# PLASTIC TURKEY: INTERNATIONAL LEAKAGES OF CHINA'S WASTE CONTAMINATION POLICY

DENIZ ATALAR
UNIVERSITY OF CAMBRIDGE
BANU DEMIR
OXFORD, BILKENT, AND CEPR
SWATI DHINGRA
CEP, LSE, AND CEPR

ABSTRACT. Global plastic production has increased dramatically over recent decades, and it has generated large volumes of plastic waste. High-income countries reduce their plastic waste burden by exporting it to developing countries. China has been a major importer of plastic waste since its integration with the global economy. But following environmental concerns over waste disposal and processing, China banned key plastic waste imports in 2017. This paper shows that China's policy led to a dramatic diversion of trade that had repercussions for emerging markets across the world. Turkey became a major importer of plastic waste from more advanced economies. Importers in Turkey got better access to plastic waste that could be recycled as inputs in production. But imports of plastic waste displaced domestic waste in production and we show that firms in Turkey that generated plastic waste became more likely to mismanage it, including through burning or dumping in water bodies. Emissions from waste management increased in Turkish regions that were more specialised in production of the waste products banned by China. While importing firms increased output, their gains were not enough to undo the losses faced by domestic waste suppliers. The policy led to economic losses and more waste emissions in Turkey, but it offered savings in emissions from reduced use of virgin resources in plastic production. We model the channels of recycling and environmental degradation in a gravity model of trade and the environment to quantify the global spillovers of environmental externalities and the welfare impacts of China's import ban.

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Preliminary & Incomplete. Please do not circulate, cite or quote. e-mails: da497@cam.ac.uk, banu.demirpakel@economics.ox.ac.uk, S.Dhingra@lse.ac.uk.

## 1. Introduction

Global plastic production has increased dramatically since the 1950s, and it has generated large volumes of plastic waste.[1] Most plastic waste -84 percent - is disposed of in landfills or in the environment, posing 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)).[2] The significant challenges posed by plastic waste to human health and biodiversity have led to its inclusion in the materials covered by the Basel Convention.[3]

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 1980s when news hit of garbage ships from OECD ports attempting to dump their unapproved cargo in various low-income countries (Baggs (2009), Kellenberg (2012)). Since then, cheaper processing fees in China and other emerging markets have led to a staggering rise in global waste trade. Global imports and exports of plastic waste increased by 723% and 817% between 1993 and 2016, and 87% of all exports have flowed from high-income countries to developing countries since 1988 (Brooks, Wang, and Jambeck (2018)).

In the 1990s, emerging markets, including 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, adding to its already burgeoning problem of domestically-generated plastic waste. Environmental and health concerns became more salient in China over time, particularly after its winter haze in 2013. The Chinese government tightened a number of air

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

[2]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)).

[3]https://storymaps.arcgis.com/stories/63f88d8da65841f3a13ba4018d26361d

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. Immediately after the policy had been notified to the World Trade Organisation, there were calls for global action to prevent the displaced waste from potentially finding its way to nations with weaker regulations (Brooks, Wang, and Jambeck (2018)).

This study examines the effects of China's overarching ONS policy on global trade in plastic waste and its environmental consequences. The policy provides a unique application to examine the pollution haven hypothesis. 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] The ONS policy presents a stark case to test the hypothesis. The environmental policy had clear bite because it amounted to a ban on waste imports into China. This could have resulted in an improvement in 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 exports 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 whether waste was more mismanaged in these destinations and their economic and environmental effects.

To examine these effects, we focus on Turkey because it emerged as a key "dumping ground" for waste generated in advanced economies after the China ban (Interpol 2020, Human Rights Watch 2022).[5] The 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

[4]This definition is taken from Brian Copeland's 2013 lecture notes on the pollution haven hypothesis.

[5]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.

summary observation because with multiple countries in an integrated global economy, the pollution haven hypothesis is more subtle. 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 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)). We therefore estimate the impacts of China's policy on waste imports into Turkey and quantify its resulting economic and environmental spillovers.

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 are manufacturing firms that re-used the plastic waste as inputs in their production process. These firms gained access to more cost-efficient imported plastic waste material which enabled them to reduce their production costs and to increase their output sales and market share.

While trade data records plastic waste at a finely disaggregated product level, domestic waste generation and management is rarely observable. Utilising unique data on waste disposal of Turkish firms, we find that China's waste ban hampered domestic waste management, ultimately leading to elevated pollution levels in Turkey. After the China ban, domestic firms in Turkey that generated ONS-affected plastic by-products faced greater competition from waste imports. As importers gained access to better quality plastic waste from abroad, they no longer wanted to buy as much plastic waste from domestic firms. 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 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 (Copeland, Shapiro, and

Taylor (2022)). The model conceptualizes 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. Global and national welfare impacts depend on three statistics: (i) the change in mismanagement of locally produced waste, (ii) the stringency of regulations in the waste products banned by China, and (iii) the change in the usage of virgin resources that are replaced through recycling waste. The first channel is similar to the choice of installing abatement technology in the trade and environment literature, and the data enables its direct estimation for waste-generating firms in Turkey. The second channel is familiar from the pollution haven hypothesis, where countries differ in the stringency of their environmental regulations. We measure this from the initial emissions per capita generated from waste across countries, that is available through Climate Trace satellite data. Finally, the third channel makes waste different from pollution-generating activities, such as transport, that emit pollutants but cannot be recycled to conserve virgin resources. We infer this together with local waste management choices from emissions and waste trade data.[6]

**Related Literature.**

Our paper makes significant contributions to three key areas of existing literature. We build on recent advances combining gravity trade with environmental externalities to examine the welfare impact of waste trade (e.g. Shapiro (2016), Shapiro and Walker (2018)). Our specific application provides a direct test of the pollution haven hypothesis in plastic waste and finds the channel of reduced domestic abatement to be empirically relevant. While a number of studies provide empirical support for pollution haven effects arising from differences in environmental policy stringency across countries, the pollution haven hypothesis has been empirically elusive because of various factors such as capital abundance that are correlated with environmental stringency and also affect trade flows. In early work, Copeland and Taylor (2004, 2003) argue that pollution haven effects could be more precisely measured

[6]In the Appendix, we show that the model can be micro-founded to endogenise waste processing and waste recycling choices.

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.

Waste trade has a long tradition of research and several papers consider its welfare consequences theoretically (e.g. Copeland (1991), Lee, Wei, and Xu (2020)). Prior empirical studies such as Baggs (2009), Bunn and Blaney (1997), 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.

Finally, our study contributes to the large literature on China's pollution policies and specifically to the relatively small literature on China's ONS policy in 2017 (e.g. Greenstone, He, Li, and Zou (2021)). Previous research on China's waste imports has shown 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)). In contrast, our paper focuses on the global consequences of this policy ban, extending beyond its national effects. We study how the diversion of waste trade to other countries affected waste management internationally. This is similar to Tanaka, Teshima, and Verhoogen (2022) which also focuses on international consequences of an environmental policy.

The rest of the paper is structured as follows. Section 2 describes China's ONS policy and its trade diversion impacts. Section 3 presents the methodology and empirical findings for importing and waste-generating firms in Turkey. Section 4 introduces a theoretical framework to enable welfare assessments. Section 5 estimates waste trade elasticities and quantifies the welfare impacts of the policy. Lastly, Section 6 provides concluding remarks.

## 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.

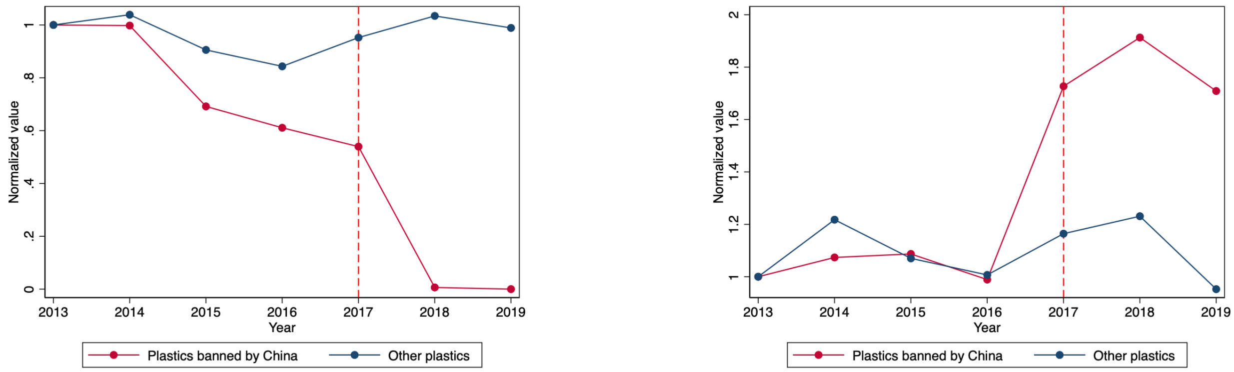
China's role as a global recycling hub led to the establishment of informal recycling and processing facilities, where imported waste materials were sorted, processed, and sometimes disposed of. However, over time, concerns grew about the environmental and health impacts of these practices. Many recycling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

The majority of these concerns revolved 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.[7] 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.[8]

[7]While the value of plastic waste trade did not recover to levels seen before the Green Fence, 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 (Brooks, Wang, and Jambeck (2018), Tran, Goto, and Matsuda (2021).

[8]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)

(B) Turkey (HS8)

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, juxtaposed with 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 developing countries.

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

$$\begin{aligned} \frac{Trade_{podt}}{\sum_d Trade_{podt}} &= \beta_1 Post_t * \mathrm{Treat}_{po} * \mathrm{CHN}_d + \beta_2 Post_t * \mathrm{Treat}_{po} \\ &+ \alpha_{pod} + \alpha_{odt} + \alpha_{pdt} + e_{podt}, \end{aligned} \tag{2.1}$$

where the dependent variable is the share of exports of product $p$ by origin country $o$ to destination country $d$ in year $t$. $\mathrm{Treat}_{po}$ indicates the set of China-banned plastic waste products and origin countries which had exported such products to China in 2015/2016, 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 ($\alpha_{pod}$), 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 $\alpha_{pdt}$, 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 $\beta_1$ because imports of banned plastic waste products to China would fall. Similarly, a positive estimate for $\beta_2$ would show that the policy led to the diversion of plastic waste trade to countries other than China.

TABLE 1. Change in Trade in Plastic Waste:

| Dependent Variable: $\frac{Trade_{podt}}{\sum_d Trade_{podt}}$ | (1) | (2) |
|---|---|---|
| $Post_t * \text{Treat}_{po} * \text{CHN}_d$ | -0.173a | -0.173a |
| | (0.014) | (0.014) |
| $Post_t * \text{Treat}_{po}$ | 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 variables 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: $Post_t$*$Treat_{po}$*$CHN_d$. Where $Post_t$ is a dummy variable indicating 1 if year is greater than 2017, $Treat_{po}$ indicates the set of China-banned plastic waste products, 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: c indicates p<0.10, b indicates p<0.05, and c indicates p<0.01.

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. 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. The second column presents results obtained from a more stringent specification which also controls for time-varying origin-product level 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.[9]

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 the dynamics of how this policy change affected firm-level characteristics and waste management within a third country, namely Turkey. Our choice of Turkey as a case study is informed by two considerations. First, Turkey has become 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 study the international economic and environmental effects on firm-level production, input sourcing, and waste management practices.

## 3. Empirical Analysis

3.1. **Importing Firms' Responses to ONS in 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

[9] Figure A1 in Appendix shows no evidence of pre-trends in exports of treated products to China.

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.

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. While the trends depicted in Figure 2.1 indicate a substantial increase in Turkish imports of scrap and waste products banned by China after 2017, 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:

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

where $\text{Imports}_{pot}$ denotes the value of imports of 8-digit HS product $p$ from country $o$ in year $t$. The sample covers the 2013-2019 period. We are interested in the estimates of $\beta_l$ 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 $\beta_l$, 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.

We also test whether our findings hold when we control for firm-specific demand or changes in country-specific supply that could correlate with the ban. To address this concern, we conduct a standard event study using the following specification:

$$\ln \text{Imports}_{ipot} = \sum_{l=2013}^{2019} \beta_l D_t^l * \text{Treat}_p + \alpha_{ipo} + \alpha_{ot} + e_{ipot}, \tag{3.2}$$

where $\text{Imports}_{ipot}$ denotes the value of imports of 8-digit HS product $p$ by Turkish firm $i$ from country $o$ in year $t$. The point estimates for $\beta_l$, along with their 90% confidence intervals are presented in Figure A2 in Appendix and supports our findings that following the ONS policy, Turkish imports of banned products increased. Furthermore, Figure A3 in the Appendix decomposes the observed change in the value of imports into quantities and unit values based on equation (3.2). The figure illustrates that the quantity of treated products rose (Panel A) after 2017 while their unit prices declined (Panel B).[10] 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.[11]

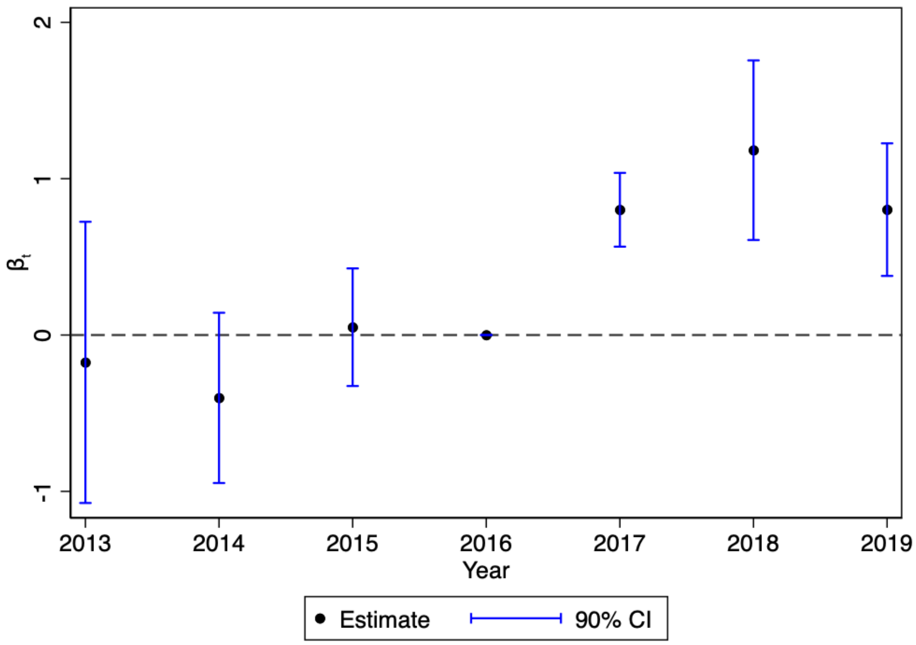
To mitigate potential errors in our findings stemming from the misclassification of products, we randomly allocated treatment status to 8-digit HS products within their corresponding 4-digit HS codes and then re-estimated Equation 3.2. This procedure is replicated 250 times. The outcomes of this robustness check, depicted in Figure A6, reveal that the distribution of estimates from the 250 simulations clusters 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. This sub-section examines the effects on domestic generators of plastic waste in Turkey.

[10]In Figure A4, 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.

[11]We also test whether Turkey only redirects these plastic waste products to other countries. As presented in Figure A5. 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 $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.2 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.

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.[12]

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 from the policy by

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

estimating the following specification:

$$\text{X}_{fpt} = \sum_{l=2012}^{2020} \beta_l D_t^l * \text{Banned}_p + \alpha_{ft} + \alpha_p + \epsilon_{fpt}. \tag{3.3}$$

The dependent variable is the share of firm $f$'s volume of waste product $p$ that is sold at time $t$. $\text{Banned}_p$ 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 reduction in the share of the volume of waste banned by China that is sold. The demand for domestic waste fell as Turkey gained access to cheaper imports in international markets. 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.

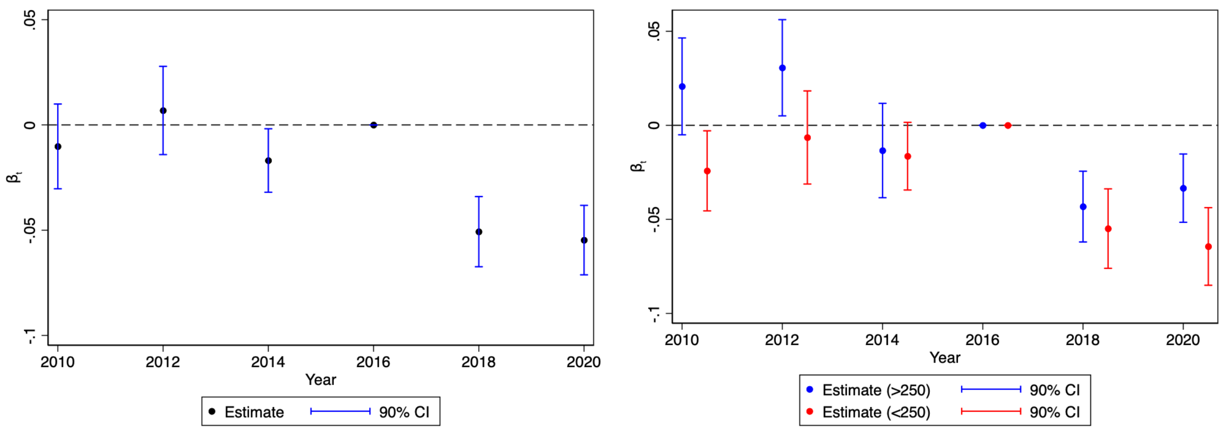
Domestic firms sold less of their waste products and this raises the question of what happened to the waste that they were unable to sell. From the point of view of environmental costs, we are interested in understanding if a greater share of waste started to get environmentally mismanaged. To understand this, we change the dependent variable of Equation 3.3 to the share of firm $f$'s volume of waste product $p$ that is 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.[13]

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

[13]As an 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 3.2. Event study: Waste Sales of Firms in Turkey

(A) Overall (B) By Size



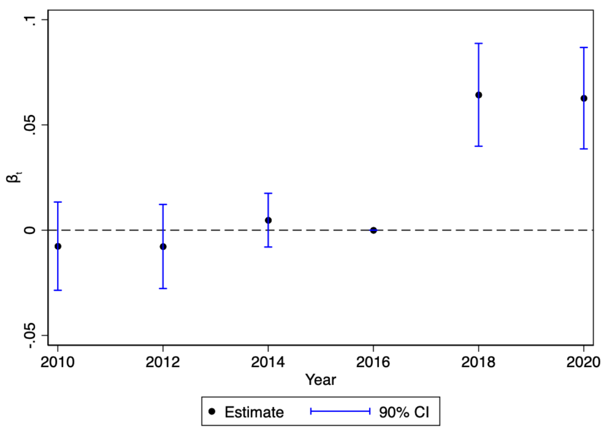

*Note:* These figures plot the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.3. Each observation is at the firm-product-year level. The dependent variable is the share of waste that firm $f$ sells of waste product $p$ at year $t$. Coefficients 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.

in mismanaged waste and not re-used waste occurs among smaller firms. Imported waste displaced domestic waste generated by smaller firms. This might seem surprising under the assumption that larger Turkish firms would be more likely to generate waste that is more similar to that of advanced exporting countries. But the finding is less surprising when recyclability of waste products is taken into account. Waste must undergo 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.

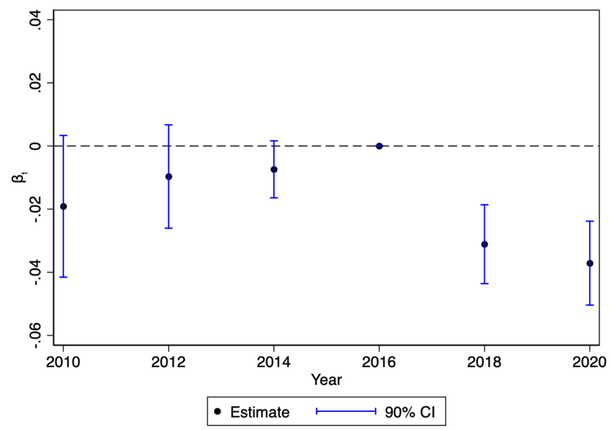
We demonstrated that following the China ban, domestic firms mismanaged a greater share of the waste they generated and re-used a smaller share of their waste. To ensure that these findings are not influenced by any changes in the total waste production (or the scale of waste generation) of these firms,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

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 $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in **??**. Each observation is at the firm-year level. 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.

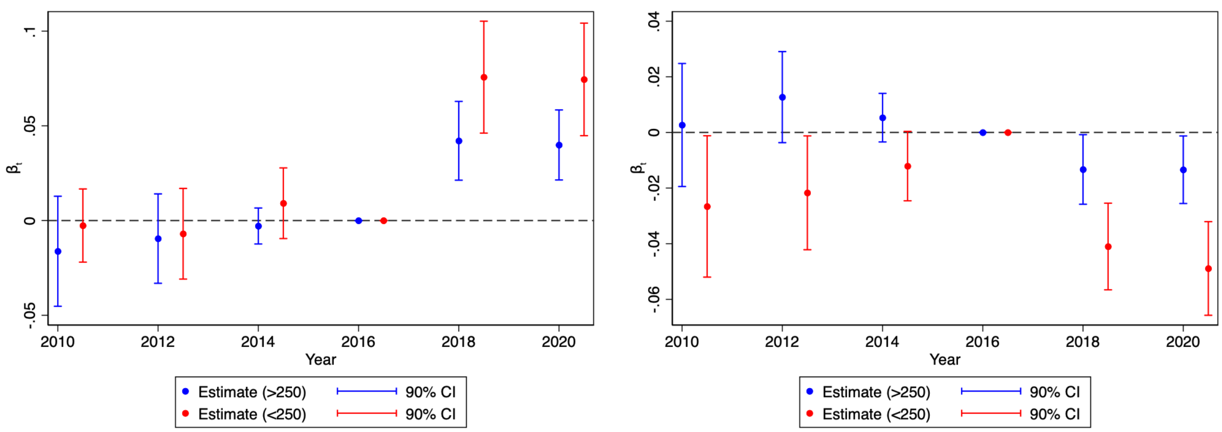
$$\text{Total waste}_{ft} = \sum_{l=2012}^{2020} \beta_l D_t^l * \text{Exposure}_f + \alpha_f + \alpha_{st} + \alpha_{pt} + \epsilon_{ft} \tag{3.4}$$

where the dependent variable is the total amount of waste generated by firm $f$ at time $t$. $Exposure_f$ is the share of China-banned waste products in the total waste generated by firm $f$ before the ONS policy. $s(f)$ and $p(f)$ denote the sector and province of firm $f$. Figure A7 plots the estimates, $\beta_l$, which do not show any noticeable change in the total waste generated by firms that were more intensive in ONS-banned waste products.

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:

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

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

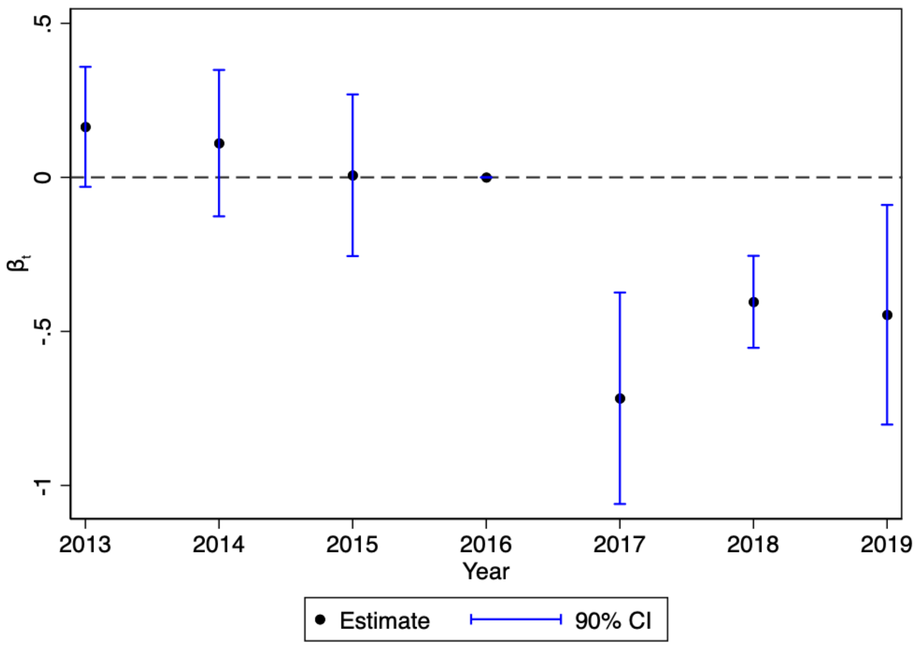



*Note:* These figures plot the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in **??**. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. Coefficients on the interaction between 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.

$$\begin{aligned} \ln(val_{f(s),s',t}) &= \sum_{l=2013}^{2019} \beta_l D_t^l * \text{Exposure}_f * \text{Exposure}_{s'} + \alpha_{ft} + \alpha_{ss't} \\ &+ \alpha_{fs'} + e_{f(s),s',t} \end{aligned} \tag{3.5}$$

The dependent variable is the logarithm of purchases by firm $f$ in the 4-digit NACE industry $s$ from industry $s'$ in year $t$. $Exposure_{s'}$ 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 $\alpha_{ft}$ 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 $\beta_l$ coefficients, along with their 90% confidence intervals estimated from equation (3.5), 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. About 70% of firms importing China-banned products belong to the manufacturing sector, and just 6% are waste management companies. Notably, only 5% of the importers of China-banned products are suppliers to waste management companies. 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:

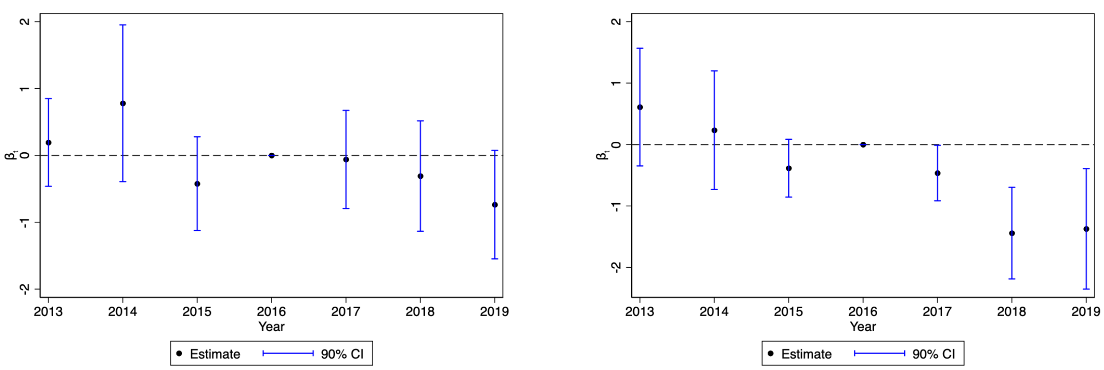
$$(3.6) \qquad X_{it} = \sum_{l=2013}^{2019} \gamma_l D_t^l * \text{Exposure}_i + \sum_{l=2013}^{2019} \delta_l D_t^l * \text{Employment}_i + \alpha_i + \alpha_t + \epsilon_{it}$$

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.[14] 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.

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 $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.6. 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 excluded to serve as a reference year. The sample covers the years from 2013 to 2019.

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

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

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. 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.[15]

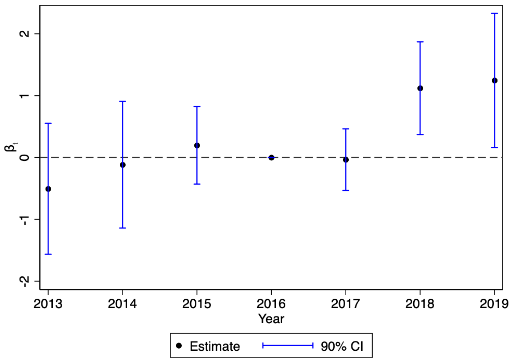
Our next test investigates whether firms that more intensively imported products that were banned by China experienced a differential change in their sales or profit margins. We estimate the specification in equation (3.6) with domestic sales and industry (4-digit NACE category) market shares as dependent variables. The top panels of Figure 3.7 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 panel of Figure 3.7 examines 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. 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 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

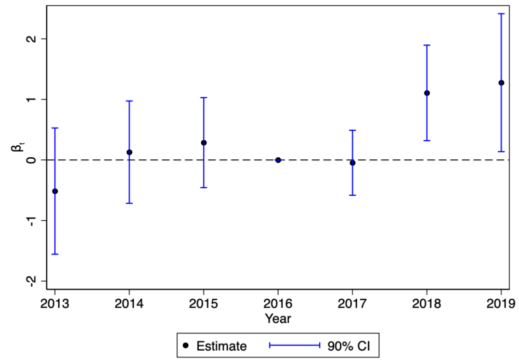
[15] This result is in line with Castro Vincenzi and Kleinman (2020), where they show causal evidence for the negative effect of materials prices on the labor share. Hummels, Jørgensen, Munch, and Xiang (2014) also shows that offshoring decreases low-skilled wages.

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

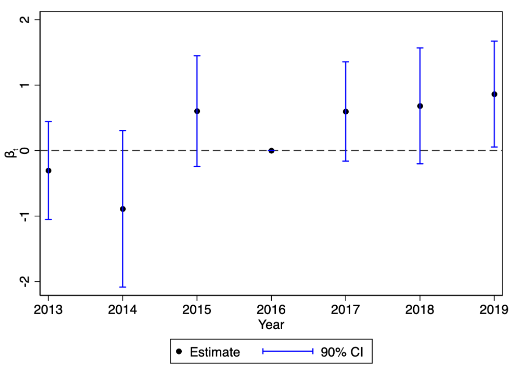
(A) Domestic sales



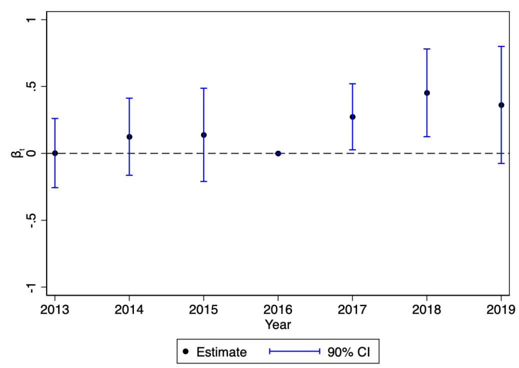

(B) Market share in own industry




(C) Gross Profit Margin




(D) Exporting probability



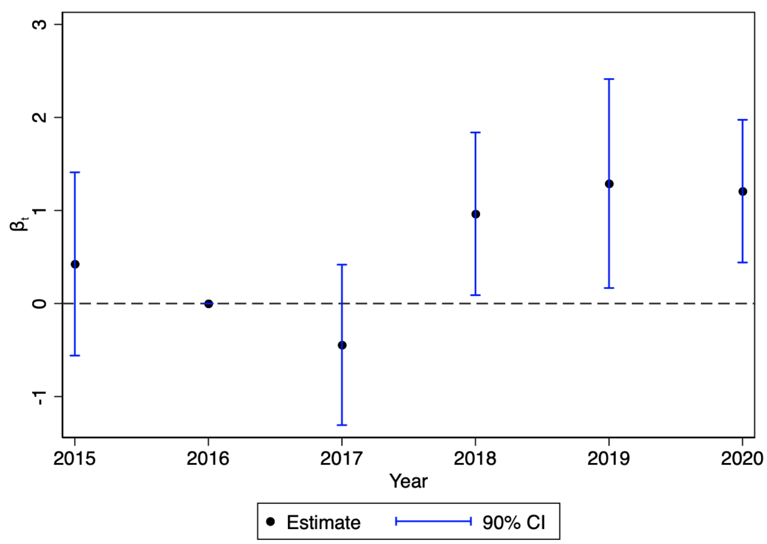

*Note:* These figures plot the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.6. Each observation is at the firm-year level. The dependent variable changes across sub-figures as stated in the title. The coefficient of interest is on an 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.

data to province-year level by constructing the maximum of all reported measurements for a given province and year. We estimate the following specification:

$$\ln PM10_{pt} = \sum_{l=2015}^{2021} \beta_l D_t^l * \text{Exposure}_p + \alpha_p + \alpha_{NUTS2,t} + \epsilon_{ct} \quad (3.7)$$

where $PM10_{pt}$ captures the extreme pollution readings within a province in year $t$.[16] Exposure$_p$ is measured by the share of plastic waste produced by firms with less than 250 employees in province $p$. 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. We control for province as well as time-varying NUTS2-level fixed effects.[17] 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).

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




*Note:* This figure plots the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.7. 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.

[16]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.

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

## 4. Theory

To interpret the main empirical findings in the light of the literature on trade and the environment, we generalise the canonical theoretical framework of Shapiro (2021) to waste as a pollutant. We then provide a mapping from waste trade and waste mismanagement outcomes to emissions and production to enable an ex-post assessment of the welfare impacts of China's ONS policy in Turkey and globally. All details are relegated to the Appendix and the main findings are discussed here.

4.1. **Welfare Impacts of China's ONS.** 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 the setting 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 fumes generated during transport cannot typically be recycled to offset virgin energy use.

4.2. **Production.** 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. 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 glass maker that neither uses nor supplies plastic waste is not exposed through supply and use and denoted by $n$ or referred to as "non-exposed" firm.

*Waste Generation.* Plastic waste producing firms can treat their plastic by-products to generate managed plastic waste. When the managed plastic waste is supplied to waste using firms, they can recycled the plastic waste as inputs 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 technology. If a firm treats its by-products, it generates $x(a)$ units of managed waste. We assume $x(a) = xa$ 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 $\gamma$ is an increasing and convex function. Better abatement technology costs more, and it extracting more and more recyclables out of a given by-product requires more labour.

Production by syringe makers $s$ uses virgin material and generates by-products that can be sorted into plastic waste $x(a)$. By-products that are mismanaged, such as through burning or open dumping, are more polluting than managed waste with emission rates $\xi^b > \xi^x$. 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.* After by-products from use of virgin materials have been sorted into recyclable waste, they can be used as inputs in sector $u$. Production in $u$ needs labour and plastic which could be virgin material $v$ or recycled plastic $x$. Let $m$ denote the amount of material used in production in $u$. Then $m = m(v, x)$ and we assume that $v$ and $x$ are partly substitutable. This distinguishes waste from some other pollutants because there is an offsetting effect on pollution through conservation of virgin resources, that would otherwise need to be exploited and hence contribute to environmental degradation.

*Firm Decisions.* Firms maximise profits, taking wages $w_d$ and input prices as given. 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 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 $\sum_{d'} r(x_{sdd'})/\tau_{dd'}$ 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 $w_d\gamma(a_d)$ for the waste management technology. Having paid this, $xa_d$ units of managed waste are available to be recycled. $\lambda_{sd}$ is the Lagrange multiplier on the constraint that sales of recyclable waste 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 $x_{uod}$, 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:

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

When $\gamma'' > 0$ and given all else equal, the share of waste that is managed $a$ and can be recycled rises with the scale of waste generated by it $x$ and falls with its sorting costs $w$.

It is worth noting here 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 summarise it below. We also show in the Appendix that the theoretical framework is consistent with gravity in waste trade that motivates the instrumental variable estimation. 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 trade takes a gravity form:

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

4.3. **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. 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 $\xi^v$) and from pollution generated by plastic waste (such as through marine pollution and greenhouse gas emissions that generates disutility at a rate $\xi^x$).

It will be convenient to refer to products, indexed by $i$, because the China ban applies to specific products $i$ within plastic that are more polluting or contaminated. Assume without loss of generality that $\xi_i^x$ is increasing in $i$. China's ONS policy bans imports of $i > \bar{i}$ and therefore removes higher disutility imported waste destined for recycling in China. Sectors $s$ and $u$ refer to products $i > \bar{i}$ while $n$ refers to all other products that are not covered by the ban. We retain the sector labels to keep track of waste supply and use, and the Appendix extends the profit maximisation problems to explicitly account for product labels $i$.

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

**Welfare W.**

$$W_d \equiv W\left(U_d, S_d, N_d, -V_d - Z_d\right)$$

$$V_d \equiv \sum_i \xi_i^v \sum_{d'} \left(v_{iudd'} + v_{isdd'}\right)$$

$$Z_d \equiv \sum_i \left( \xi_i^b \left(1 - a_{id}\right) x_{isd} + \sum_o \xi_i^x x_{iuod} \right)$$

where $W$ is increasing in final consumption of goods produced by sectors $u, s$ 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 we will later also discuss 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 $\xi_i^b > \xi_i^x$ as explained before.

4.4. **China ONS Policy.** China's ONS policy bans imports of $i > \bar{i}$ and therefore removes higher disutility imported waste destined for recycling in China, indexed by $c$. Let $\Delta x_{iuoc} \equiv x_{iuoc}\left(\tau_{ioc}^{ONS}\right) - x_{iuoc}\left(\tau_{ioc}\right)$ denote the change in imports into China where $\tau_{ioc}^{ONS}$ is prohibitively high for $i > \bar{i}$ and for all $o \neq c$ after the ONS policy in 2017. Under a prohibitive tariff, imports after the policy would be zero. Hence $\Delta x_{iuoc} = -x_{iuoc}$ and we can define the ban as a shift to an equilibrium with a prohibitive price for the banned waste imports.

4.5. **Income Impacts.** We start with quantifying income changes in Turkey where we have more domestic data on waste management. Under labour market clearing, the change is labour demand of Turkish firms from the policy must equal $0 = \Delta l_{ud} + \Delta l_{nd} + \Delta l_{sd}$. For each firm in Turkey, we observe how much each using and supplying firm relies on banned waste products relative to total waste, as explained earlier. This enables an estimation of the log change in employment of firms exposed to the policy through use and supply of banned products, relative to non-exposed firms. Let $\beta_{lu}$ denote the estimated DiD employment coefficient for waste using firms $u$ relative to $n$ and $\beta_{ls}$ for waste supplying firms $s$. Then labour market clearing gives

$$0 = \left(\beta_{lu} Exposure_u + \beta_{ln}\right)\left(l_u/L\right) + \left(\beta_{ls} Exposure_s + \beta_{ln}\right)\left(l_s/L\right) + \beta_{ln} l_n/L$$

and we can infer $\beta_{ln} = 0.0007\%$, which is al almost negligible employment effect for non-exposed firms.

From this, we calibrate $\Delta R_{nd}(l_{nd}) = \beta_n R_{nd}$ by scaling with the revenue elasticity of labour in the non-exposed sector. With a labour share of 21 percent of total costs and constant markups, $\beta_n$ turns out to also be negligible. Combining this with the DiD specification for revenues of using and supplying firms, we obtain the overall revenue effect $\Delta R = \sum_{j=u,s,n} \Delta R_j$ in Turkey as:

$$\Delta R = \Delta R_u + \Delta R_s + \Delta R_n = \left(\beta_u Exposure_u \left(R_u/R\right) + \beta_s Exposure_s \left(R_s/R\right) + \beta_n\right) R$$

Revenues of using firms rise by 17 percent while that of supplying firms fall by 13 percent. Evaluated at the mean exposures and initial revenue shares, the overall revenue falls by -0.027% or a loss of USD 118.233 million. This is because there are waste supplying firms make up a much larger share of sales than waste using firms in the Turkish economy. This generally implies that sales at home and abroad of non-exposed firms is not affected by China's ban, and therefore $\Delta E_n = 0$ in Turkey under gravity.

4.6. **Trade Impacts.** The difference-in-differences trade specification that we have considered gives changes in waste trade, relative to a baseline of less exposed countries. The budget constraint in each country implies a set of balanced trade conditions that we now exploit to determine the absolute changes in waste trade for the baseline country. Let $E$ denote the value of net foreign exports, $X$ denote net foreign plastic waste imports and $V$ denote net foreign virgin resource imports ($E, X, V$ can be positive or negative to denote exports or imports). Then in changes with respect to the ONS policy, the balanced trade condition of destination $d$ is

**Balanced Trade BoT.**

$$\Delta E_{ud} + \Delta E_{sd} + \Delta E_{nd} - \Delta X_d - \Delta V_d = 0$$

We have already estimated the change in waste trade values for Exporters, China and Turkey, relative to the average change in trade value that is uniform across all countries. The latter is denoted by *RoW* which is the excluded category in the first stage of the difference-in-differences specification and corresponds to the uniform effect across all countries, which would typically include countries that have a zero exposure to the instrument (that never happens in our setting because distance is positive for all countries). In particular, let $G_d$ denote the instrument that turns on after 2017. Then the first difference change in the level of export values is $\Delta X_d = \beta_x G_d X_d + (X_d/X_{RoW})\,\Delta X_{RoW}$. Virgin resource imports can be expressed similarly as $\Delta V_d = \beta_v \Delta X_d + \Delta V_{RoW}$.

Similarly, we can specify reduced form DiD specifications to obtain $\beta_u, \beta_s$ from country-level net exports of using and supplying firms, and infer $\Delta E_{jd} = \beta_j G_d E_d + (E_{jd}/E_{jTurkey})\,\Delta E_{jTurkey}$ for $j = u, d$. For Turkey, we have also estimated a difference-in-differences coefficient $\beta_{uTurkey}$ of the change in exports of using firms relative to non-exposed firms, giving $\Delta E_{jTurkey} = \beta_{jTurkey} \cdot Exposure_{jTurkey} \cdot E_{jTurkey} + (E_{jTurkey}/E_{nTurkey})\,\Delta E_{nTurkey}$ and inferred $\Delta E_{nTurkey}$ from factor market clearing.

Together with these relationships, the balanced trade condition for the four types of destinations fix the absolute changes in the BoT conditions and we combine them with the DiD estimates to arrive at the missing intercept for waste trade changes.

With these relationships in hand, there are four BoT conditions for $d$ =Exporter, China, Turkey and Rest of the World. We observe $(G_d, X_d, V_d, E_{sd}, E_{ud})$ and have estimated $(\beta_x, \beta_v, \Delta E_{nTurkey}, \beta_{uTu}$ The BoT conditions in levels can be solved to get $E_{nd}$ for each destination. The remaining unknowns are $(\Delta X_{RoW}, \Delta V_{RoW})$ and $\Delta E_{nd}$ for destinations other than Turkey. A reduced form relationship can also be specified for the non-exposed sector to obtain $\beta_n$ and to infer $\Delta E_{nd} = \beta_n G_d E_{nd} + (E_{nd}/E_{nTurkey})\,\Delta E_{nTurkey}$ for $d$ =RoW. The RHS geography variable is not applicable to Exporters and China, and we therefore have four unknowns $(\Delta X_{RoW}, \Delta V_{RoW}, \Delta E_{nChina}, \Delta E_{nExporter})$ that can be solved for through the four BoT conditions in changes.

Having obtained the changes in trade, we proceed to an examination of income effects. Together with $\Delta X_{Turkey}$ and $\Delta V_{Turkey}$, we obtain the change in income in Turkey as $\Delta I_{Turkey} = \sum_{j=u,s,n} \Delta R_{jTurkey} - \Delta X_{Turkey} - \Delta V_{Turkey}$. To do the same in other countries, we need to determine the impact on domestic trade of all firms, together with the incomes change on account of the waste using and supplying sectors. This can be inferred as the difference between plastic waste generation and plastic waste trade (work in progress).

4.7. **Welfare Impacts.** Having estimated the trade and expenditure effects of the policy, we summarise the welfare impacts for Turkey and globally. We provide the market-implied conversion factor between an additional unit of income and an extra unit of emissions for each set of countries. This overcomes the usual problem of assigning shadow values to environmental externalities (denoted by $\xi$ in the welfare function), which by their very nature are not directly observable.

Because we estimate virgin resource consumption, the consumption units need to be converted into emissions to compare with the emissions from waste. The global warming potential (GWP) of virgin plastic production is taken from values of carbon dioxide, methane and nitrous oxide in the United States Environmental Protection Agency worksheet for plastics in 2018. The overall 100-year GWP is $2928.08 = 2850 + 25 \times 1216/1000 + 298 \times 160/1000$ kg of carbon dioxide equivalent per short ton of plastic where 2850kg, 1216g and 160g are the quantities of carbon dioxide, methane and nitrous oxide respectively for plastics and 25 and 298 are the 100-Year GWP carbon dioxide equivalents for methane and nitrous oxide in 2018.

As a starting point, we first assume no change in trade of final outputs. Then $\Delta E_{jd} = 0$ for $j = u, s, n$ and $(1 + \beta_v)\left(\beta_x G_d X_d + (X_d/X_{RoW})\,\Delta X_{RoW}\right) + \Delta V_{RoW} = 0$ for $d =$Turkey and RoW. This enables a solution for $\Delta X_{RoW}$ and $\Delta V_{RoW}$ and we can substitute for them in the $\Delta X_d$ and $\Delta V_d$ DiD specifications to arrive at the following aggregate impacts. (TBD is work in progress, including with less stringent assumptions).

| Region | Waste Imports | Income | Waste Emissions | Virgin Production |
|---|---|---|---|---|
| | $\Delta X_d$ (%) | $\Delta I_d$ (USD) | $\Delta Z_d^x$ (CO2e) | $\Delta y_d^v$ |
| China | -66.04% | TBD | -3.17% | 7.4% |
| Turkey | 11.37% | +17% for waste using firms | 0.05% | -1.3% |
| | | -13% for waste supplying firms | | |
| | | -USD 118 million | | |
| Exporters | 3.72% | TBD | -0.02% | 0.4% |
| Rest of the World | 3.51% | TBD | -0.02% | 0.4% |
| Global | TBD | TBD | TBD | TBD |

## 5. Conclusion

In conclusion, our paper highlights the international spillover effects of domestic environmental policy, focusing on China's policy to make its waste contamination laws more stringent. This policy shift led to a significant displacement of waste exports from advanced economies to China, much of which then got diverted to Turkey. We find that plastic manufacturing firms in Turkey gained access to cheaper waste 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. This increased emissions in Turkish regions that specialize in the production of products affected by China's policy, despite potentially offsetting effects on emissions from the need to produce less virgin plastic.

We incorporate waste trade and study the effects of the policy through a gravity model of trade and the environment. This model suggests that change in global and national welfare depends on three main variables: the change in domestic waste mismanagement, the production gains from recycling, and savings in the use of virgin resources. We quantify global environmental and welfare impacts and future work will enrich the framework to determine waste generation responses globally.

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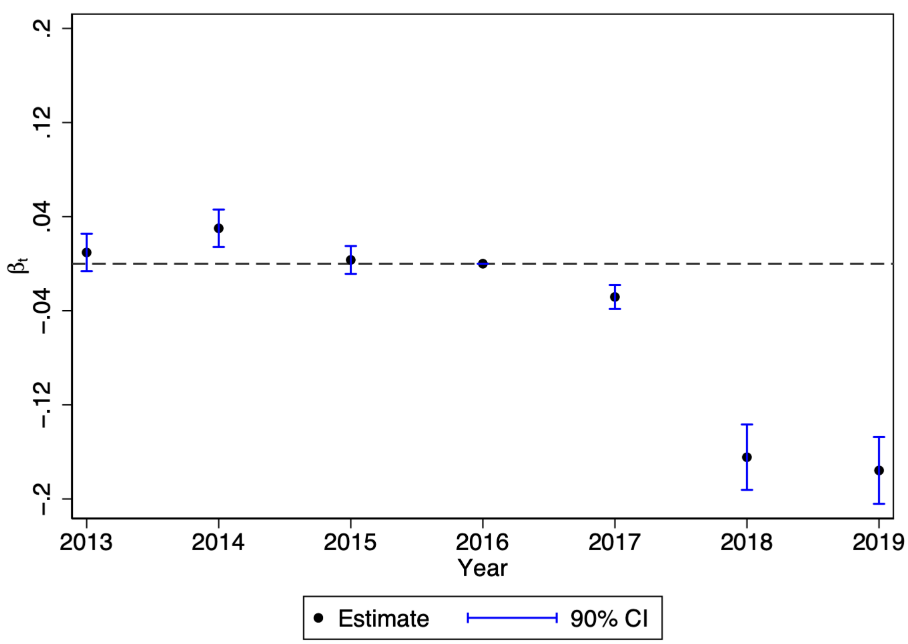
## Appendix

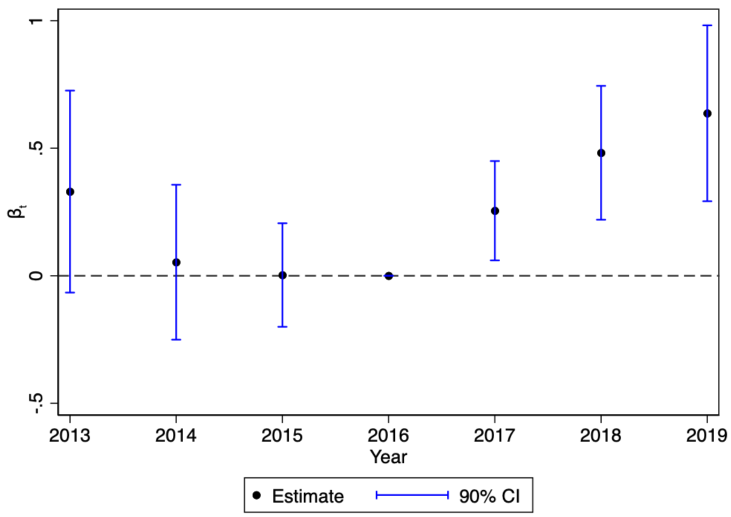
### Appendix A. Additional Tables and Figures

Figure A1. Event Study: Global trade after the National Sword Policy



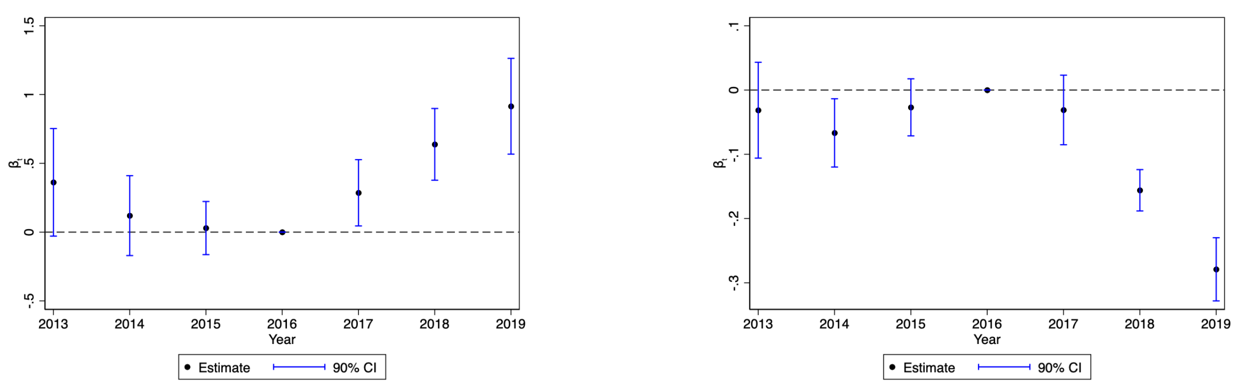

Note:

Figure A2. Event Study: Firm-level Value of Imports




*Note:* The figure plots the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.2 in addition to the 90% confidence intervals. The dependent variables is the (log) value imports of the Turkish firm $f$ of product $p$ by 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 removed from the equation to serve as a reference year. The sample covers the years 2013-2019.

Figure A3. Event Study: Decomposition of Turkish imports




(A) Quantity

(B) Unit prices

Note:

Figure A4. Event Study: Quality Adjusted Import Prices

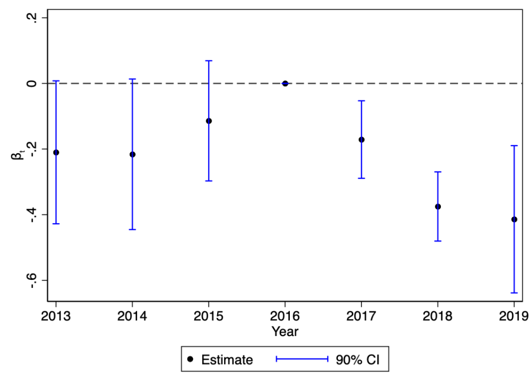
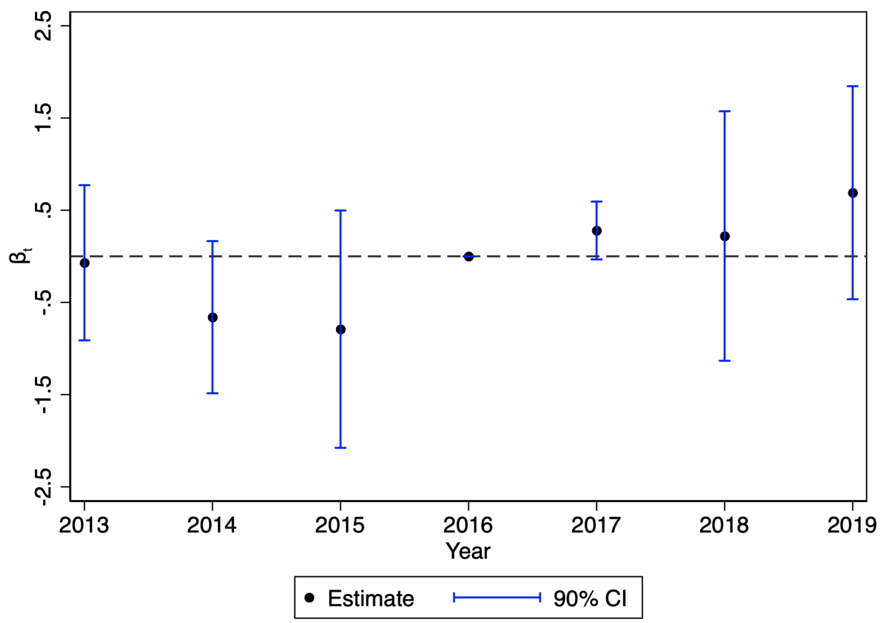



Figure A5. Event Study: Exports




Note:

Figure A6. Imports of Plastic Products Randomly Assigned Treatment

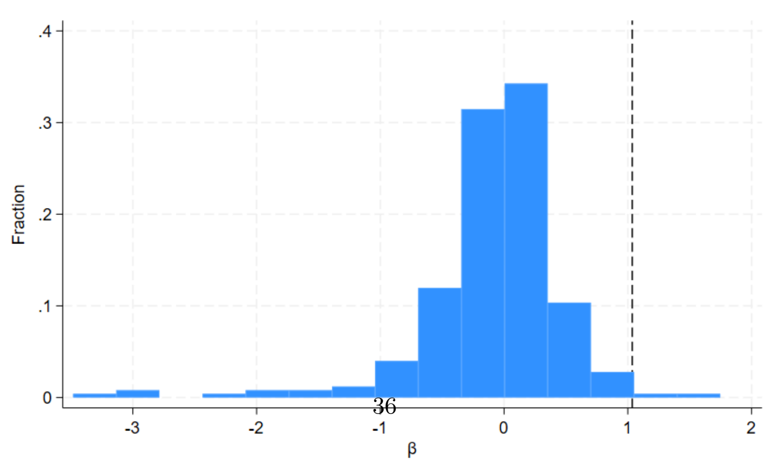
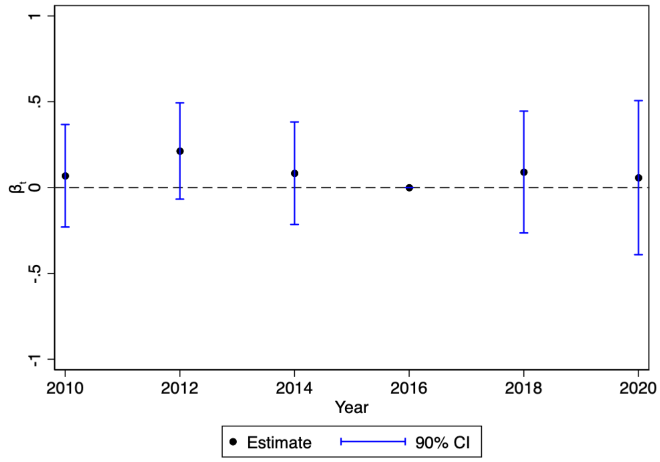
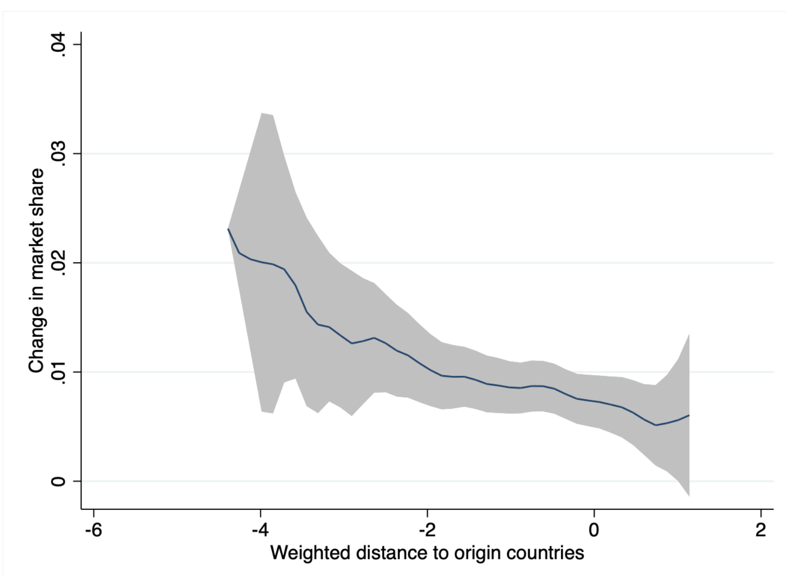


FIGURE A7. Total waste Production of Domestic Waste producers




*Note:* This figure plots the estimates of $\beta_l$, together with 90% confidence intervals, obtained from estimating the specification in 3.4. Each observation is at the firm-year level. The dependent variable is the amount of waste that firm $f$ produces at year $t$. The coefficient of interest is on an interaction term of year dummies $D_t^l$ and $Exposure_f$. Where $Exposure_f$ is the share of firm $f$'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. Market Share and Distance




Note:

| | $\ln x_{dt}$ FS | $\ln prod^v_{dt}$ OLS | $\ln prod^v_{dt}$ 2SLS | $\ln x_{dt}$ FS | $\ln CO2^{waste}_{dt}$ OLS | $\ln CO2^{waste}_{dt}$ 2SLS |
|---|---|---|---|---|---|---|
| $\ln x_{dt} * \mathbb{1}\{t \geq 2017\}$ | | 0.00219 | -0.0758c | | 0.000835 | 0.00388c |
| | | (0.0349) | (0.0424) | | (0.000954) | (0.00222) |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2012\}$ | 0.308 | | | | | |
| | (0.283) | | | | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2013\}$ | 0.0463 | | | | | |
| | (0.287) | | | | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2014\}$ | 0.0944 | | | | | |
| | (0.306) | | | | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2015\}$ | 0.0619 | | | 0.415 | | |
| | (0.158) | | | (0.251) | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2017\}$ | 1.035c | | | 0.976a | | |
| | (0.550) | | | (0.370) | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2018\}$ | -0.211 | | | 0.448 | | |
| | (0.178) | | | (0.430) | | |
| $\ln\left(\sum_o \frac{dist_{od}}{dist_{oChina}} \cdot \frac{x_{ihoChina}}{\sum_o x_{ihoChina}}\right) * \mathbb{1}\{t = 2019\}$ | -0.116 | | | 0.313 | | |
| | (0.344) | | | (0.468) | | |
| $\frac{x_{dChina}}{\sum_d x_{dChina}} * \mathbb{1}\{t \geq 2017\}$ | 0.299 | -0.102 | -0.0764 | -0.131 | 0.00399 | 0.00401 |
| | (0.342) | (0.0733) | (0.0807) | (0.317) | (0.00494) | (0.00504) |
| GDP $\text{pc}_{dt} * \mathbb{1}\{t \geq 2017\}$ | -0.153 | 0.0724b | 0.0600c | -0.237a | -0.00428b | -0.00359b |
| | (0.121) | (0.0284) | (0.0318) | (0.0848) | (0.00191) | (0.00179) |
| $\ln Population_d * \mathbb{1}\{t \geq 2017\}$ | -0.0314 | 0.0303c | 0.0260 | 0.155 | 0.00112 | 0.000861 |
| | (0.0859) | (0.0162) | (0.0180) | (0.125) | (0.00105) | (0.000950) |
| $R^2$ | 0.956 | 0.838 | -0.00811 | 0.929 | 0.998 | 0.00714 |
| # observations | 323 | 323 | 323 | 656 | 666 | 666 |
| KP-Stat | | | 11.62 | | | 7.305 |
| **Fixed Effects**: | | | | | | |
| Country | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |

## Appendix B. Appendix

B.1. **Firm Choices.** Firms maximise profits and let $\lambda$ denote the Lagrange multipliers on the production constraints:

$$\begin{aligned}
\max_{l,m,v,x} \Pi_{ud} =& R_u\left(l_{ud}, m_{ud}\right) - w_d l_{ud} - \sum_i \sum_o z_d v_{iuod} - \sum_i \sum_o p_{iod} x_{iuod} + \lambda_{ud}\left(m\left(v_{iuod}, x_{iuod}\right) - m_{ud}\right) \\
\max_{a,v,x} \Pi_{sd} =& R_s\left(v_{isod}\right) - \sum_i \sum_o z_d v_{isod} + \sum_i \sum_{d'} r_{dd'}\left(x_{isdd'}\right)/\tau_{idd'} - \sum_i w_d \gamma\left(a_{id}\right) \sum_o v_{isod} \\
&+ \sum_i \lambda_{isd}\left(x_{id} a_{id} \sum_o v_{isod} - \sum_{d'} x_{isdd'}\right) \\
\max_{l} \Pi_{nd} =& R_n\left(l_{nd}\right) - w_d l_{nd}
\end{aligned}$$

Optimal choices are given by the FOCs below:

$$\begin{aligned}
&(1) R_{lu}\left(l_{ud}, m\left(v_{iuod}, x_{iuod}\right)\right) - w_d = 0 \\
&(2) R_{mu}\left(l_{ud}, m\left(v_{iuod}, x_{iuod}\right)\right) m_{v_{iuod}}\left(v_{iuod}, x_{iuod}\right) - z_d = 0 \\
&(3) R_{mu}\left(l_{ud}, m\left(v_{iuod}, x_{iuod}\right)\right) m_{x_{iuod}}\left(v_{iuod}, x_{iuod}\right) - p_{iod} = 0 \\
&(4) r'\left(\bar{x}_{id}\right) x_{id} - w_d \gamma'\left(a_{id}\right) = 0 \\
&(5) R_{v_i s}\left(v_{isod}\right) - z_d + r'\left(\bar{x}_{id}\right) x_{id} a_{id} - w_d \gamma\left(a_{id}\right) = 0 \\
&(6) r'_{idd'}\left(x_{isdd'}\right)/\tau_{idd'} = \lambda_{isd} \equiv r'\left(\bar{x}_{id}\right) \\
&(7) R_{ln}\left(l_{nd}\right) - w_d = 0 \\
&(8) x_{id} a_{id} \sum_o v_{isod} - \sum_{d'} x_{isdd'} = 0
\end{aligned}$$

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 $\gamma'' > 0$.

B.2. **Market Equilibrium.** Equations (1) to (8) give 8 equations in 8 unknowns $(l_{ud}, v_{iuod}, x_{iuod}, a_{id}, v_{isod}, x$ given input prices and revenue functions $(z_d, w_d, p_{iod}, R_{ud}, R_{sd}, R_{nd})$. 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 $\tau_d$ 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).

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

$$(10) L_d = l_{ud} + l_{nd} + l_{sd}, l_{sd} \equiv \sum_i \gamma\left(a_{id}\right)$$

$$(11) x_{isod} = x_{iuod}$$

Finally, factor incomes $I$ equal expenditures $Y$ on final consumption in the economy. And, these in turn, equal the profits and factor 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.

$$\begin{aligned}(12) I_d =& Y_{sd} + Y_{ud} + Y_{nd} \\ =& R_{sd} + R_{ud} + R_{nd} + z\bar{V}_d \\ &+ \sum_i \left( \sum_{d' \neq d} p_{idd'} x_{isdd'} - \sum_{o \neq d} z_d v_{iuod} - \sum_{o \neq d} z_d v_{isod} - \sum_{o \neq d} p_{iod} x_{iuod} \right)\end{aligned}$$

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

B.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

$$r'\left(x_{isod}\right) = \tau_{iod} w_o \gamma'\left(a_{io}\right) / x_{io}$$

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

$$\frac{r'\left(x_{isod}\right)}{r'\left(x_{isoc}\right)} = \frac{\tau_{iod}}{\tau_{ioc}}.$$

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

$$x_d \equiv \sum_{i>\bar{i}} \sum_o x_{isod} = \sum_{i>\bar{i}} \sum_o r'^{-1}\left(\frac{\tau_{iod}}{\tau_{ioc}} r'\left(x_{isoc}\right)\right)$$

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

$$x_d = \sum_{i>\bar{i}} \sum_o r'^{-1}\left(\frac{\tau_{iod}}{\tau_{ioc}} r'\left(x_{isoc}\right)\right) = \sum_{i>\bar{i}} \sum_o \frac{g_{od}}{g_{oc}} x_{isoc}.$$

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

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

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

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

This is operationalised empirically as

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

B.4. **Balanced Trade and Market Clearing.** Equation (12) gives balanced trade in the country, and can be written in exports and imports notation as:

$$E_{sd} + E_{ud} + E_{nd} - X_d - V_d = 0$$

where $E_{ud} \equiv R_{ud} - Y_{ud}$ denotes exports of $u$ and similarly for $E_{sd}$ and $E_{nd}$, while $X_d \equiv \sum_i \left( \sum_{o \neq d} p_{iod} x_{iuod} - \sum_{d' \neq d} p_{idd'} x_{isdd'} \right)$ is the net import of waste and $V_d \equiv \sum_{o \neq d} z_d v_{iuod} + \sum_{o \neq d} z_d v_{isod} - z\bar{V}_d$ are net imports of virgin resources. In changes, the balanced trade condition is

$$(13)\; \Delta E_{ud} + \Delta E_{sd} + \Delta E_{nd} - \Delta X_d - \Delta V_d = 0$$

and the labour market clearing condition is

$$(14)\; 0 = \Delta l_{ud} + \Delta l_{nd} + \Delta l_{sd}.$$

B.5. **Income Impacts in Turkey.** For Turkey, we have estimated DiD specifications of log employment in using and supplying firms, relative to firms that neither use nor supply banned waste products. The estimated DiD coefficients evaluated at the mean exposure to banned products and the initial labour shares of using, supplying and non-exposed firms give a tiny change in labour among non-exposed firms of $\Delta l_{nd} = \beta_{ln} l_{nd}/L_d = -0.0007\% \times 3,010,000 \approx 22$ because

$$\begin{aligned} 0 &= \Delta l_{ud} + \Delta l_{sd} + \Delta l_{nd}, d = Turkey \\ &= (\beta_{lu} Exposure_u + \beta_{ln})(l_{ud}/L_d) + (\beta_{ls} Exposure_s + \beta_{ln})(l_{sd}/L_d) + \beta_{ln} l_{nd}/L_d \\ &= \beta_{lu} Exposure_u (l_{ud}/L_d) + \beta_{ls} Exposure_s (l_{sd}/L_d) + \beta_{ln} \\ &= 0.107 \times 0.0002 \times 0.0429 + 0.00579 \times 0.0050 \times 0.2194 + \beta_{ln} \\ &= 0.0007\% + \beta_{ln}. \end{aligned}$$

Labour costs in non-exposed firms make up 21 percent of total costs. Under Cobb-Douglas production (or a first order approximation to production changes) and constant markups, revenues therefore change by $\Delta R_{nd} = 0.21 \times \Delta l_{nd} \approx 0$. (This generally implies that sales at home and abroad of non-exposed firms is not affected by China's ban, and therefore $\Delta E_{nd} = 0$ in Turkey under gravity. But we will estimate it from the national income identities as a cross check).

The output of $u$ and $s$ relative to non-exposed firms $n$is estimated in a DiD specification of log Sales of Turkish firms. Let $\beta_u, \beta_s$ denote the DiD coefficients on $Exposure_u$ and $Exposure_s$ (that are equal to zero for the non-exposed firms). Then the output changes imply the following aggregate income changes:

$$
\begin{aligned}
\Delta R_d =& \Delta R_{ud} + \Delta R_{sd} + \Delta R_{nd} \\
=& \beta_u Exposure_u \left( R_{ud}/R_d \right) R_d + \beta_s Exposure_s \left( R_{sd}/R_d \right) R_d + \beta_n R_d \\
=& \left( 0.170 \times 0.0002 \times 0.0048 - 0.132 \times 0.0050 \times 0.4085 + 0 \right) R_d \\
=& -0.027\% \times 437.9 = -\$118.233 mn.
\end{aligned}
$$

B.6. **Trade Impacts.** For each destination, the balanced trade condition in terms of the residual category of the Rest of the World ($RoW$) is

$$
\begin{aligned}
(13)\; 0 =& \Delta E_{ud} + \Delta E_{sd} + \Delta E_{nd} - \Delta X_d - \Delta V_d, d \neq RoW \\
=& \beta_u G_d E_{ud} + \left( E_{ud}/E_{uRoW} \right) \Delta E_{uRoW} + \beta_s G_d E_{sd} + \left( E_{sd}/E_{sRoW} \right) \Delta E_{sRoW} \\
&+ \Delta E_{nd} - \beta_x G_d X_d - \left( X_d/X_{RoW} \right) \Delta X_{RoW} - \beta_v G_d V_d - \left( V_d/V_{RoW} \right) \Delta V_{RoW}
\end{aligned}
$$

where $\beta_x, \beta_v$ are estimated in the destination-level DiD specifications. In particular, $\Delta X_d = \beta_x G_d X_d + \left( X_d/X_{RoW} \right) \Delta X_{RoW}$ and $\Delta V_d = \beta_v G_d X_d + \left( V_d/V_{RoW} \right) \Delta V_{RoW}$. We have also estimated $\beta_{uTurkey}$ for the exports of firms in Turkey in the using sector relative to non-exposed firms, and similarly for $\beta_{sTurkey}$ in the DiD specifications for Turkish firms, which gives:

$$\begin{aligned}\Delta E_{uTurkey} =&\beta_{uTurkey} \cdot Exposed_u \cdot E_{uTurkey} + \left(E_{uTurkey}/E_{nTurkey}\right)\Delta E_{nTurkey} \\ =&\beta_u G_{Turkey} E_{uTurkey} + \left(E_{uTurkey}/E_{uRoW}\right)\Delta E_{uRoW} \\ \Delta E_{sTurkey} =&\beta_{sTurkey} \cdot Exposed_s \cdot E_{sTurkey} + \left(E_{sTurkey}/E_{nTurkey}\right)\Delta E_{nTurkey} \\ =&\beta_s G_{Turkey} E_{sTurkey} + \left(E_{sTurkey}/E_{sRoW}\right)\Delta E_{sRoW}\end{aligned}$$

where the last line follows from the DiD for using firms across destinations and we get

$$\begin{aligned}\Delta E_{uRoW} &= \beta_{uTurkey} \cdot Exposed_u \cdot E_{uRoW} + \left(E_{uRoW}/E_{nTurkey}\right)\Delta E_{nTurkey} - \beta_u G_{Turkey} E_{uRoW} \\ \Delta E_{sRoW} &= \beta_{sTurkey} \cdot Exposed_s \cdot E_{sRoW} + \left(E_{sRoW}/E_{nTurkey}\right)\Delta E_{nTurkey} - \beta_s G_{Turkey} E_{sRoW}\end{aligned}$$

that is substituted into the BoT equations for $d \neq RoW$:

$$\begin{aligned}0 =& \left(\beta_u E_{ud} + \beta_s E_{sd} - \beta_x X_d - \beta_v V_d\right) G_d \\ &+ \sum_{j=u,s} E_{jd}\left(\beta_{jTurkey} \cdot Exposed_j + \Delta E_{nTurkey}/E_{nTurkey} - \beta_j G_{Turkey}\right) \\ &+ \Delta E_{nd} - \left(X_d/X_{RoW}\right)\Delta X_{RoW} - \left(V_d/V_{RoW}\right)\Delta V_{RoW}\end{aligned}$$

and the first line is zero for $d = RoW$. We observe $(E_{ud}, E_{sd}, X_d, V_d, G_d, Exposed_j)$ and have estimated $(\beta_x, \beta_v, \beta_{jTurkey}, \Delta E_{nTurkey})$. We can infer $E_{nd}$ from the BoT as we have all the other components and need to estimate reduced form DiD specifications to obtain $(\beta_u, \beta_s)$.

The four BoT equations for $d$ =Exporter, China, Turkey and Rest of the World- therefore have five remaining unknowns $(\Delta X_{RoW}, \Delta V_{RoW}, \Delta E_{nd \neq Turkey})$. We therefore specify a similar reduced form DiD for $\Delta E_{nd}, d \neq China$:

$$\begin{aligned}0 =& \left(\beta_u E_{ud} + \beta_s E_{sd} - \beta_x X_d - \beta_v V_d\right) G_d \\ &+ \sum_{j=u,s} E_{jd}\left(\beta_{jTurkey} \cdot Exposed_j + \Delta E_{nTurkey}/E_{nTurkey} - \beta_j G_{Turkey}\right) \\ &+ \beta_n G_d E_{nd} + \left(E_{nd}/E_{nTurkey}\right)\Delta E_{nTurkey} - \left(X_d/X_{RoW}\right)\Delta X_{RoW} - \left(V_d/V_{RoW}\right)\Delta V_{RoW}\end{aligned}$$

There are four unknowns ($\Delta X_{RoW}, \Delta V_{RoW}, \beta_n, \Delta E_{nChina}$) and we can solve for them to obtain the absolute changes after China's ONS policy.

B.7. **Estimation of Trade and Expenditure Effects.**

B.7.1. *Trade.* To be able to identify what happens to imports, we run the following regression. The results are shown in Table A1.

$$
\begin{aligned}
\text{(B.1)} \qquad \ln x_{podt} \quad = \quad & \sum_{D=China,Exporter,Turkey} \beta_x^d * \mathbb{1}\{Treat_p\} * \mathbb{1}\{d=D\} * \mathbb{1}\{t \geq 2017\} \\
& + \text{Tariff Rate}_{pod2016} * \mathbb{1}\{t \geq 2017\} \\
& + \alpha_{odt} + \alpha_{odp} + \alpha_{opt} + \epsilon_{podt}
\end{aligned}
$$

Table A1. Gravity

| Dependent Variable: | $ln(x_{podt})$ (1) | $ln(x_{podt})$ (2) | $ln(val_{podt})$ (3) | $ln(val_{podt})$ (4) |
|---|---|---|---|---|
| $\mathbb{1}\{Treat_{HS6}\} * \mathbb{1}\{China_d\} * \mathbb{1}\{t \geq 2017\}$ | -0.518a | -0.518a | -0.597a | -0.597a |
| | (0.179) | (0.179) | (0.180) | (0.180) |
| $\mathbb{1}\{Treat_{HS6}\} * \mathbb{1}\{SelectedExporters_d\} * \mathbb{1}\{t \geq 2017\}$ | -0.0191 | -0.0191 | -0.0472 | -0.0472 |
| | (0.0520) | (0.0520) | (0.0471) | (0.0471) |
| $\mathbb{1}\{Treat_{HS6}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{t \geq 2017\}$ | 0.159a | | 0.108a | |
| | (0.0355) | | (0.0285) | |
| $\mathbb{1}\{Treat_{HS6}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{\text{Higher Emissions}_{d,CHN}\} * \mathbb{1}\{t \geq 2017\}$ | | 0.181a | | 0.140a |
| | | (0.0440) | | (0.0343) |
| $\mathbb{1}\{Treat_{HS6}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{\text{Lower Emissions}_{d,CHN}\} * \mathbb{1}\{t \geq 2017\}$ | | 0.126b | | 0.0540 |
| | | (0.0606) | | (0.0507) |
| $\mathbb{1}\{Treat_{HS2}\} * \mathbb{1}\{China_d\} * \mathbb{1}\{t \geq 2017\}$ | -0.0949a | -0.0949a | -0.0634a | -0.0634a |
| | (0.0265) | (0.0265) | (0.0232) | (0.0232) |
| $\mathbb{1}\{Treat_{HS2}\} * \mathbb{1}\{SelectedExporters_d\} * \mathbb{1}\{t \geq 2017\}$ | 0.0336a | 0.0336a | -0.0372a | -0.0372a |
| | (0.00798) | (0.00798) | (0.00590) | (0.00590) |
| $\mathbb{1}\{Treat_{HS2}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{t \geq 2017\}$ | -0.00565 | | -0.0288a | |
| | (0.00381) | | (0.00318) | |
| $\mathbb{1}\{Treat_{HS2}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{\text{Higher Emissions}_{d,CHN}\} * \mathbb{1}\{t \geq 2017\}$ | | 0.00465 | | -0.0263a |
| | | (0.00447) | | (0.00373) |
| $\mathbb{1}\{Treat_{HS2}\} * \mathbb{1}\{ROW_d\} * \mathbb{1}\{\text{Lower Emissions}_{d,CHN}\} * \mathbb{1}\{t \geq 2017\}$ | | -0.0315a | | -0.0351a |
| | | (0.00725) | | (0.00609) |
| Tariff Percentage Points$_{pod2016} * \mathbb{1}\{t \geq 2017\}$ | -0.231a | -0.230a | -0.139a | -0.139a |
| | (0.0261) | (0.0261) | (0.0173) | (0.0173) |
| $R^2$ | 0.871 | 0.871 | 0.850 | 0.850 |
| # observations | 23,848,529 | 23,848,529 | 27,358,952 | 27,358,952 |
| **Fixed Effects**: | | | | |
| Origin×Destination×Product | Yes | Yes | Yes | Yes |
| Destination×Product×Time | Yes | Yes | Yes | Yes |

B.7.2. *Revenue.* We find the percentage change in using and supplying industries with respect to the non-using industry. To do so, we run the following specification:

(B.2)

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

Results are depicted in the Table A2.

TABLE A2. Regression Results

| | (1) | (2) |
|---|---|---|
| | $\ln(Sales)$ | $\ln(Employment)$ |
| $Exposure_{f(u)} * Post_t$ | 0.170*** | 0.107*** |
| | (0.0238) | (0.0106) |
| $Exposure_{f(s)} * Post_t$ | -0.132** | 0.00579 |
| | (0.0551) | (0.0444) |
| $Employment_f * Post_t$ | 0.122*** | 0.0727*** |
| | (0.00357) | (0.00171) |
| $N$ | 618907 | 662989 |
| $r^2$ | 0.803 | 0.881 |
| Firm FE | Yes | Yes |
| Sector x Year FE | Yes | Yes |

B.7.3. *Emissions and Virgin Plastic Usage.* We run the following regression to find changes in $CO_2 percapita$ emissions from waste and production of primary plastic in each destination $d$ at year $t$.

B.8. **Quantification.** For the quantification in the text, $0 = (1 + \beta_v)\left(\beta_x G_d X_d + (X_d/X_{RoW})\, \Delta X_{RoW}\right) + \Delta V_{RoW}$. From $d =$RoW

$$\Delta V_{RoW} = -\,(1 - 0.112)\,(0.652 \times G_{RoW} X_{RoW} + \Delta X_{RoW})$$

Table A3

| | $\ln x_{dt}$ (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 |
|---|---|---|---|---|---|
| $\ln x_{dt}$ | | 0.00509*** | 0.0476*** | -0.0226*** | -0.112* |
| | | (0.00134) | (0.0146) | (0.00604) | (0.0628) |
| $\left(\sum_o \frac{x_{do}-x_{od}}{x_{do}+x_{od}} \cdot \frac{x_{oChina}}{\sum_o x_{oChina}} > 0\right) * \mathbb{1}\{t \geq 2017\}$ | 0.652*** | | | | |
| | (0.212) | | | | |
| GDP $\text{pc}_{dt} * \mathbb{1}\{t \geq 2017\}$ | -0.0225** | -0.00111* | 0.000189 | 0.000809 | -0.00191 |
| | (0.00873) | (0.000610) | (0.000586) | (0.00239) | (0.00214) |
| $\frac{x_{dChina}}{\sum_d x_{dChina}} * \mathbb{1}\{t \geq 2017\}$ | 11.26*** | 0.360 | -0.221 | 1.199 | 2.420*** |
| | (3.690) | (0.263) | (0.251) | (0.968) | (0.829) |
| $\ln m_{d16}^{v} * \mathbb{1}\{t \geq 2017\}$ | 0.0529 | 0.00445* | 0.00128 | -0.0649*** | -0.0583*** |
| | (0.0386) | (0.00260) | (0.00251) | (0.0181) | (0.0193) |
| $\ln CO2_{d16}^{waste} * \mathbb{1}\{t \geq 2017\}$ | 0.446*** | 0.0113** | -0.0138 | -0.0209 | 0.0319 |
| | (0.123) | (0.00424) | (0.0110) | (0.0320) | (0.0312) |
| N | 273 | 273 | 273 | 273 | 273 |
| r2 | 0.801 | 1.000 | -3.296 | 0.994 | -0.234 |
| KP-Stat | | | 9.471 | | 9.471 |

and from $d =$Turkey,

$$\Delta X_{RoW} = 0.652 \times \left(G_{Turkey} X_{Turkey} - G_{RoW} X_{RoW}\right) / \left(1 - X_{Turkey}/X_{RoW}\right)$$

The change in waste imports of Turkey, Exporters and China can be obtained as $\Delta X_d = 0.652 \times G_d X_d + (X_d/X_{RoW})\,\Delta X_{RoW}$ and its waste emissions are $\Delta Z_d^x = 0.0476 \times \Delta X_d / X_d \times Z_d$. Virgin resource imports of Turkey change by $\Delta V_d = -0.112 \times \Delta X_d / X_d \times V_d + \Delta V_{RoW}$ and the emission savings are $\Delta Z_d^v = 2928.08 \times \Delta V_d$.