\text{billion} + (-0.132) * 0.005 * \$178.9\text{billion}) * 0.10 \\
=&-\$11,800,260
\end{aligned}
$$

[19]These results reflect the total effect, as we demonstrated that the ONS policy had negligible effects on firms that neither used nor supplied banned plastic waste products, based on the labor market clearing condition.

Similarly, the change in exports due to ONS, could be calculated using our findings in Table A2:[20]

$$
\begin{aligned}
&\Delta Export^{TR}_{HS6} + \Delta Export^{TR}_{HS2} \\
&\quad = \left((e^{\beta^{TR}_x} - 1) + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right) Export^{TR}_{HS6} + \left((e^{\beta^{TR,HS2}_x} - 1) + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right) Export^{TR}_{HS2} \\
&\quad = \left(0 + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right) * \$12,084,230 + \left(0 + \frac{\Delta Export^{All}_n}{Export^{All}_n} \right) * \$15.9 billion \\
&\quad = \$15,912,084,230 \left(\frac{\Delta Export^{All}_n}{Export^{All}_n} \right)
\end{aligned}
$$

Equating the estimated change in exports in Turkey from the firm-level regressions (Table 2) with the estimated change in exports from the aggregate-level regressions (Table A2), we find that the relative change in global exports of non-plastic products is -0.002.

$$\Delta Export^{TR}_u + \Delta Export^{TR}_s = \Delta Export^{TR}_{HS6} + \Delta Export^{TR}_{HS2} \tag{D.2}$$

$$\rightarrow \quad \left(\frac{\Delta Export^{All}_n}{Export^{All}_n} \right) = \frac{-\$11,800,260}{\$15,912,084,230} = -0.001 \tag{D.3}$$

Recall that our goal was to estimate the change in global imports for non-plastic products to determine the absolute change in banned plastic waste imports for all country groups. To solve for this, we need to address a 6-unknowns and 6-equations problem.

The 6 unknowns are:

(1) The change in global exports for non-plastic products, $\Delta Export^{All}_n$ (which we solved for above).

(2) The change in global imports of non-plastic products, $\Delta Import^{All}_n$.

(3) The change in net exports of non-plastic products in Turkey, ΔE^{TR}_n.

[20] In line with our finding that there were no GE effects on revenue for non-affected firms, we assume that the change in exports for non-affected firms in Turkey, $\Delta Export^{TR}_n$, is 0. It is important to note that we allow for the change imports of non-affected firms, $\Delta Import^{TR}_n$, to be non-zero. This will capture any GE effects in addition to any changes in imports of virgin plastic due to substitution.

(4) The change in net exports of non-plastic products in China, ΔE_n^{CHN}.

(5) The change in net exports of non-plastic products for Heavy Exports, ΔE_n^{Exp}.

(6) The change in net exports of non-plastic products in the Rest of the World, ΔE_n^{RoW}.

The 6 equations are:

- The Balance of Trade for the four country groups (Eq D.4-D.7).

- Net exports for each country should equal global net exports in the reference sector (Eq D.8).
- The change in exports in Turkey estimated from firm-level specifications should equal the change in exports in Turkey estimated from the country-product specifications (Eq D.9).

$$
\begin{aligned}
0 = &\left((e^{\beta_x^{TR}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS6}^{TR} - \left((e^{\beta_m^{TR}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS6}^{TR} \\
&+ \left((e^{\beta_x^{TR,HS2}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS2}^{TR} - \left((e^{\beta_m^{TR,HS2}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS2}^{TR} + \Delta E_n^{TR}
\end{aligned}
\tag{D.4}
$$

$$
\begin{aligned}
0 = &\left((e^{\beta_x^{CHN}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS6}^{CHN} - \left((e^{\beta_m^{CHN}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS6}^{CHN} \\
&+ \left((e^{\beta_x^{CHN,HS2}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS2}^{CHN} - \left((e^{\beta_m^{CHN,HS2}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS2}^{CHN} + \Delta E_n^{CHN}
\end{aligned}
\tag{D.5}
$$

$$
\begin{aligned}
0 = &\left((e^{\beta_x^{RoW}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS6}^{RoW} - \left((e^{\beta_m^{RoW}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS6}^{RoW} \\
&+ \left((e^{\beta_x^{RoW,HS2}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS2}^{RoW} - \left((e^{\beta_m^{RoW,HS2}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS2}^{RoW} + \Delta E_n^{RoW}
\end{aligned}
\tag{D.6}
$$

$$
\begin{aligned}
0 = &\left((e^{\beta_x^{Exp}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS6}^{Exp} - \left((e^{\beta_m^{Exp}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS6}^{Exp} \\
&+ \left((e^{\beta_x^{Exp,HS2}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS2}^{Exp} - \left((e^{\beta_m^{Exp,HS2}} - 1) + \frac{\Delta Import_n^{All}}{Import_n^{All}}\right) Import_{HS2}^{Exp} + \Delta E_n^{Exp}
\end{aligned}
\tag{D.7}
$$

$$
\Delta E_n^{TR} + \Delta E_n^{CHN} + \Delta E_n^{RoW} + \Delta E_n^{Exp} = \Delta Export_n^{All} - \Delta Import_n^{All}
\tag{D.8}
$$

$$
\begin{aligned}
&((e^{\beta_u^{R}} - 1) * Exposure_u^{TR} * Revenue_u^{TR} + (e^{\beta_s^{R}} - 1) * Exposure_s^{TR} * Revenue_s^{TR}) * \text{Export Share}^{TR} \\
&= \left((e^{\beta_x^{TR}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS6}^{TR} + \left((e^{\beta_x^{TR,HS2}} - 1) + \frac{\Delta Export_n^{All}}{Export_n^{All}}\right) Export_{HS2}^{TR}
\end{aligned}
\tag{D.9}
$$

The solution to this 6-unknown and 6-equation problem is:

$$\frac{\Delta Export_n^{All}}{Export_n^{All}} = -0.0007$$
$$\frac{\Delta Import_n^{All}}{Import_n^{All}} = -0.0008$$
$$\frac{\Delta E_n^{TR}}{E_n^{TR}} = 0.0013$$
$$\frac{\Delta E_n^{CHN}}{E_n^{CHN}} = -0.0014$$
$$\frac{\Delta E_n^{RoW}}{E_n^{RoW}} = -0.0005$$
$$\frac{\Delta E_n^{Exp}}{E_n^{Exp}} = -0.0006$$

Now that we have determined the change in global imports for non-plastic products due to the ONS policy ($\Delta Import_n^{All}$), we can compute the logarithmic change in imports for each country c. This will allow us to estimate the impact of the ONS policy on emissions. The logarithmic change in imports for each country group c is:

$$\text{(D.10)} \qquad \ln\left(e^{\beta_m^c} + \frac{\Delta\text{Import}_n^{\text{All}}}{\text{Import}_n^{\text{All}}}\right) = \begin{cases} 1.105 & \text{if } c = \text{Turkey} \\ -4.27 & \text{if } c = \text{China} \\ 0.19 & \text{if } c = \text{RoW} \\ 0.002 & \text{if } c = \text{Exporters} \end{cases}$$

The logarithmic change in exports for each country group c is:

$$\text{(D.11)} \qquad \ln\left(e^{\beta_x^c} + \frac{\Delta\text{Export}_n^{\text{All}}}{\text{Export}_n^{\text{All}}}\right) = \begin{cases} 0 & \text{if } c = \text{Turkey} \\ 0 & \text{if } c = \text{China} \\ -0.44 & \text{if } c = \text{RoW} \\ -0.71 & \text{if } c = \text{Exporters} \end{cases}$$

D.2. **Virgin Plastic Usage.** In addition to the baseline calibration of global estimates of emissions that relies on raw data and emission factors, we can directly examine emissions from waste using satellite data (from Climate Trace) and primary production of plastics from EXIOBASE. While this is more appealing in that the impacts can be directly estimated, the mapping to China's ONS policy is not exact because the measures covers all waste emissions and all primary plastic production, and therefore we use the direct estimates for China and Turkey in our quantification, and consider scaling factors from emissions to waste mismanagement based on the direct evidence from Turkey.

We estimate the following specifications to measure the effects of the ONS on per capita CO_2 emissions, $CO2pc$, and production of primary plastic for each destination d at year t:

$$\begin{aligned} \ln CO2pc_{dt} &= \beta_x \ln x_{dt} + \Gamma_x X_{dt} + \alpha_d + \alpha_t + e_{dt} \\ \ln m^v_{dt} &= \beta_v \ln x_{dt} + \Gamma_v X_{dt} + \alpha_d + \alpha_t + \varepsilon_{dt} \end{aligned} \tag{D.12}$$

where X_{dt} denotes the vector of destination specific controls, such as initial per capita income, CO_2 emissions, and virgin plastic production, all interacted with a post-ONS dummy.

To account for the potential endogeneity of plastic waste imports, we use a dummy variable that indicates whether destination d had, on average, a trade surplus against the main exporters of plastic waste to China before the implementation of the ONS. We calculate the trade balance as a weighted average of bilateral trade imbalances run by d against the main exporters of plastic waste, where weights reflect the importance of each exporter for Chinese plastic waste imports in 2016. The reasoning is that running a trade surplus against the main exporters of plastic waste reduces the cost of importing plastic waste due to a surplus of empty containers on the way back to the home country.

As presented in the first column of Table A3, the instrument is informative: running a trade surplus against the main exporters of plastic waste before China's ban was associated with more imports of plastic waste to destination d after the ONS. Both OLS and 2SLS results suggest that more imports of plastic waste after the ONS led to an increase in CO_2 emissions and a reduction in the production of virgin plastic in new destinations. This is consistent with our baseline of increased imports of banned plastic waste increasing waste emissions but reducing virgin resource use.

Table A3. Effects on CO_2 Emissions and Virgin Plastic Production

	$\ln x_{dt}$ (1) FS	$\ln CO2pc_{dt}^{waste}$ (2) OLS	$\ln CO2pc_{dt}^{waste}$ (3) 2SLS	$\ln m_{dt}^{v}$ (4) OLS	$\ln m_{dt}^{v}$ (5) 2SLS
$\ln x_{dt}$		0.00704a	0.0347a	-0.0262a	-0.0785c
		(0.00157)	(0.00519)	(0.00920)	(0.0409)
$\left(\sum_o \frac{x_{do}-x_{od}}{x_{do}+x_{od}} \cdot \frac{x_{oChina}}{\sum_o x_{oChina}} > 0\right) * \mathbb{1}\{t \geq 2017\}$	1.041a				
	(0.231)				
$\sum_o \ln\left(\frac{dist_{od}}{dist_{oChina}}\right) * \mathbb{1}\{t \geq 2017\}$	0.813c				
	(0.469)				
GDP $\text{pc}_{dt} * \mathbb{1}\{t \geq 2017\}$	-0.0107	-0.000326	-0.000647b	-0.000637	-0.0000298
	(0.0103)	(0.000567)	(0.000313)	(0.00140)	(0.00154)
$\frac{x_{dChina}}{\sum_d x_{dChina}} * \mathbb{1}\{t \geq 2017\}$	14.64b	0.175	0.0526	1.541	1.774c
	(5.639)	(0.238)	(0.161)	(0.965)	(0.937)
$\ln m_{d16}^{v} * \mathbb{1}\{t \geq 2017\}$	-0.0660	0.00262	0.00327	-0.0615a	-0.0628a
	(0.0823)	(0.00193)	(0.00246)	(0.0182)	(0.0171)
N	273	273	273	273	273
r2	0.793	1.000	-1.510	0.994	-0.0211
KP-Stat			13.30		13.30
J-Stat			0.220		0.219
			(0.6396)		(0.6390)

D.3. **Derivations of CO_2 Emission Estimations.** We start our analysis by estimating the emissions from waste. For Turkey, we distinguish between domestically produced and imported waste, reflecting our firm-level analysis that indicated a rise in mismanagement levels of domestically produced waste from 45% to 52%. For other countries, in the absence of micro-level data, we assume uniform mismanagement levels for both domestically produced and imported waste, as detailed in Table 4.

For each country group, we compute CO_2e emissions generated from both managed and mismanaged, imported, and domestically produced waste. The data used in the calculations are as follows:

- Changes in plastic waste imports and exports from the difference-in-differences analysis (D.10 and D.13).
- CO_2e emissions per ton of mismanaged and managed plastic waste, listed in Table A1.
- Post-policy mismanagement levels of plastic waste (domestically produced and imported), as documented in Table 4.
  - For Turkey, our firm-level analysis had told us that mismanagement levels rose by 7 pp.
  - For China, Shi and Zhang (2023) estimate that mismanagement levels rose by 5% post-ONS.
  - For RoW and Exporters, the change in mismanagement post-ONS are calculated by multiplying the percentage change in ONS-banned plastic within a country (net imports-net exports) with 0.0476, which comes from the results from our IV regression depicted in Column 3 of Table A3.
- Pre-policy import levels of plastic waste, referenced in Table A4.
- Pre-policy domestic waste production and export levels, referenced in Table A4.

The formula to compute the net change in emission levels from waste management and mismanagement for each country c is given by:

$$\begin{aligned}
\Delta CO_2^{w,c} = & \underbrace{(P^c_{post} - X^c_{post}) * (j^c_{post}) * 2.40}_{\text{Emissions from Mismanaged Domestic Waste post ONS}} + \underbrace{(P^c_{post} - X^c_{post}) * (1 - j^c_{post}) * 0.02}_{\text{Emissions from Managed Domestic Waste post ONS}} \\
& \underbrace{+ M^c_{post} * (j^c_{post}) * 2.40}_{\text{Emissions from Mismanaged Imported Waste post ONS}} + \underbrace{M^c_{post} * (1 - j^c_{post}) * 0.02}_{\text{Emissions from Managed Imported Waste post ONS}} \\
& - \{ \underbrace{(P^c_{pre} - X^c_{pre}) * (j^c_{pre}) * 2.40}_{\text{Emissions from Mismanaged Domestic Waste pre ONS}} + \underbrace{(P^c_{pre} - X^c_{pre}) * (1 - j^c_{pre}) * 0.02}_{\text{Emissions from Managed Domestic Waste pre ONS}} \\
& + \underbrace{M^c_{pre} * (j^c_{pre}) * 2.40}_{\text{Emissions from Mismanaged Imported Waste pre ONS}} + \underbrace{M^c_{pre} * (1 - j^c_{pre}) * 0.02}_{\text{Emissions from Managed Imported Waste pre ONS}} \}
\end{aligned}$$

where:

- P^c_{post} and P^c_{pre} are the amounts of domestic plastic waste produced in country c post- and pre-ONS policy, respectively.
- X^c_{post} and X^c_{pre} are the exports of plastic waste from country c post- and pre-ONS policy, respectively.
- M^c_{post} and M^c_{pre} are the imports of plastic waste into country c post- and pre-ONS policy, respectively.
- j^c_{post}, and j^c_{pre} represent the proportion of mismanaged plastic waste post- and pre-ONS policy, respectively.

The values for each of these are referenced in Table A4.

Table A4. Variables

Variable	**Turkey**	**China**	**Exporters**	**RoW**
P^c_{pre} (million tons)	4.30	125.88	254.63	311.62
P^c_{post} (million tons)	4.30	125.88	254.63	311.62
X^c_{pre} (million tons)	0.02	0.17	8.68	4.87
X^c_{post} (million tons)	$e^0 * 0.02 = 0.02$	$e^0 * 0.17 = 0.17$	$e^{-0.71} * 8.67 = 4.25$	$e^{-0.44} * 4.86 = 3.14$
M^c_{pre} (million tons)	0.34	19.4	9.97	6.41
M^c_{post} (million tons)	$e^{1.11} * 0.34 = 1.02$	$e^{-4.27} * 19.4 = 0.27$	$e^0 * 9.97 = 9.97$	$e^{0.19} * 6.41 = 7.75$
$j^c_{d,pre}$	0.45	0.32	0.05	0.34
$j^c_{d,post}$	0.52	0.30	0.05	0.35

Notes: Data on domestic plastic waste production, P^c, and plastic mismanagement shares, j^c are obtained from the OECD Plastic Outlook. Data on exports and imports of plastic waste, X^c and M^c, is obtained from UN Comtrade.

Solving the change in CO_2 emissions from mismanaged/managed waste for each country group, we obtain:

$$\Delta CO_2^{w,c} = \begin{cases} 1.83 & \text{if } c = \text{Turkey} \\ -20.53 & \text{if } c = \text{China} \\ 6.20 & \text{if } c = \text{RoW} \\ 1.58 & \text{if } c = \text{Exporters} \end{cases} \tag{D.13}$$

Similarly, the change in emissions resulting from the consumption of virgin plastic by each country-group can also be calculated. This analysis incorporates several factors:

- The substitution rate between virgin and recycled plastic, as previously determined.
- Emission levels associated with the production of virgin plastic, as detailed in Table A1.
- Pre-ONS consumption levels of basic plastics, expressed in million euros, obtained from the EXIOBASE database.
- The 2016 commodity price of basic plastic, valued at 1410 Euros per ton.

Using this data, the change in CO2 emissions from virgin plastic consumption can be calculated with the following equation:

$$(e^{1.105}-1)*(-0.1)*\frac{(2,918.3\text{million euros})}{1410\text{Euros per ton}}*(1.39\text{ton } CO_2) = -0.64\text{million tons } CO_2 \quad \text{if } c = \text{Turkey}$$

$$(e^{-4.27}-1)*(-0.1)*\frac{(121,219.6\text{million euros})}{1410\text{Euros per ton}}*(1.39\text{ton } CO_2) = 12.98\text{million tons } CO_2\text{if } c = \text{China}$$

$$(e^{0.19}-1)*(-0.1)*\frac{(239,147.9\text{million euros})}{1410\text{Euros per ton}}*(1.39\text{ton } CO_2) = -5.44\text{million tons } CO_2 \quad \text{if } c = \text{RoW}$$

$$(e^{0.002}-1)*(-0.1)*\frac{(231,960.8\text{million euros})}{1410\text{Euros per ton}}*(1.39\text{ton } CO_2) = -0.05\text{million tons } CO_2 \quad \text{if } c = \text{Exporter}$$