Ripple Through Garbage:
The Impact of China's Solid Waste Import Ban on U.S. Firms

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Abstract

The global supply chain encompasses not only good production but also the byproduct of waste. Do firms exploit this property to benefit domestic production? Utilizing China's Solid Waste Import Ban (CSWIB) as a regulatory shock, we observe that the Producer Price Index (PPI) for U.S. waste-generating industries rose by 2.94% due to increased production costs post-CSWIB. Furthermore, firms within waste-generating sectors also exhibit a 5.55% drop in Tobin's Q. Our findings suggest that global waste management significantly affects inflation and firm valuation in the U.S., which carry important normative implications for global green transitions.

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1. Introduction

Most production processes generate wastes that are pollutive or even hazardous to the environment. As more wastes are generated each year, a rich set of waste management methods has also been adopted to minimize environmental impacts, including recycling, composting, landfilling, and combustion.[1] However, since waste management is costly in most developed countries, firms often find it lucrative to export waste to developing countries with the cheapest disposal options. These countries, widely referred to as "waste havens", tolerate lower environmental standards—e.g., allowing waste to be burned to pollute the air (Kellenberg 2012, Shi and Zhang 2023)—and thus present a loophole in the global regulatory system that may exaggerate environmental externalities through the moral hazard of firms (e.g., Drake and Just 2016; Wijnsma, Lauga, Toktay 2023). Despite the negative implications, evidence of how waste havens and their associated global waste supply chain impact waste-exporting firms remains scarce, making it difficult to estimate the regulatory costs needed to address this issue.

Our paper aims to fill this economic void by examining a recent regulatory shock that disrupts the exporting of solid waste from US firms to China—i.e., China's Solid Waste Import Ban (hereafter, CSWIB or simply "the Ban" if there is no confusion). Before the Ban, 32.7% of the waste produced in the US was exported, among which approximately 36% went to China, making the US export of waste to China one of the most pronounced parts of the global waste supply chain.[2] Starting from January 1, 2018, however, the Ban forbids nearly all kinds of solid waste from entering China. Since no other countries can replace China in importing such a large amount of solid waste, the Ban forced many US firms to manage their waste domestically, which essentially increase their waste management costs.[3]

[1] The Guardian estimates in 2019 that 2.01 billion tons of solid waste are generated globally each year (https://www.theguardian.com/us-news/2019/jul/02/us-plastic-waste-recycling), which highlights the importance of waste management. The technologies of waste management includes recycling, where used materials are processed into new products to conserve resources and reduce pollution; composting, which transforms organic waste into nutrient-rich soil enhancers; landfill disposal, where non-recyclable waste is safely buried to prevent environmental contamination; and combustion with energy recovery, where waste is incinerated to generate energy, reducing waste volume and harnessing energy from materials that cannot be recycled.

[2] The two numbers come from, respectively, the "Advancing Sustainable Materials Management: 2018 Fact Sheet" report of the Environmental Protection Agency (EPA) and the General Administration of Customs of the People's Republic of China, 2017.

[3] As reported in New York Times in 2018, "Recycling companies used to get paid to sell recyclable materials, but now they're paying someone else to take them away." (https://www.nytimes.com/2018/05/29/climate/recycling-landfills-plastic-papers.html) This change implies a hiking waste management costs for U.S. companies. Appendix B shows that more than a third of U.S. solid waste is affected by the Ban.

This regulatory shock provides an ideal testing ground to address two important questions to illuminate the impact of the global waste supply chain on U.S. firms and the U.S. economy. First, since the Ban increases waste management costs, how do affected firms strategically respond to it? We hypothesize that firms may pass the costs on to customers, thereby creating a direct link between waste exporting and inflation. Alternatively, the pressure on short-term net income may prompt firms to cut long-term expenditures, such as R&D. However, if these firms are more concerned about the long-term impact of increased waste management costs, they may be incentivized to explore better technologies by increasing their R&D investments. Lastly, firms may choose to do nothing initially, hoping to find a replacement waste haven country soon.

The second economic question concerns firm value: could it be affected by a firm's ability to export waste cheaply? To address this question, we investigate how the Ban affect the two essential components of firm valuation: cash flows and discount rates. If affected firms cannot fully absorb the cost impact of the Ban, it is reasonable to expect their future cash flows to suffer. Furthermore, waste havens offer regulatory arbitrage opportunities, and losing this advantage may expose firms to higher regulatory risks in their domestic market. We therefore hypothesize that the ban may also increase the cost of capital for the affected firms. These two effects imply that waste havens could have positively contributed to the value of US firms.

Collectively, these questions and hypotheses provide a counterfactual analysis to understand the extensive implications that waste havens may have had on U.S. firms and the U.S. economy. These implications range from influencing inflation to affecting the risk and cost of capital for firms. To test these hypotheses, we employ a difference-in-difference (DiD) approach to estimate the impact of the Ban on US firms. We define the industries that generate banned solid wastes in their production process as "treated industries" and the remaining industries as the control group. We use all listed firms and the 6-digit NAICS code to construct the sample of treated and control industries. Our testing period spans from 2015 to 2019.

We start with the analysis of firm costs and their strategic responses. Post-CSWIB, U.S. companies need to find new ways to manage their solid waste, such as paying higher recycling fees, developing green technologies, and/or outsourcing the waste-

generating production process. Each of these adaptations leads to increased costs. As a result, we observe that the cost of goods sold by the treated industries rose by 10.8% compared to the control group during the post-CSWIB period. Since not all firms in the affected industries utilized the export option before the Ban, our estimation likely indicates a lower bound of the cost implication of the Ban.

Interestingly, we also observe an insignificant impact of the Ban on firm profitability, proxied by ROA, suggesting that affected firms somewhat absorbed the impact of increased costs. Since how firms managed to absorb these costs could have important implications, we next move on to investigate these actions.

We first examine whether firms can pass through the elevated cost to consumers. If so, the product prices of the treated industries, proxied by the Producer Price Index (PPI), should significantly increase for treated industries. Indeed, we observe that, in our preferred empirical specification, PPIs of the treated (i.e., U.S. solid waste-generating) industries rose by 2.94% compared to the control group during the post-CSWIB period. Furthermore, this passing-through effect is more prominent among industries in which firms have more pricing power, proxied by a high concentration of firms within the industry.

Compared to the 2% average annual PPI inflation rate before the CSWIB, the passing-through effect implies a significant impact of the Ban on increased product prices.[4] Since the PPI provides an early signal for CPI movements (Balcilar, Gupta, Jooste, and Wohar, 2014; Wei and Xie, 2018; Federal Reserve Bank of Richmond, 2022), our results suggest that waste havens could have contributed significantly to the observed high inflation in the US for a long period.

We then examine whether treated firms devote more or less resources to developing better technologies, proxied by R&D. On the one hand, since R&D is typically treated as expenditure, reducing R&D can help mitigate the hiking costs introduced by the Ban. On the other hand, more R&D can potentially benefit treated firms in the long run by reducing waste or the cost of processing waste in production. We observe that firms in the treated industry cut their R&D expenditure after the Ban

[4] The the 2% average PPI-inflation number comes from the US Bureau of Labor Statistics.

by an average of 17% compared to the control group, suggesting that the first short-term goal of firms dominates their response.

After establishing how firms respond to the Ban, we move on to examine the impact of the Ban on firm value and its two channels. We first observe that firms in the treated industries experience an average reduction as high as 16.9% in Tobin's Q when compared to the control group. One potential interpretation of this result is that the global waste supply chain had allowed U.S. firms to enjoy approximately 16.9% higher market valuations before its disruption.

We then further delve into the cash flow and discount rate channels of firm valuation. Our main findings are threefold. First, we find that the Ban is negatively associated with the one-year forecasted earnings of firms by analysts, though this effect is only marginally significant in statistical terms. Second, the Ban significantly reduces the forecasted long-term growth in earnings by analysts, suggesting that analysts are more concerned about the long-term growth rather than the short-term profitability after the Ban. This view is consistent with our previous observation of the insignificant impact of the Ban on the short-term ROA of firms. Thirdly, we observe that firms in the treated industry exhibit a significantly higher implied cost of capital after the Ban. In economic magnitude, the cost of capital increases, in absolute terms, by 2.1% for treated firms, consistent with the view that these firms are now considerably more risky.

Overall, our results suggest that, when the ban increases operational costs, affected firms can largely mitigate the negative impact on profitability by partially passing these costs on to customers and partially reducing long-term R&D investments. However, this leads to an increase in PPI-implied inflation. Furthermore, these firms become riskier, face higher costs of capital, and experience a significant decrease in market valuation following the ban. These findings collectively suggest that the presence and removal of waste havens can have extensive and profound effects on both firms and the broader economy.

Our research is connected to several strands of literature. The concept of waste havens relates to environmental leakage, where companies circumvent environmental regulations by relocating their polluting operations, selling pollutive plants to less regulated investors, and dumping their waste in waste havens (see, e.g., Bartram, Hou,

and Kim, 2022; Duchin, Gao, and Xu, 2024; Wijnsma, Lauga, and Toktay, 2024). We contribute to this literature by examining the recent regulatory shock that disrupted the export of solid waste from U.S. firms to China, providing a comprehensive analysis of how (the disruption of) an important waste haven country and its associated global waste supply chain impact US firms. Our results highlight both the significance and the costs associated with global regulatory coordination.

A substantial body of literature discusses effective methods for treating solid waste, focusing on approaches such as recycling, landfill management, and incineration (Souza, 2013; Smith, 1972; Esenduran, Kemahliog, Swaminathan, 2016).[5] However, many companies opt to export waste to other countries, shifting the burden to less developed regions and exacerbating environmental and health issues (Gui, Atasu, and Toktay 2016; Shi and Zhang 2023). Our paper contributes to this discourse by examining the firm perspective, offering new insights into how these practices directly affect firm behavior, compliance, and operational outcomes within the international waste management ecosystem, as well as broader economic consequences such as inflation and firm risk.

More broadly, our work relates to the literature on environmental, social, and governance (ESG) factors and corporate social responsibility (CSR). Environmental concerns have become an increasingly important aspect of company evaluations (Deng, Kang, and Low, 2013; Bartram, Hou, and Kim, 2022; Caroline, 2021; Stroebel and Wurgler, 2021, etc.). Investors incorporate environmental issues into their investment decisions (Liang and Renneboog, 2020), and consumers tend to favor socially responsible companies (Bhattacharya and Sen, 2003). While many of the discussions focus on carbon emissions and sewage discharge by companies (Azar, Duro, Kadach, and Ormazabal, 2021; Dai, Duan, Liang, and Ng, 2021; He, Wang, and Zhang, 2020), the issue of solid waste is largely overlooked. Our study highlights the importance of

[5] Recycling is widely advocated for its ability to convert waste into reusable materials, thereby conserving natural resources and reducing environmental impact. Landfill management, though less desirable than recycling, remains a common practice that involves the controlled disposal of waste to minimize environmental harm. Souza (2013) provides a critical review of closed-loop supply chains, highlighting the benefits of recycling within this context. Smith (1972) explores the dynamics of waste accumulation, comparing disposal and recycling methods. Incineration, another method, reduces waste volume and can generate energy, though it requires careful management to avoid harmful emissions. Esenduran, Kemahlioğlu-Ziya, and Swaminathan (2016) investigate the effects of take-back legislation, which encourages proper disposal and recycling of products at the end of their lifecycle, promoting more sustainable waste management practices.

solid waste management as a crucial aspect of a firm's ESG activities, with profound implications for firm value, resource allocation, and the broader economy.

The remainder of the paper proceeds as follows: Section 2 introduces the CSWIB policy and the challenges it brings to U.S. firms. Section 3 describes the data and sample we use to conduct the empirical analyses of this study. Section 4 contains the empirical results of this study and the interpretations of these results. Section 5 is to conclude this paper.

2. Institutional Background

"One man's trash is another man's treasure." This proverb was true of China's massive import of solid waste in the last 20 years.[6] China has been the world's largest importer of solid waste. From 1995 to 2016, China's annual waste imports increased from 4.5 million tons to 40.2 million tons[7]. It was a nearly tenfold increase, among which the U.S. accounts for the most part. In 2017, nearly half of China's solid waste imports come from U.S. (Panel A, Appendix B), and more than one thirds of US's solid wastes were exported to China (Panel B, Appendix B). In 2016, U.S. companies earned $5.5 billion by exporting solid waste to China[8].

On July 18, 2017, the Ministry of Ecology and Environment of China (MEE) submitted a document to the World Trade Organization, calling for an urgent adjustment of the list of imported solid waste. China planned to ban the import of 24 kinds of solid waste in 4 classes by the end of 2017, including plastic waste from living sources, vanadium slag, unsorted waste paper, and waste textile materials. On the same day, the General Office of the State Council of China issued an implementation scheme, requesting a total ban on foreign solid waste imports by the beginning of 2021. In the first year of the waste import ban, China investigated 481 criminal cases of waste

[6] China lacked the technology to produce materials such as plastics and did not have enough foreign exchange to buy them from developed countries; many firms began to import waste materials from developed countries. In addition, the cost of labor in China was low. After solid waste from developed countries is imported, Chinese workers manually cull, clean, and recycle, which is much cheaper than all other waste disposal methods.

[7] United Nations Statistics Division

[8] USnews

smuggling, the growth rate was 68% compared with before the ban was implemented[9]. China's total imports of solid waste fell 80% in 2020 comparing with 2017[10].

In fact, besides being exported to other countries, solid waste can be disposed of in many other ways, like burning, composting, landfill and deep-well injection. But above ways are also harmful to the neighboring environment and costly. Thus, before CSWIB, U.S. companies chose to export solid wastes to China — it was money-making, and could avoid being punished by the U.S. local government for polluting the environment.

Under such huge interest, environmental pollution is getting worse and worse in China. Some imported solid waste that is not effectively sorted is fatal to the health of the sorting workers, some incinerated and drifts into the air as fly ash and organic exhaust and trap heavy metals in the lungs of nearby residents, some pollute rivers during recycling... These problems are actually derived from the nature of solid waste itself, no matter how much companies in solid waste exporting countries claim to have done all they can to protect the environment, the harm caused by solid waste in China is serious. That is why the waste import ban has been implemented so strictly that China has even described it as part of "National Sword".

For waste-generating firms in the U.S., the first alternative way to dispose of the solid waste is exporting to other countries. However, it is difficult for the U.S. to export all of its excess solid waste to other countries. Other countries are unlikely to have the capacity comparable to China to accept such a large amount of solid waste. In the three years after the ban (2018-2020), the amount of plastic waste the U.S. exported fell to one-third of what it had been in the three years before the import ban (2015-2017), from 2,167,077 tonnes to 5,862,082 tonnes. Besides, around the same time, some countries also imposed restrictions on solid waste import (i.e. Malaysia[11]). Thus, solid waste that cannot be absorbed by the international trade market stays within the U.S. domestic market. Most U.S. companies that exported solid wastes have to adopt other ways to dispose of these wastes domestically. For example, paying the recycling companies to

[9] General Administration of Customs of the People's Republic of China, 2018
[10] Ministry of Commerce of China, 2020
[11] Malaysia announced in October 2018 it's banning the import of plastic scrap and cracking down on factories that process such waste illegally.

dispose the solid wastes (including composting, landfilling, and recycling), which leads to higher costs of goods sold. The rising cost of disposing solid waste disposal reduces the profit margin of treated companies, and even makes some high-waste projects not profitable anymore, forcing firms to abandon related products. The most sustainable and environmentally friendly way might be conducting research activities to develop technologies that produce fewer solid wastes or developing technologies to recycle solid waste. While it is likely that companies looking to sustainable growth would do so, the payoffs of such "green innovations" are risky and take a long time to realize. And doing so involves extra cost or cash outlay in the short run. Due to the above reasons, the production costs of U.S. companies will increase following China's waste import ban.

Starbucks is an example that can illustrate the effect of CSWIB. Each year, Starbucks disposes 6 billion paper cups and mugs worldwide[12]. Some of these cups were shipped to China with large quantities of polyethylene, which are nondegradable even after centuries. After China announced the waste ban, Jim Ace, project manager of Stand Earth, pointed out that China's restrictions on the import of waste paper, scrap metal and other foreign waste will indirectly cause Starbucks to increase the amount of landfill in the US. However, landfilling solid waste in U.S. is not cheap after the waste ban.

The ban has been bringing effects to the daily life of U.S. citizens and U.S. firms. In 2018, the Department of Environmental Quality of Oregon released a fact sheet encouraging residents to be more cautious about the items they place in their recycling bins and to avoid "wishful recycling." The department also indicated potential challenges in finding markets to sell recyclable materials. Peter Spandlow, a policy analyst with the Oregon Department of Environmental Quality, said to the New York Times, "Recycling companies used to get paid to sell recyclable materials, but now they're paying someone else to take them away."[13] In 2019, City officials of Florida noted that the increasingly tight import restrictions in China have resulted in soaring costs that now come with processing recyclables. According to legislative documents,

[12] Starbucks https://about.starbucks.com/stories/2018/starbucks-and-closed-loop-to-develop-recyclable-compostable-cup-solution/
[13] USnews

in 2017, processing companies received about $120 per ton of mixed paper at a processing cost of $80, Just a year later, processing costs remain the same, but companies are earning $5 or less per ton. Apparently, the cost of goods sold of U.S. waste-generating firms has gone up a lot due to China solid waste import ban.

3. Data and Sample

We start with obtaining all HS codes of banned commodities from the General Administration of Customs of the People's Republic of China (GACC), the headquarters of China Customs, which is a key border agency of China. GACC publishes every policy related to international trade on their official website, from which we get all the documents related to solid waste ban policy, including HS codes of all banned commodities. There are twenty-four 10-digit HS codes of goods that are banned from importing to China according to the file that China handed in to WTO in 2017. A complete list of these HS codes is reported in Appendix A.

To define treated industries (that is, the industries generating wastes of banned HS codes), we mainly rely on the Commercial Waste National Totals by NAICS and U.S. Satellite Tables for USEEIO provided by U.S. EPA Office of Research and Development (ORD). EPA provides the details of commercial waste generation in the US, classified by NAICS codes. One challenge is to match the definition and remarks of the banned HS codes announced by GACC in Chinese[14] to the definition of waste flow name provided by EPA in English. The description of each HScode contains one or more specific categories, while the EPA solid waste list contains names of products. For instance, an EPA waste named "Ethyl acrylate" should be matched with HScode description "Degras; residues resulting from the treatment of fatty substances of animal or vegetable waxes". Not even a single word is exactly the same between them. Completing the matching task using traditional character search methods is almost impossible. To tackle this, we developed a natural language processing (NLP) algorithm to understand the latent semantic connections between China HScode

[14] Since the 10-digit HS codes are set by each country, the Chinese version of the import ban announcement is more detailed than the English version and has some additional remarks. Thus we match the waste type based on the Chinese meaning of the banned list announced by China.

definition and EPA waste flow. The matching is based on the algorithm comprised of traditional language processing routines and the calculation of cosine similarities of words. Details are provided in Appendix D. After the matching, we meticulously conduct manual checks and corrections with the help of the experts from the Singapore Centre for Environmental Life Sciences Engineering to ensure accurate matches.

After the matching process, we obtain the NAICS industries that may generate those waste in the production process from the EPA lookup table. We require that the total solid waste generated by an NAICS exceeds 30,000 kg to be in our treated group. Finally, we got 155 treated NAICS, including 2 NAICS with 3 digits, 29 with 5 digits, and 119 with 6 digits. We define these industries as "waste-generating industries" or "treated industries", the firms in the treated industries are "treated firms".

We use the level of PPI to measure the dynamics of prices across industries. The Bureau of Labor Statistics (BLS) reports the monthly PPI data for each NAICS industry. I obtain industry-level PPIs from 2015 to 2019 from BLS's website,15 drop financial and service industries (NAICS code 500000-699999), and calculate the average PPI value for each industry (classified by NAICS code) every month. Finally, we have 30,420 industry-month observations over the entire sample period of 507 industries.

For firm-level analysis, we obtain financial and stock information of U.S. listed firms from WRDS and Compustat for further analysis. We define the firms in treated industries classified by waste-generating NAICS as treated firms. The rest of the firms are in the control group. Similar to our industry-level analysis, we exclude financial and service industries (NAICS code 500000-699999) and drop the observations with missing regression variables.

To conduct the robustness tests, we obtain the shipment information of banned commodities from Panjiva database. Panjiva provides a world trade database that contains transaction-level data of cross-border goods. Under the "Customs Duties" at chapter 19 of Code of Federal Regulations (CFR), U.S. firms are required to report detail information of shipment in cargo declarations to U.S. Customs and Border Protection (CBP). Such declarations help Panjiva to obtain information on the detail of every transaction of U.S. export to China, including shipment data (commodity

[15] We exclude the data after 2019 in our analysis because the covid pandemic starts from 2020.

description, consignee, shipper, cargo weight, product classifications by HS code, etc.), company data (company contact information, parent company and subsidiaries, etc.), and location data (country of origin and destination, port of lading & unlading, etc.).

We search the HS codes subject to the import ban in the Panjiva, and then download all the shipment information of these banned commodities exported from U.S. to China during 2014 to 2020. For each U.S. consigner, we fetch its ultimate parent company name, resulting in 2,668 ultimate parent companies. To find the public firms that have exported banned commodities to China, and to construct firm characteristics used in the empirical analysis, we match these company names to the company names in Compustat, resulting in 114 matched public firms that have exported banned commodities to China. We define these firms as "waste-exporting firms".

We also obtain data on industry-level market competition from U.S. CENSUS, Manager's short-term and long-term earnings forecasts from IBES, and firm-level implied cost of capital from Lee, So, Wang (2021). Table 1 shows the summary statistics for the variables that we use for empirical analysis.

4. Empirical Analysis

4.1 Validation tests: U.S. waste exports and market reaction for treated firms

Figure 1 shows that the import ban policy does have a significant effect on the U.S. waste export. Taking 2015 as the base period, Figure 1 clearly shows that since the official implementation of China's solid waste import ban in 2018, the export of solid waste from the U.S. has decreased significantly, and the reduction is close to 11%. This suggests that the China waste ban has significantly affected solid waste exports from the US.

To find out whether the announcement of China's waste import ban affects the firm value of treated firms, we further conduct an event study. We apply the market model, Fama-French 3-factor model, and excess return relative to the market portfolio, respectively, to estimate the abnormal return.

Figure 2 shows the abnormal return on each day of the event window. t_0 is 18th July 2017, when the Chinese government announced the waste import ban. The

estimation window is [-255, -11] and the event window is [-2,+2]. The cumulative abnormal return of either waste-exporting firms or waste-generating industries is negative. The results of the event study demonstrate that the treated firms' stock price experienced a significant decline after the China waste import ban was announced.

4.2 Direct effects of CSWIB on U.S. firms: cost of goods sold

Following the implementation of the CSWIB, U.S. firms in waste-intensive industries faced increased costs associated with domestic waste disposal. To examine the impact of the CSWIB on these costs, we focus on the ratio of the cost of goods sold (COGS) to sales as the dependent variable. Specifically, we use the financial information of U.S. listed firms from Compustat and estimate the following DiD models:

$$Y = \gamma_0 + \gamma_1 Treat * Post + \gamma_2 Control + \boldsymbol{FE} + \varepsilon$$

where Y is the cost of goods sold. The definitions of all variables are shown in Appendix C. $\boldsymbol{FE}$ includes fixed. ε is the usual error term. Standard errors are clustered at the firm level. γ_1 measures the differential effect of China solid waste ban on firms' outcomes. In the subsequent firm-level analysis, we also apply this DiD approach with Y as other outcome variables.

Table 2 presents the results of our difference-in-differences (DiD) estimation, capturing the differential impact of the ban on treated versus control firms. The interaction term, Treat*Post, is positive and statistically significant across all specifications. These results suggest that firms in the treated industries experience a notable increase in production costs compared to the control group after the ban, consistent with the hypothesis that losing access to low-cost waste disposal in China has raised domestic waste management costs for affected firms. The regulatory restrictions lead to higher operational costs in the U.S..

4.3 CSWIB and Return on Assets (ROA)

Interestingly, our analysis reveals an insignificant impact of the CSWIB on firm profitability, as proxied by Return on Assets (ROA). Table 3 presents the results of our difference-in-differences (DiD) estimation, showing the differential effect of the ban on

treated versus control firms. The coefficient on the interaction term, Treat*Post, though negative across all specifications, does not consistently reach statistical significance, particularly in models with more stringent fixed effects. These results suggest that, while the ban increased waste disposal costs, firms in the affected industries appear to have partially absorbed these costs, thereby mitigating the direct impact on their profitability. This ability to absorb cost increases points to potential adjustments within the firm, such as cost-cutting measures, efficiency improvements, or strategic pricing adjustments. Given the importance of understanding how firms managed to offset the financial burden followed by the ban, we proceed to investigate these potential actions in subsequent sections 4.4 to 4.7.

4.4 CSWIB and U.S. PPI

We use the difference-in-differences (DiD) design to test the effect of China solid waste import ban on U.S. product prices. It calculates the treatment effect on PPI by comparing the average change in PPI over time of the treatment group with the average change of the control group. We employ the following regression model:

$$PPI = \beta_0 + \beta_1 Treat * Post + \boldsymbol{FE} + \varepsilon$$

where PPI is the yearly Producer Price Indexes. Treat equals 1 for firms that belong to industries classified by NAICS codes as treated industries, and 0 otherwise. $\boldsymbol{FE}$ includes fixed effects. The pre-ban period is 2015 to 2017 (Post = 0), and the post-ban period is 2018 to 2019 (Post = 1). The definitions of all variables are shown in Appendix C. ε is the usual error term. We use robust standard errors clustered by industry (2-digit NAICS). β_1 is the coefficient of my interest, which measures the differential effect that China waste import ban brings to U.S. product prices after its implementation.

Table 3 presents the results. It shows that the coefficient on Treat*Post is positive and significant (0.030, t-statistic=4.12). Coefficient on Treat*Post divided by the mean value of PPI is 0.030/1.019=2.94%, suggesting that China waste import ban leads to a 2.94% rise in treated industries' product prices relative to control industries. Figure 4 shows the annual average producer price index in the time window around the China waste import ban after controlling for industry fixed effect. It shows an obvious upshift of U.S. PPI of treated industries relative to control industries after CSWIB. The results

in both Table 4 and Figure 4 suggest that U.S. companies pass through the rising costs of dealing with solid waste to U.S. consumers.

4.5 Cross-sectional test: The effect of product market competition

As our baseline results show, the product price of U.S. treated industries goes up after China's implementation of the waste ban. A greater price elasticity can discourage managers from significantly increasing product prices. While we do not have data for price elasticity, we use product market competition to examine this insight as fiercer competition is typically associated with a greater price elasticiy. We use concentration ratios and Herfindahl-Hirschman index, respectively, to measure the intensity of competition in the product market. The concentration ratio data and HHI data are from U.S. Census.

Table 5 shows the results of the effect of the product market competition on our baseline results. In panel A, we use the concentration ratio to measure the intensity of product market competition. In panel B, we use HHI to measure the intensity of product market competition. The result of Table 5 indicates that in industries with lower competition, firms have a stronger ability to transfer the burden of environmental costs to consumers. When an industry is highly concentrated (has a higher concentration ratio, higher HHI, or higher profit margin), producers have more bargaining power than consumers. In such an industry, producers would have more space to raise their prices. Therefore, when a cost is imposed on the industry with lower competition, more of this cost can be borne by consumers. The findings in Table 5 are consistent with the neoclassical economic theory of price elasticity and serve as strong supporting evidence of our main results.

4.6 CSWIB and Long-Term Investments: R&D and Capital Expenditures.

We then analyze how firms adjusted their long-term investments in response to the CSWIB, focusing on research and development (R&D) expenditures and capital investments. These two areas are critical indicators of a firm's commitment to innovation and growth, and changes here may reflect strategic reallocations in response to the increased waste disposal costs imposed by the ban.

Table 6 presents the results of our difference-in-differences (DiD) estimation on R&D expenses. The coefficient on the interaction term, Treat*Post, is negative and statistically significant across all specifications, indicating that firms in the treated industries reduced their R&D expenditures following the CSWIB.

The reduction in R&D expenditures suggests that, in the face of higher waste management costs, firms in treated industries may prioritize short-term financial stability over long-term innovation. This choice likely reflects the financial pressures imposed by the ban, as firms adjust by cutting discretionary spending to preserve profitability and manage immediate financial needs.

Table 7 examines the impact of the CSWIB on firms' investments. Similar to the R&D findings, the coefficient on Treat*Post are also negative and statistically significant across all specifications.These results suggest that treated firms also reduced their capital investments following the ban, likely as part of a broader strategy to mitigate the financial burden of increased operational costs.

This reduction in capital investments may reflect that with the ban disrupting the cost-effective disposal of waste, firms in the treated industries may find it prudent to conserve resources rather than engage in capital-intensive projects. This approach aligns with our hypothesis from the introduction, where we anticipated that affected firms might reduce long-term investments if they view the increased waste management costs as a persistent burden that could limit future profitability. By scaling back on capital investments, firms could maintain short-term financial stability while reassessing their strategies for complying with new regulatory landscapes.

The findings indicate that firms responded to the CSWIB by curtailing both R&D and capital investments, reflecting a shift towards short-term cost control at the expense of long-term growth and innovation. This strategic adjustment aligns with the earlier observation of insignificant impacts on profitability(ROA), suggesting that firms may have absorbed the costs of the ban through reductions in growth-oriented expenditures. These results underscore the broader implication that access to low-cost disposal options may have previously enabled firms to allocate more resources to innovation and expansion, a flexibility that is now constrained under the ban. However, this choice could have longer-term implications.

4.7 Real effects of CSWIB: firm performance

The real effects should manifest in treated firms' long-run stock returns. To capture this long-run value implication, we calculate buy-and-hold abnormal stock returns of treated firms relative to control firms in the 500-day window following the execution of the regulation. We use daily stock return data provided by CRSP to conduct this analysis. On each day we subtract the weighted-average stock returns of control industries from that of treated industries. We calculate 500-day buy-and-hold abnormal returns (BHAR) for every firm in the treated industries, using the return of control group as expected return benchmarks:

$$BHAR_{treated} = \prod_{t=1}^{T}(1 + R_{treated,t}) - \prod_{t=1}^{T}(1 + R_{control,t})$$

the mean buy-and-hold abnormal return is the weighted average of the individual BHARs:

$$\overline{BHAR} = \sum_{i=1}^{n} w_i \times BHAR_i$$

Figure 3 illustrates the buy-and-hold abnormal returns (BHAR) for treated firms, with Day 0 marking July 18, 2017, the date China officially announced the waste ban policy. The figure shows a clear downward trend in abnormal returns for treated firms, indicating a negative market reaction to the CSWIB. The downward trend began about half a year after the policy was announced. Since the waste ban was announced on 18th July 2017 and implemented officially on 1st Jan 2018, this result is reasonable and consistent with our prediction. Over the subsequent 500 days, treated firms consistently underperformed, suggesting a substantial reduction in firm value. This trend reflects investors' recalibration of expectations, factoring in the anticipated increase in operational costs and regulatory risks associated with the ban.

To further quantify the effect of the CSWIB on firm valuation, we analyze Tobin's Q, which serves as a proxy for market valuation by capturing the market's assessment of a firm's future profitability and growth potential. Table 8 presents the results of our difference-in-differences (DiD) estimation, showing a consistently negative and statistically significant impact on Tobin's Q for treated firms. The interaction term Treat*Post is negative across all specifications, with the magnitude 0.150/2.702=5.55%.

These results indicate that the CSWIB led to a reduction in the market valuation of firms within waste-intensive industries, likely driven by increased operational costs due to the loss of low-cost disposal options. The negative effect on Tobin's Q suggests that investors re-evaluated the growth prospects and profitability of affected firms, incorporating expectations of higher regulatory scrutiny and cost burdens in the domestic market as a result of the ban.

4.8 The decreased firm value: cash flow channel

The significant decline in Tobin's Q observed in treated firms suggests a reduction in firm value due to the CSWIB. We explore cash flow and discount rate as two potential channels underlying the decrease in firm value. In this sub-section, we focus on the cash flow channel, examining how the increase in waste management costs imposed by the ban impacts expected cash flows.

First, we observe a negative association between the ban and the one-year EPS forecast. However, this effect is only marginally significant and diminishes in later years, indicating a limited impact of the CSWIB on short-term earnings. This finding aligns with the insignificant effect of the ban on short-term ROA, suggesting that treated firms may have managed to partially absorb the immediate cost increases without significantly affecting their short-term profitability.

In contrast, the CSWIB shows a substantial impact on long-term growth forecasts, indicating a significant reduction in the expected long-term earnings growth of treated firms. This result suggests that analysts are more concerned about the long-term implications of the increased waste management costs, anticipating that the sustained financial burden will limit future growth potential. The pronounced effect on long-term growth forecasts reflects the market's expectation that treated firms will face enduring cost pressures, which may hinder their ability to invest in growth and innovation over time.

These findings underscore the role of cash flow disruptions, particularly in long-term growth, as a key factor in the observed decline in firm value. The significant reduction in forecasted long-term growth aligns with the drop in Tobin's Q, indicating

that investors adjust firm valuations to account for the anticipated challenges in sustaining growth following the CSWIB.

4.9 The decreased firm value: discount rate channel

In addition to the impact on cash flows, the CSWIB appears to affect firm value through an increase in the discount rate, reflecting higher perceived risk associated with treated firms. Table 10 presents the difference-in-differences (DiD) estimation results for the implied cost of capital (ICC), providing insights into how the CSWIB influences the discount rate for treated firms. The interaction term Treat*Post is consistently positive and statistically significant across all specifications, with magnitudes of 2.1%. These results indicate that, following the CSWIB, treated firms experienced a significant increase in their implied cost of capital relative to the control group. In economic terms, this increase corresponds to an absolute rise of 2.1% in the cost of capital for treated firms. The rise in ICC suggests that investors perceive treated firms as carrying higher risk post-CSWIB, likely due to the loss of low-cost waste disposal options and the resulting exposure to stricter regulatory environments within domestic markets. With higher expected operational and regulatory costs, investors demand a greater return to compensate for the perceived increase in risk, which translates into a higher discount rate for these firms. This adjustment in the discount rate aligns with the observed decline in Tobin's Q, as a higher cost of capital reduces the present value of expected future cash flows, thereby lowering firm value.

In sum, the CSWIB has contributed to the observed decline in firm value for treated firms through two primary channels. First, by increasing waste management costs, the ban reduces expected cash flows, as reflected in analyst earnings forecasts showing significant declines in long-term growth expectations. This anticipated financial pressure suggests that firms face ongoing challenges to profitability. Second, the CSWIB has led to an increase in the implied cost of capital. This reflects heightened risk perceptions among investors, as firms are now exposed to stricter regulatory requirements and higher operational costs domestically. Together, these channels—reduced cash flows and an elevated discount rate—explain the substantial decrease in Tobin's Q observed for firms within waste-intensive industries.

4.10 Robustness check

To provide further evidence supporting our results, we apply an alternative method to define treated firms. Specifically, we hand-match the names of U.S.-listed firms in Compustat with Panjiva data on firms that exported solid waste to China from 2014 to 2017, identifying a sample of 114 public firms directly engaged in waste export. Since some firms may have exported waste through agent exporters rather than under their own names, this sample may not fully capture the universe of firms exporting solid waste to China. Nevertheless, it is reasonable to assume that most companies within the same industry employ similar production processes, thereby generating a homogeneous set of solid waste. Consequently, firms operating within the same NAICS codes as these 114 Compustat firms are likely to be similarly impacted by the CSWIB.

We initially presented the event study results using only the waste-exporting firms as the treated group in Figure 2. In this robustness check, we define a broader treated group, the "unified treated firms," which includes both the directly identified waste-exporting firms and their industry peers. Using this unified treated sample, we re-examine the same set of outcome variables for U.S. firms following the implementation of the CSWIB. Our findings in this alternative sample show consistent directional effects with those in our primary analysis, with some results exhibiting stronger statistical significance and others weaker. Overall, this provides additional support for the robustness of our conclusions.

5. Conclusion

This paper examines the economic impact of China's Solid Waste Import Ban (CSWIB) on U.S. firms, focusing on how the policy shift affects firm costs, strategic responses, and overall firm value. By restricting access to low-cost waste disposal options in China, the CSWIB forced U.S. firms in waste-intensive industries to manage waste domestically, resulting in higher operational costs. Our analysis reveals that treated firms responded by passing some of these increased costs onto consumers, as evidenced by higher Producer Price Index (PPI) inflation for affected industries, and by reducing long-term investments, such as R&D and capital expenditures, to preserve short-term financial stability.

The empirical results further indicate a significant decline in firm value, as measured by Tobin's Q, among firms affected by the CSWIB. We identify two primary channels driving this decrease in firm value: a reduction in long-term growth (LTG) expectations, reflecting anticipated cash flow constraints, and an increase in the implied cost of capital, indicating heightened risk perceptions among investors. These channels underscore the dual impact of the ban, as it not only places direct financial burdens on waste-intensive firms but also shifts investor perceptions of risk, leading to an elevated discount rate. Meanwhile, in the long run, U.S. listed firms that are under the influence of CSWIB have worse stock market performance.

Our study contributes to the broader literature on environmental regulation and corporate strategy by highlighting the real effects of regulatory changes on firm behavior and market valuation. The findings emphasize the importance of global regulatory coordination in waste management and shed light on the role of "waste havens" in sustaining firm value. As environmental standards continue to evolve worldwide, our results suggest that firms heavily reliant on waste exports may face increased financial and strategic challenges, prompting further examination of corporate responses to environmental regulations.

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Figure 1. U.S. Total Export and Waste Export

This figure presents the trend of the total export and waste export value in dollars in the US. 2015 is set as the base period. The export data comes from the U.S. Census.

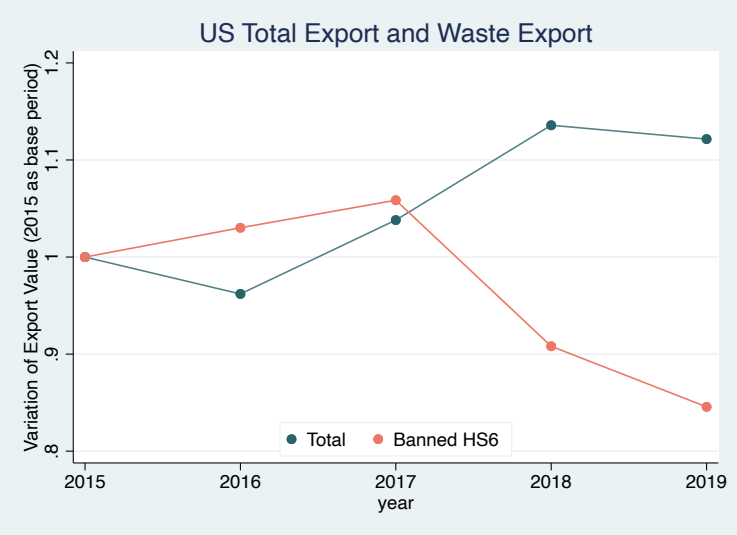


Figure 2. Eventstudy of Treated Industries or Treated Firms

This table shows the cumulative abnormal return in the [-2, +2] window around the announcement date of the China waste import ban. In the three graphs on the left, we examine the CAR of treated industries (industries that generate banned waste in their production processes). In the three graphs on the right, we examine the CAR of treated firms (U.S. publicly listed companies with records of exporting banned waste to China in the three years preceding the policy announcement).We apply the market model, Fama-French 3-factor model, and excess return relative to the market portfolio, respectively, to estimate the abnormal return. We take value-weighted return (including dividends) as market return. The estimation period is [-255, -11].

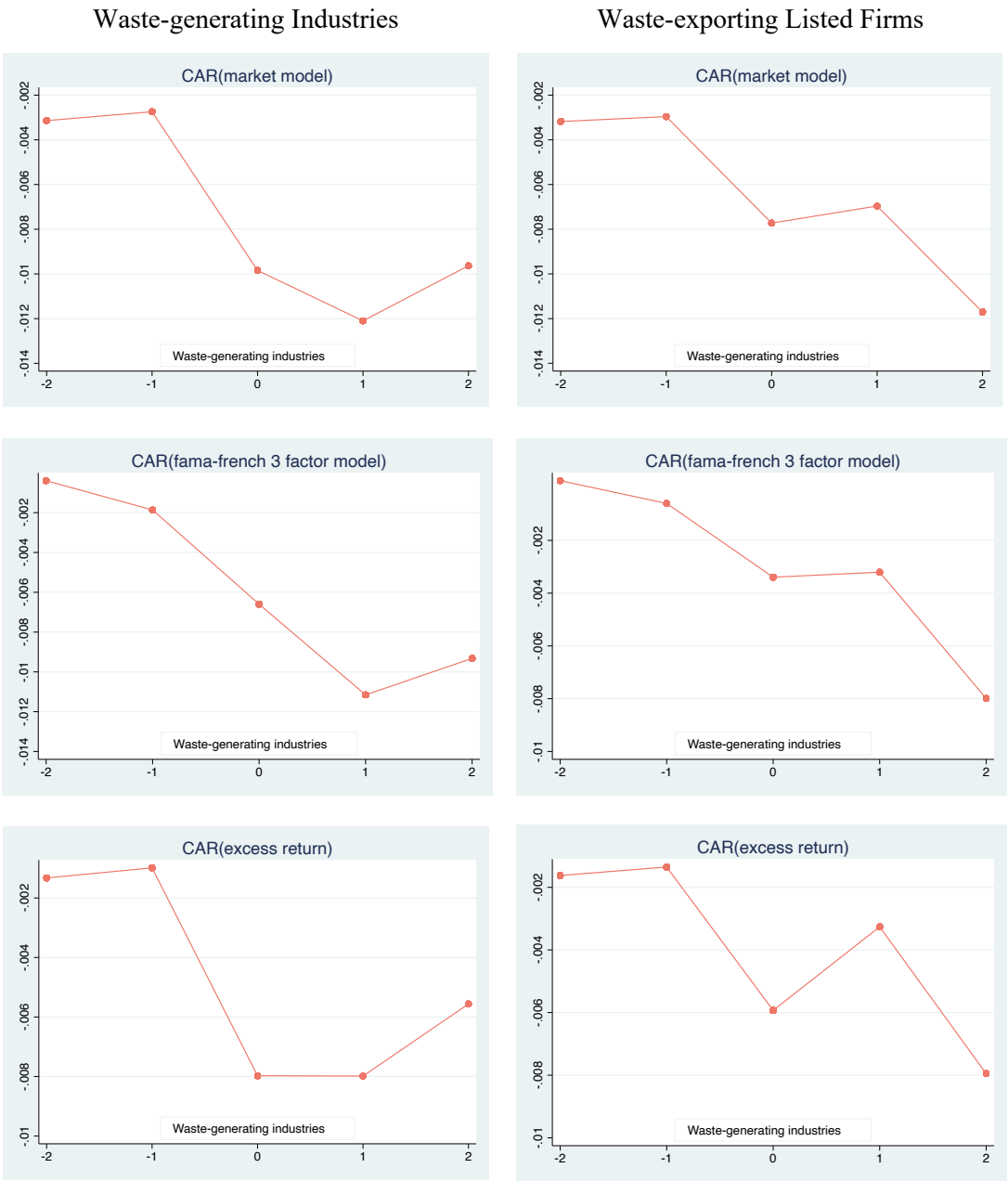


Figure 3. Buy-and-Hold Abnormal Returns

This figure illustrates the cumulative buy-and-hold abnormal returns (BHAR) of the treated group, using the control group as the benchmark. The stock return and market return data are sourced from CRSP. Day 0 corresponds to July 18, 2017, when China officially announced the waste ban policy. Financial firms are excluded from this analysis.

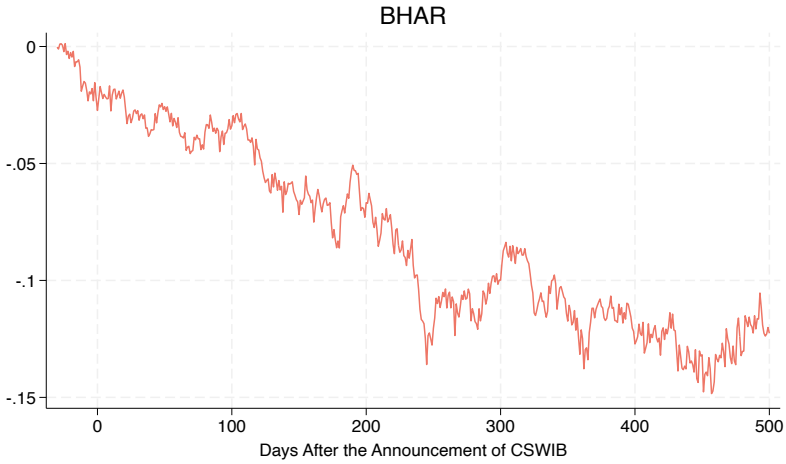


Figure 4. PPI of Treated Industries and Control Industries

This figure shows the annual producer price index in the time window around the China waste import ban after controlling for the industry (6-digit NAICS) fixed effect. We take the average of monthly PPI values to get annual PPI values of treated and control industries respectively. Financial and service industries are dropped from our sample.

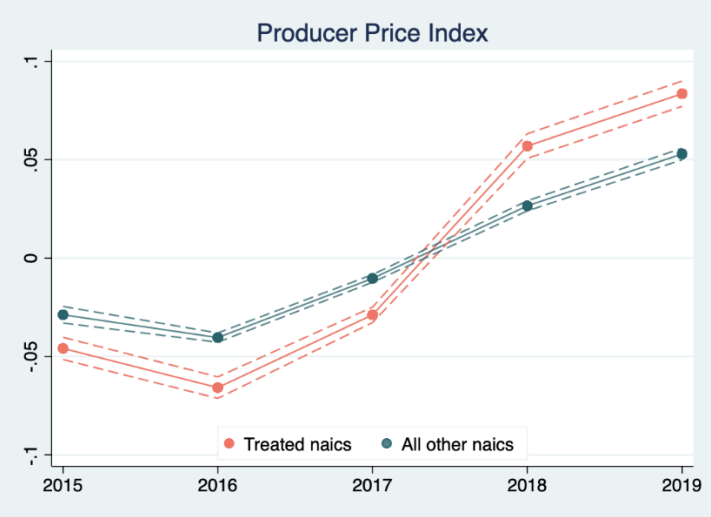


Table 1. Summary Statistics

This table shows summary statistics for the sample we used in the regressions. PPI is at the industry-year level and other observations are at the firm-year level. We drop financial firms, firm-years with missing total asset, and non-US firms. All variables are winsorized by 1% at both tails.

	N	Mean	Std.	Median	p25	p75
Cost/Sale	14435	0.796	1.202	0.642	0.460	0.774
R&D	13668	1.565	5.819	0.000	0.000	0.464
Investment	13190	2.361	7.087	0.347	0.140	1.375
Tobin's Q	13441	2.702	3.788	1.612	1.162	2.651
ROA	14432	-0.122	0.586	0.025	-0.056	0.063
EPSf_price_1	9551	-0.115	0.958	0.037	0.005	0.059
EPSf_price_2	9534	-0.038	0.582	0.045	0.015	0.069
EPSf_price_3	8997	0.028	0.256	0.054	0.026	0.079
LTG	5755	13.882	17.403	11.600	6.440	18.800
ICC	9224	-0.099	0.215	-0.125	-0.233	0.001
Tang	13713	0.264	0.261	0.157	0.058	0.408
Total asset	14305	6.438	2.564	6.780	4.779	8.297
Leverage	14251	0.318	0.388	0.261	0.068	0.424
Invturn	10639	24.390	66.415	5.729	3.140	14.325
Cashflow	14305	-0.078	0.567	0.059	-0.006	0.106
Liquidity	13269	2.588	2.672	1.804	1.120	2.939
Risk	11579	25.161	15.717	20.828	14.213	31.034
PPI	30420	1.019	0.075	1.006	0.989	1.041

Table 2. Waste Ban and Cost of Goods Sold

This table presents the estimation of China waste ban on U.S. firms' cost of goods sold. Column (1) to (3) are the estimation results of cost of goods sold scaled by total asset. Column (4) to (6) are the estimation results of cost of goods sold scaled by sale. The standard errors are clustered at the industry level. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are showed in the appendix table.

	Cost/Sale	Cost/Sale	Cost/Sale
	(1)	(2)	(3)
Treat*Post	0.114**	0.112**	0.086**
	[2.00]	[2.42]	[2.18]
Tang	0.270**	0.143	0.137
	[1.97]	[0.89]	[0.85]
AT	-0.015***	0.024	0.000
	[-2.64]	[0.56]	[0.00]
Lev	-0.095	-0.197*	-0.203*
	[-1.58]	[-1.89]	[-1.93]
Invturn	0.003***	0.000	0.000
	[4.03]	[0.12]	[0.13]
Cashflow	-0.230***	-0.126	-0.113
	[-3.26]	[-1.62]	[-1.45]
Adj.R-sq	0.146	0.623	0.624
N.of Obs.	10566	10543	10543
Ind FE	Y		
Firm FE		Y	Y
Year FE	Y	Y	
Sector-year FE			Y

Table 3. Waste Ban and ROA

This table presents the estimation of China waste ban on U.S. firms' ROA. The standard errors are clustered at the firm level. In column (1) we control for industry fixed effect. In column (2) we control for firm fixed effect and year fixed effect. In column (3) we control for firm fixed effect and industry(NAICS2) by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are shown in the appendix table.

	ROA	ROA	ROA
	(1)	(2)	(3)
Treat*Post	-0.049**	-0.033*	-0.030
	[-2.47]	[-1.70]	[-1.53]
Tang	0.150**	0.055	0.061
	[2.41]	[0.41]	[0.46]
AT	0.098***	-0.021	-0.006
	[16.84]	[-0.82]	[-0.26]
Lev	-0.440***	0.088	0.086
	[-8.31]	[1.57]	[1.52]
Liquidity	0.018***	0.005	0.004
	[4.78]	[1.31]	[1.02]
Tobin's Q	-0.000	-0.000*	-0.000*
	[-1.46]	[-1.84]	[-1.81]
Adj.R-sq	0.424	0.716	0.718
N.of Obs.	12103	12083	12083
Ind FE	Y		
Firm FE		Y	Y
Year FE	Y	Y	
Sector-year FE			Y

Table 4. Waste Ban and Producer Price Index

This table presents the estimation of China waste ban on U.S. Producer Price Index value. The standard errors are clustered at the industry level. T-statistics are presented in brackets below the coefficients. *, **, *** Indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The definitions of all variables are shown in Appendix C.

	PPI				
	(1)	(2)	(3)	(4)	(5)
Treat*Post	0.051***	0.025***	0.030***		
	[31.95]	[3.31]	[4.12]		
Treat*Year$_{-2}$				-0.003	-0.004
				[-0.52]	[-0.60]
Treat*Year$_{-1}$				0.002	0.004
				[0.35]	[1.07]
Treat*Year$_{1}$				0.022***	0.027***
				[2.90]	[4.43]
Treat*Year$_{2}$				0.026***	0.032***
				[3.28]	[5.48]
Adj.R-sq	0.032	0.436	0.448	0.436	0.448
N.of Obs.	30420	30420	30300	30420	30300
Year-Month FE		Y	Y		
Ind FE		Y	Y	Y	Y
Sector-year-Month FE				Y	Y

Table 5. The Effect of Product Market Competition

This table presents the effect of product market competition on the price of U.S. PPI. We use the concentration ratio of 20 or 50 largest firms, and HHI, respectively, to measure the intensity of competition. For each measure we divided our sample into high and low groups using the median as a boundary. The standard errors are clustered at the industry level. T-statistics are presented in brackets below the coefficients. *, **, *** Indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The definitions of each variable are in Appendix C.

Panel A: Concentration ratio

	PPI							
	Concentration Ratio Percentages							
	20 largest firms				50 largest firms			
	high		low		high		low	
Treat*Post	0.036***	0.036***	0.017*	0.012	0.039***	0.038***	0.012	0.012
	[2.75]	[3.04]	[1.69]	[1.14]	[3.05]	[3.31]	[1.44]	[1.25]
Adj.R-sq	0.432	0.459	0.458	0.419	0.416	0.456	0.469	0.374
N.of Obs.	18120	18180	9420	9120	18240	18480	9540	9240
Ind FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE		Y		Y		Y		Y
Sector-year-Month FE	Y		Y		Y		Y	

Panel B: HHI

	PPI			
	HHI			
	high	high	low	low
Treat*Post	0.032**	0.026**	0.010	0.017
	[2.58]	[2.04]	[0.99]	[1.42]
Adj.R-sq	0.395	0.419	0.471	0.467
N.of Obs.	14280	14100	7740	7560
Year-Month FE	Y		Y	
Ind FE	Y	Y	Y	Y
Sector-year-Month FE		Y		Y

Table 6. Waste Ban and R&D Expense

This table presents the estimation of China waste ban on U.S. firms' research & development expense. The standard errors are clustered at the firm level. In column (1) we control for industry fixed effect. In column (2) we control for firm fixed effect and year fixed effect. In column (3) we control for firm fixed effect and industry(NAICS2) by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are shown in the appendix table.

	R&D		
	(1)	(2)	(3)
Treat*Post	-0.707***	-0.843***	-0.481***
	[-2.64]	[-3.67]	[-2.99]
Tang	-4.083***	-2.330***	-2.353***
	[-8.93]	[-2.67]	[-2.69]
AT	-0.185***	-0.534***	-0.531***
	[-3.76]	[-3.16]	[-3.10]
Lev	-0.869**	0.244	0.225
	[-2.05]	[0.35]	[0.31]
Tobin's Q	0.245***	0.036	0.021
	[2.86]	[0.53]	[0.30]
Cashflow	-3.341***	0.062	0.025
	[-4.83]	[0.23]	[0.09]
Risk	0.009	0.011*	0.011*
	[1.27]	[1.84]	[1.83]
Adj.R-sq	0.320	0.797	0.800
N.of Obs.	10926	10881	10881
Ind FE	Y		
Firm FE		Y	Y
Year FE	Y	Y	
Sector-year FE			Y

Table 7. Waste Ban and Investments

This table presents the estimation of China waste ban on U.S. firms' investments. The standard errors are clustered at the firm level. In column (1) we control for industry and year fixed effect. In column (2) we control for firms and year fixed effect, and in colomn （3）we control for firm fixed effect and induatry by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are showed in the appendix table.

	Investment		
	（1）	（2）	（3）
Treat*Post	-0.869***	-0.857***	-0.427**
	[-2.60]	[-2.95]	[-2.09]
Tang	-6.280***	-2.612**	-2.590**
	[-11.03]	[-2.43]	[-2.39]
AT	-0.223***	-1.560***	-1.581***
	[-3.49]	[-4.96]	[-4.99]
Lev	-0.638	-1.030	-1.024
	[-1.15]	[-1.21]	[-1.19]
R&D	0.306***	0.159*	0.143*
	[2.84]	[1.87]	[1.66]
ROA	-3.281***	0.590	0.588
	[-3.82]	[1.22]	[1.17]
Risk	0.014	0.012	0.013
	[1.44]	[1.36]	[1.47]
Liquidity	-0.869***	-0.857***	-0.427**
	[-2.60]	[-2.95]	[-2.09]
Adj.R-sq	0.268	0.695	0.696
N.of Obs.	10502	10441	10441
Ind FE	Y		
Firm FE		Y	Y
Year FE	Y	Y	
Sector-year FE			Y

Table 8. Waste Ban and Tobin's Q

This table presents the estimation of China waste ban on U.S. firms' Tobin's Q value. The standard errors are clustered at the firm level. In column (1) and（3）we control for firm fixed effect and year fixed effect. In column (2) we control for industry and year fixed effect, and in colomn（4）we control for firm fixed effect and induatry by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are showed in the appendix table.

	Tobin's Q			
	（1）	（2）	（3）	（4）
Treat*Post	-0.219**	-0.316***	-0.251***	-0.150**
	[-2.03]	[-4.08]	[-3.62]	[-2.22]
Tang		-0.810***	-0.336	-0.255
		[-2.86]	[-1.18]	[-0.86]
AT		-0.131***	-0.467***	-0.502***
		[-4.70]	[-7.23]	[-7.58]
Lev		1.070***	0.631***	0.618**
		[3.50]	[2.61]	[2.56]
R&D		0.007	0.004	0.004
		[1.25]	[1.17]	[1.16]
ROA		-0.434**	-0.144	-0.084
		[-2.11]	[-0.83]	[-0.47]
Risk		-0.026***	-0.004**	-0.005**
		[-10.23]	[-2.04]	[-2.15]
Liquidity		0.044***	-0.012	-0.013
		[2.68]	[-0.91]	[-1.01]
Adj.R-sq	0.777	0.268	0.750	0.751
N.of Obs.	13437	10537	10496	10496
Ind FE		Y		
Firm FE	Y		Y	Y
Year FE	Y	Y	Y	
Sector-year FE				Y

Table 9. Waste Ban and Analyst Earnings Forecasts

This table examines the impact of CSWIB on analyst earnings forecasts. The dependent variables are EPS forecast for 1-year to 3-year horizons scaled by price in column (1) to (9) and long term growth forecast in column (10) to (12). We use the stock price one year prior to CSWIB enactment year to scale EPS forecasts. The unit of analysis is at firm-year level. The standard errors are clustered at the firm level. In column (1)(4)(7)(10) we control for industry and year fixed effect. In column (2)(5)(8)(11) we control for firm and year fixed effect and year fixed effect. In column (3)(6)(9)(12) we control for firm fixed effect and industry(NAICS2) by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are shown in the appendix table.

	EPS forecast 1 year			EPS forecast 2 year			EPS forecast 3 year			LTG		
	(1)	(2)	(3)	(1)	(1)	(1)	(7)	(8)	(9)	（10）	（11）	（12）
Treat*Post	-1.852**	-0.002	-0.087*	-3.533	-3.533	-3.533	-1.172*	-0.029	-0.031	-3.533	-3.900*	-4.806***
	[-2.40]	[-0.05]	[-1.74]	[-1.36]	[-1.36]	[-1.36]	[-1.78]	[-1.05]	[-1.11]	[-1.36]	[-1.77]	[-2.87]
Tang	-0.346	-0.019	-0.004	4.588*	4.588*	4.588*	-0.126	0.501	0.474	4.588*	20.141*	19.118*
	[-0.50]	[-0.01]	[-0.00]	[1.75]	[1.75]	[1.75]	[-0.41]	[0.57]	[0.53]	[1.75]	[1.85]	[1.81]
AT	0.061	0.336	0.356	-1.259***	-1.259***	-1.259***	0.023	0.192	0.199	-1.259***	-1.484	-2.010
	[1.11]	[1.08]	[1.00]	[-4.50]	[-4.50]	[-4.50]	[0.79]	[1.27]	[1.11]	[-4.50]	[-1.06]	[-1.52]
Lev	0.517	1.588	1.553	2.107	2.107	2.107	0.156	1.198	1.163	2.107	0.525	-0.093
	[1.07]	[1.32]	[1.32]	[0.95]	[0.95]	[0.95]	[0.76]	[1.17]	[1.17]	[0.95]	[0.19]	[-0.03]
Cashflow	3.056***	-1.152	-1.224	-22.582***	-22.582***	-22.582***	1.145**	-2.250	-2.344	-22.582***	-14.181**	-12.499**
	[2.92]	[-0.36]	[-0.37]	[-3.43]	[-3.43]	[-3.43]	[2.44]	[-0.74]	[-0.76]	[-3.43]	[-2.55]	[-2.50]
Inv	0.015***	0.000	-0.000	0.561	0.561	0.561	0.006**	-0.624	-0.708	0.561	-3.279	-2.867
	[2.79]	[0.04]	[-0.03]	[0.19]	[0.19]	[0.19]	[2.30]	[-1.23]	[-1.21]	[0.19]	[-0.93]	[-0.81]
Cash	-0.061	3.155	3.286	9.626***	9.626***	9.626***	-0.517	2.416	2.536	9.626***	1.605	0.462
	[-0.09]	[1.61]	[1.60]	[2.60]	[2.60]	[2.60]	[-1.02]	[1.32]	[1.30]	[2.60]	[0.37]	[0.11]
Roa	-0.531***	0.154	0.113	6.807	6.807	6.807	-0.222**	0.300	0.277	6.807	1.591	3.516
	[-2.83]	[0.32]	[0.23]	[0.91]	[0.91]	[0.91]	[-2.11]	[0.72]	[0.68]	[0.91]	[0.30]	[0.61]
Risk	-0.038*	-0.015	-0.014	-0.048	-0.048	-0.048	-0.023	-0.011	-0.011	-0.048	-0.006	-0.009
	[-1.86]	[-1.31]	[-1.28]	[-0.84]	[-0.84]	[-0.84]	[-1.19]	[-1.02]	[-0.99]	[-0.84]	[-0.14]	[-0.22]
Adj.R-sq	-0.037	0.381	0.375	0.156	0.156	0.156	-0.052	0.363	0.356	0.156	0.373	0.390
N.of Obs.	8780	8698	8698	5438	5438	5438	8280	8186	8184	5438	5306	5304
Ind FE	Y			Y			Y			Y		
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Year FE	Y	Y		Y	Y		Y	Y		Y	Y	
Sector-year FE			Y			Y			Y			Y

Table 10. Waste Ban and Implied Cost of Capital

This table examines the impact of CSWIB on analyst earnings forecasts. The dependent variables are the implied cost of capital. The unit of analysis is at firm-year level. The standard errors are clustered at the firm level. In column (1) we control for industry and year fixed effect. In column (2) we control for firm and year fixed effect and year fixed effect. In column (3) we control for firm fixed effect and industry(NAICS2) by year fixed effect. T-statistics are presented in brackets below the coefficients. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests). The computational processes of all variables are shown in the appendix table.

	ICC		
	(1)	(2)	(3)
Treat*Post	0.024***	0.016**	0.021**
	[2.73]	[2.09]	[2.37]
Tang	0.033	-0.029	-0.045
	[1.11]	[-0.50]	[-0.78]
AT	-0.028***	0.071***	0.074***
	[-8.36]	[6.75]	[6.99]
Lev	-0.104***	-0.126***	-0.115***
	[-4.59]	[-4.00]	[-3.73]
Cashflow	-0.052	0.143*	0.123
	[-0.66]	[1.67]	[1.47]
Inv	-0.034**	-0.021	-0.021
	[-2.20]	[-1.53]	[-1.52]
Cash	-0.285***	-0.018	-0.018
	[-11.63]	[-0.65]	[-0.64]
Roa	0.228***	0.054	0.055
	[3.45]	[0.74]	[0.79]
Risk	0.004***	0.002***	0.002***
	[6.33]	[4.18]	[4.08]
Adj.R-sq	0.417	0.727	0.735
N.of Obs.	9089	9012	9012
Ind FE	Y		
Firm FE		Y	Y
Year FE	Y	Y	
Sector-year FE			Y

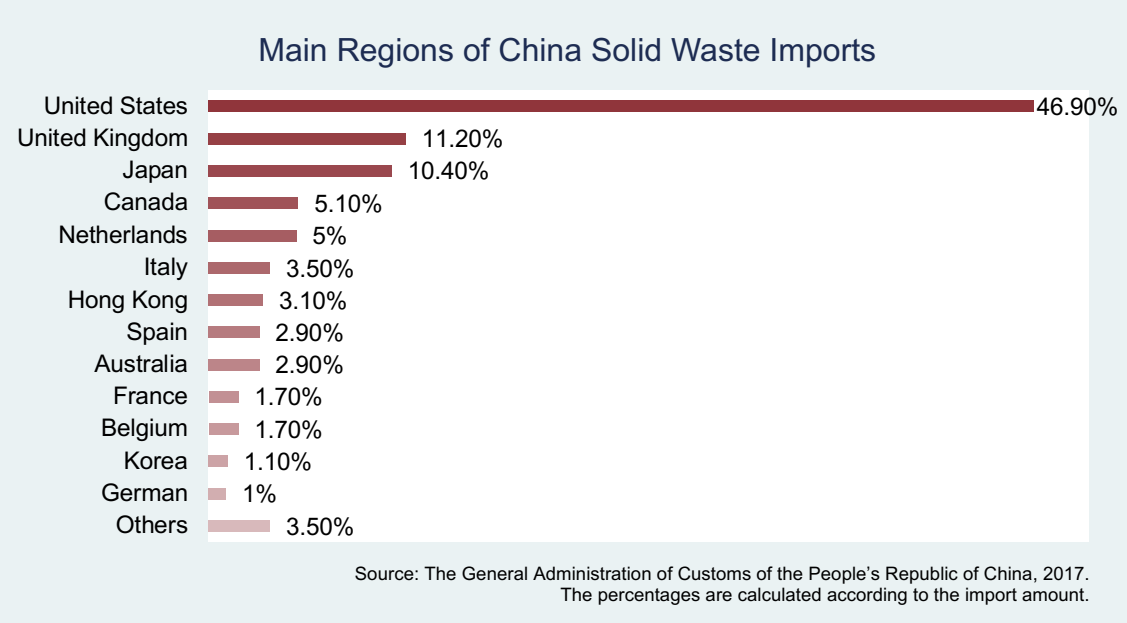
Appendix A. HS Codes that are Banned from Importing to China

HS	Description
3915100000	Waste, parings and scrap of polymers of ethylene
3915200000	Waste, parings and scrap of polymers of styrene
3915300000	Waste, parings and scrap of polymers of vinyl chloride
3915901000	Waste, parings and scrap of polyethylene glycol terephthalate
3915909000	Other waste, parings and scrap, of plastics
2619000021	The scum and slag with vanadium produced by smelting the steel, containing vanadium pentoxide more than 20%(other than granulated slag produced by smelting the steel)
2619000029	Other scum and slag with vanadium produced by smelting the steel(other than granulated slag produced by smelting the steel)
2620999011	Slag, ash and residues, containing by weight more than 20% of V2O5(other than from the manufacture of iron or steel)
2620999019	Slag, ash and residues, containing by weight more than 10% but not exceeding 20% of V2O5(other than from the manufacture of iron or steel)
4707900090	Other recovered paper or paperboard, including unsorted waste and scrap
5103109090	Noils of fine hair of other wild animal
5103209090	Waste of fine hair of other animal, including yarn waste but excluding garnetted stock
5103300090	Waste of coarse hair of other animal, including yarn waste but excluding garnetted stock
5104009090	Garnetted stock of fine or coarse hair of other animal
5202100000	Yarn waste(including waste cotton yarn)
5202910000	Garnetted stock
5202990000	Other cotton waste
5505100000	Waste of synthetic fibres (including noils, yarn waste and garnetted stock)of man-made fibres
5505200000	Waste of artificial fibres (including noils, yarn waste and garnetted stock)of man-made fibres
6310100010	Sorted new or not used rags, including scrap twine, cordage, rope and cables and worn out articles of twine, of textile materials
6310900010	Other new or not used rags, including scrap twine, cordage, rope and cables and worn out articles of twine, of textile materials

This table lists the 10-digit HS codes of goods that were banned from importation by the Chinese government as announced in 2017.

Appendix B. Main Regions of China Waste Imports and U.S. Waste Exports

Panel A. Main Regions of China Solid Waste Imports



Source: The General Administration of Customs of the People's Republic of China, 2017.
The percentages are calculated according to the import amount.

Panel B. Main Regions of U.S. Solid Waste Exports



Source: United Nations Comtrade Database 2014-2017.
The percentages are calculated according to the export net weight.

Appendix C. Variable Definitions

***Dependent variables*:**

PPI	US producer price index that reported by U.S. Bureau of Labor Statistics, scaled by 100.
Cost/Sale	Cost of goods sold, scaled by total sales (cogs/sale).
R&D	Research and development expense, scaled by total asset (xrd/at).
Tobin's Q	The lagged term of Tobin's Q value. Calculated as the ratio (total assets − stockholders' equity + common shares outstanding × price close at the end of fiscal − deferred taxes)/total assets ((at-ceq + csho*prcc_f -txdb)/at).
Investment	The sum of Capital expenditure, R&D and acquisitions, scaled by the total asset. ((capx+xrd+aqc)/at)
EPS forecast	The earliest available consensus forecast of EPS after the earnings announcement for 1-year to 3-year horizons, scaled by stock price. For the post-treatment years, the price is fixed to be one year before the enactment year. For the pre-treatment years and never treated firms, we use stock price from the previous year.
LTG	The earliest available consensus forecast of LTG after the earnings announcement.
ICC	Implied cost of capital, measured as the mechanical based implied cost of return using Claus and Thomas mechanical model. We use the data provided by Lee, So, Wang (2021).

***Other variables*:**

Treat	Whether the firm or the industry is affected by China waste import ban. Yes=1, No=0.
Post	Equals to 1 during 2015 to 2017, equals to 0 during 2018 to 2020.
AT	Total assets. Calculated as the natural logarithm of the company's total assets at the beginning of the fiscal year (at).
Tang	Tangibility. Calculated as the lagged term of total property, plant and equipment scaled by the total asset (ppent/at).
Cash	The lagged term of cash and short-term investments, scaled by the total asset (che/at).
Lev	Lagged term of leverage in the fiscal year t, calculated as long-term debt plus debt in current liabilities scaled by the sum of long-term debt, debt in current liabilities, and total shareholders' equity at the end of the year ((dltt+dlc)/seq).
Cashflow	Cashflow, calculated by the income before extraordinary items plus depreciation and amortization, scaled by total assets ((ib+dp)/at).
ROA	Return on assets, calculated by the ratio of the net income to the total asset(ni/at).
Risk	The risk associated with the excess return of the stock, calculated by the standard deviation of a stock's excess return.
Liquidity	Liquidity. Measured by the current ratio (act/lct).
Invturn	Inventory turnover, calculated by the ratio of the cost of goods sold to the average of the inventory stock(cogs*2/(invt+l.invt)).
Concentration Ratio	The concentration ratio of U.S. industries, provided by U.S. Census.
HHI	Herfindahl-Hirschman index provided by U.S. Census.

Appendix D. A Text-based Matching of China HScode and U.S. EPA Waste Flow

To match EPA waste flow to banned HScode, we rely on a popular approach, namely word embedding. First, we use regular expressions to remove punctuation marks and other non-character content from the text. Although many pre-trained word embedding models now have vectors for these symbols, the meaning of the symbols in our dataset differs from that in the pre-trained model. Second, we use "punkt"(Kiss, Tibor, and Jan Strunk, 2006) as a tokenizer. As the most popular tokenizer, "punkt" can split complete sentences into words and complete the task well, even without punctuation, to help understand the end or pause of the sentence.

Next, we eliminate all stop words based on the data provided by nltk. Stop words are common words in English that do not provide helpful information. After that, we use the Part-of-Speech Tag function provided by nltk and then lemmatize all the words. During this procedure, the form of words became simpler for us to manipulate. In the next step, we acquire word embeddings through a pretrained Word2Vec model (Mikolov and Tomas, 2013). Specifically, we used GoogleNews-vectors-negative300, which provided a 300-dimension vector representation for each word. This model was trained on Google News dataset, consisting 100 billion words data. This model is widely applicable due to its wide coverage. High-dimension vectors will give the algorithm more comprehensive capabilities.

In the final step, we calculate two scores of similarity: "sentence similarity" and" word max similarity." In the task of text matching in NLP applications, the vector of each word in the current sentence is averaged as the vector representation of the current sentence. Then, the cosine similarity of the two sentence vectors to be compared is calculated. An empirical threshold is set, and sentences above the threshold are marked as matched. In our circumstances, HScode and EPA waste flow have unequal status, considering only sentence similarities may biased. Therefore, we introduce "word max similarities" to eliminate the bias. The origin of this idea is that EPA waste flow and HScode that can be matched together should have at least one word with high similarity, not only the whole sentence. This method gives tighter constraints, making the results more precise. In practice, we set the threshold of "sentence similarity" to 0.85 and that of "word max similarity" to 0.9.

We end up with a list of many-to-many relationships between HScode and EPA waste flow, along with sentence similarities and word similarities. The mean of the sentence similarity score is 0.911 and the median is 0.923. Some of the matched examples give us a more intuitive understanding of the similarity score: an HSCODE with a description of "Waste pharmaceuticals" has a similarity score of 0.999 with EPA "WASTE PHARMACEUTICAL." Another example is HSCODE "Waste and scrap of stainless steel," which has a similarity score of 0.943 with EPA "Remainder/Composite Metal". We found that the similarity scores are more distributed in higher values. We sorted them in descending order during the manual check process according to the similarity score for further screening. Data with a similarity score lower than 0.9 has a low reference value in our dataset.

Since the pre-trained model we use is trained by Google on Internet information as a corpus, it covers a wide range of content. However, the data we use for testing may be limited to the description of some waste, so there may be a problem of data imbalance. Using this model directly will result in similar results that are too fine-grained, and setting an appropriate threshold is a challenge. Fine-tuning a model requires additional training data that fully reflects the relationship between various HScodes and EPA waste, but we do not have enough data for training.

Furthermore, we use the average of word embeddings to calculate sentence embeddings, which is a bag-of-words approach. This will lead to the loss of some sentence-meaning information. For example, the semantics of "other than" in a sentence, which indicates exclusion, cannot be accurately expressed in the sentence embedding. Although we added constraints that consider word similarity, this only partially solves the problem.