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Evading the ban: smuggling, pollution, and the welfare effects of China's waste import restrictions

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Abstract

While import restrictions are increasingly deployed to achieve non-trade objectives such as environmental protection, they often create distortions and leakage through illicit trade. We examine this trade-off in the context of China's waste import ban. Although the policy produced measurable improvements in air and water quality, it also induced significant behavioral responses, including surging evasion via quantity underreporting, heightened smuggling-related criminal activity, and deteriorating performance among affected firms. To quantify the welfare effects, we develop a hybrid sufficient statistic framework that integrates reduced-form evasion elasticities with structural estimates of shadow costs. We find that the environmental gains were more than offset by the costs of smuggling and losses from distortions.

Keywords: Waste; Smuggling; Quota; Pollution; Firm Performance; Sufficient Statistics; Welfare; China
JEL codes: F13; F14; F18

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1 Introduction

Import restrictions are increasingly used to pursue non-trade objectives, including the mitigation of environmental externalities embodied in traded goods. Under perfect enforcement, restricting an environmentally harmful import reduces domestic exposure and can raise welfare when damages are sufficiently large (Shapiro and Walker, 2018). However, when enforcement is incomplete, the policy wedge created by the restriction induces endogenous avoidance through misreporting and illicit trade (Fisman and Wei, 2004; Yang, 2008). Despite its significance, systematic evidence on smuggling activities and their socioeconomic impacts remains scarce, largely because such behavior is inherently clandestine. In addition, the effectiveness of environmental trade policy and its welfare implications depend on unobserved primitives, including the resource cost of operating outside the formal system, the elasticity of evasion with respect to policy tightness, and the degree of environmental externality.

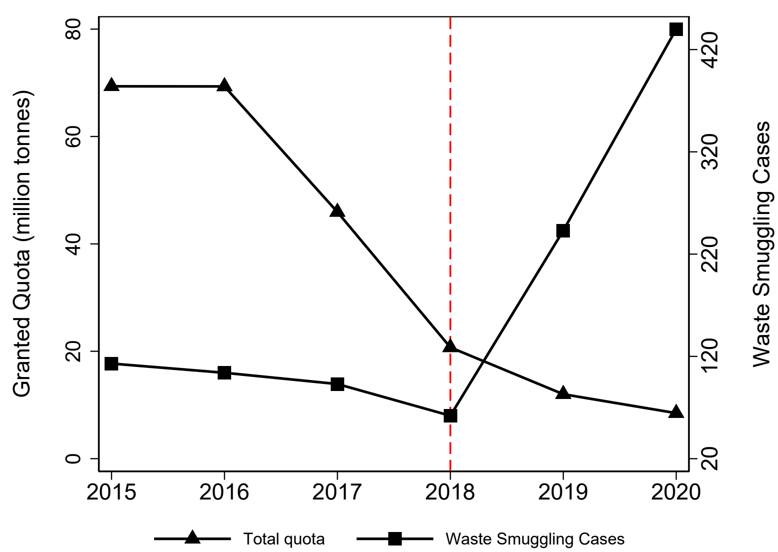


Figure 1: Granted Waste Import Quota and Waste Smuggling Activities

Notes: The figure shows China's waste import quota (left axis) and court-reported smuggling cases (right axis). The import restrictions on waste we studied were announced in late 2017 and implemented in January 2018.

This paper addresses these issues using China's ban on waste imports. In response to rising domestic pollution, China announced in 2017 that it would tighten controls on waste imports, banning or reducing quotas for almost all types of imported waste starting in 2018. Subsequently, we witnessed a sharp rise in the number of criminal cases that are related to waste smuggling (see Figure 1). This naturally raises the following questions: Did the restriction lead to increased smuggling, reduced pollution, and greater losses for firms? How can the leakage and distortion be mapped into welfare when policy wedges are not directly observed?

Our first contribution is to document the avoidance margin. Using product-level mirror trade data, we find that the ban significantly enlarged the reporting gaps in the trade value and quantity of waste relative to other products, suggesting the existence of illicit waste trade. We corroborate this finding using data from China's court records and find that criminal cases related to waste smuggling rose sharply relative to those involving the smuggling of ordinary goods following the implementation of the ban. Our mechanism analysis suggests that, unlike tariff evasion, quota evasion occurs through quantity leakage rather than through transfer pricing.

We extend the analysis beyond the evasion behavior to its economic and environmental consequences. We find that firms with pre-ban dependence on imported waste inputs experience a decline in performance relative to importers without waste imports. Regarding environmental consequences, air and water quality improved on average after the restriction, but the gains were markedly heterogeneous. Locations with high pre-ban exposure to waste smuggling experienced significantly attenuated improvements, suggesting that illicit imports weaken the policy's environmental effectiveness precisely where enforcement frictions are severe.

The second contribution of this paper is methodological. While the sufficient statistic approach is well-suited for welfare evaluation, its quantification depends on unobserved policy wedges in our context, including the shadow price of restricted waste and the real resource cost of evasion. This paper, therefore, develops a hybrid sufficient statistic framework that combines reduced-form evasion elasticities with shadow costs estimated from a parsimonious structural model.

Our hybrid approach proceeds in three steps. First, we derive a welfare formula capturing the first-order effects of quota tightening using a small set of sufficient statistics, including the unobserved policy-induced wedges. Second, we embed these wedges into a heterogeneous-firm model (Melitz, 2003; Chaney, 2008). Firms source homogeneous waste inputs through three modes: domestic procurement, legal imports (subject to quotas), or smuggling (which entails confiscation risks and smuggling costs). In equilibrium, tightening the quota raises the quota rent and increases the relative return to illicit sourcing, thereby inducing more smuggling. Third, we estimate structural parameters via the method of moments to match observed smuggling volumes and quota limits. We find substantial smuggling costs and quota rents: in the post-ban period (2018-2020), variable smuggling costs averaged 14.3% ad valorem, fixed smuggling costs were about ten times those of legal imports, and the quota rent was roughly 23.9% ad valorem.

Our third contribution is quantitative. Armed with the estimates, we apply the sufficient statistic formula to quantify the welfare effect of the policy and its components: (i) the environmental benefit from reduced waste processing, (ii) the increased distortion from tightened quantity constraint, and (iii) real resource dissipation in smuggling. Our welfare accounting reveals that while the policy generates meaningful environmental benefits, these gains are more than offset by real resource costs from smuggling and rising distortions from reduced imports. We estimate that the import restriction results in a net welfare loss of \$25.65 per tonne. This comprises an environmental gain of \$70.2 per tonne, which is outweighed by smuggling costs of \$20.14 per tonne and distortion-related losses of \$75.71 per tonne. We also show that smuggling eases quota constraints, lowering distortionary losses, but undermines environmental gains and imposes deadweight costs.

This paper contributes to several strands of literature. First, it speaks to the literature on illicit trade. A large body of work documents how firms respond to tariffs and border frictions via misreporting, including under-invoicing, misclassification, and outright smuggling (Fisman and Wei, 2004; Yang, 2008; Mishra et al., 2008; Javorcik and Narciso, 2017; Ferrantino et al., 2012; Che et al., 2025). We contribute by examining a restriction defined not by a price wedge but by a binding quantity constraint. We provide evidence that avoidance in this setting operates predominantly through physical quantities, rather than transfer-price manipulation. More broadly, our setting complements work showing that sharp non-tariff shocks such as bans and sanctions induce illicit trade through indirect routing and smuggling outside formal channels (Juhász, 2018; Kee and Nicita, 2022; Tyazhelnikov and Romalis, 2024), and that changes in customs enforcement shift avoidance behavior across margins (Yang, 2008). Finally, we connect this trade-evasion evidence with a key insight from the public finance literature: when avoidance/evasion entails resource costs, the welfare consequences depend critically on the elasticity of evasion and the marginal resource cost of sheltering (Chetty, 2009a).

Second, we contribute to the literature on quantitative trade restrictions and their equilibrium consequences. Early work on Japan's voluntary export restraints modeled binding quotas as implicit per-unit taxes (i.e., shadow prices) affecting firm pricing (Feenstra, 1988; Berry et al., 1999). Evidence from the Multi-Fiber Arrangement suggests that quotas generate substantial misallocation and shape firm outcomes (Khandelwal et al., 2013; Bloom et al., 2016). More recent studies show that China's waste import ban diverted waste and pollution to other countries (Atalar et al., 2025; Gao et al., 2025) and rare earth export restriction induced smuggling and more domestic pollution and directed technological change in other countries (Alfaro et al., 2025; Chen et al., 2026). Advances have also been made in the theoretical and quantitative analyses of quotas under general equilibrium (Xiao et al., 2017; Baqaee and Sangani, 2025). We contribute by documenting how an environmentally motivated import restriction induces leakage via illicit trade, and by quantifying how enforcement reshapes the incidence and welfare consequences of quantity-based trade policy.

Our final contribution concerns the sufficient statistic approach. This approach facilitates welfare analysis by combining policy wedges with estimated behavioral elasticities, and has gained significant traction in public finance for evaluating fiscal policies (Chetty, 2009b; Kleven, 2021). Our work aligns closely with research on the welfare implications of tax evasion (Feldstein, 1999; Chetty, 2009a). Trade economists have likewise adopted this framework to quantify welfare gains from trade (Arkolakis et al., 2012, 2019; Melitz and Redding, 2015), comparative advantage (Huang and Ottaviano, 2025), and the welfare effects of tariffs (Amiti et al., 2019). Unlike taxes or tariffs, our setting faces a unique challenge: the wedges are not directly observable. To address this challenge, we estimate them using a structural model, yielding a hybrid method that combines reduced-form estimates, structural modeling, and the sufficient statistic approach.

We proceed as follows: Section 2 provides institutional context and describes the data. Section 3 presents reduced-form evidence. Section 4 develops the theoretical model, and Section 5 conducts the quantitative analysis. Section 6 concludes.

2 Institutional Background and Data

2.1 Waste Trade and China's Import Ban

The Global South, particularly China, has long occupied a central position in global recycling networks, serving as a major processing hub for waste materials from the Global North, including scrapped plastics, paper, and metals. For instance, between 1992 and 2016, China imported a cumulative 106 million metric tons of plastic waste, accounting for 45% of global plastic waste imports over this period (Brooks et al., 2018).

Several factors explain China's key role in waste recycling (Gregson and Crang, 2015). First, its rapid economic growth spurred demand for raw materials, prompting China to seek cheaper resources worldwide, including secondary materials derived from waste. Second, containerization facilitated the shipment of relatively small consignments of discarded goods in standard containers at lower costs than bulk carriers. China's growing trade surplus further enabled cheap backhaul transport of low-value waste (Lee et al., 2024). From 2002 to 2007, the waste share in Chinese imports surged from 0.11% to 1.9% (see Appendix Table D3). Finally, China's lower labor costs and lax environmental standards enabled labor-intensive sorting, separation, and purification processes essential to recycling – activities that often generate significant pollution (Kellenberg, 2012).

To mitigate increasing pollution from waste processing and the broader environmental damages since its WTO accession (Bombardini and Li, 2020; Carattini et al., 2025; Gao et al., 2025), China enacted the *2017 Implementation Plan for Banning the Entry of Foreign Waste* (effective January 2018). Under this policy, the government systematically tightened waste import quotas over time (see Figure 1) before imposing a complete ban in 2021. Concurrently, China Customs shifted toward the proactive interdiction of waste smuggling. Under the nationwide *Blue Sky 2018* initiative, China Customs increased inspection intensity at major ports nationwide. As a result, the share of waste imports in total Chinese imports declined from 1.03% in 2017 to 0.37% in 2020.

2.2 Data and Summary Statistics

Mirrored Trade Data We use the United Nations Comtrade database (2015–2021) to construct a dataset of bilateral trade flows at the HS 6-digit level. Comtrade compiles trade records from both exporters and importers, allowing us to construct "mirror statistics" for each product. By comparing discrepancies between reported exports from the origin and imports recorded in the destination, we can systematically detect anomalies indicative of trade evasion. To reduce noise from unrelated product categories, the analysis focuses on HS 6-digit products within HS 2-digit chapters containing at least one waste item listed in the import restriction catalog.

Criminal Records of Smuggling To further quantify illicit activity, we rely on China Judgments Online (CJO), a centralized platform publishing semi-structured court documents. Following recent studies validating CJO as a reliable source of criminal data (Ma et al., 2025; Zhang et al., 2025), we extract key fields, including court location, case titles, charges, and narrative facts, to identify relevant prosecutions. These data are then aggregated to the prefecture–year level to derive the frequency of waste smuggling versus common smuggling cases.

List of Waste Products We collect and concord all regulated HS 10-digit codes from the 2017 waste import plan to the HS 6-digit level, defining an HS 6-digit product as 'treated' if any of its constituent 10-digit codes appear in the Catalog. Appendix Table B2 lists the products covered by the policy at the HS 4-digit level.

Tariff and Non-Tariff Measures We source China's Most Favored Nation (MFN) tariffs (at HS 6-digit level) and partner export Non-Tariff Measures (NTMs) from WITS–TRAINS. Since higher tariffs raise returns to illicit trade (Fisman and Wei, 2009; Che et al., 2025), we control for China's annual ad valorem MFN duties to isolate tariff-driven evasion from waste regulations. Likewise, we control for exporters' NTMs to disentangle them from China's import restrictions.

Air and Water Pollution To measure air pollution at the granular level and at a relatively high frequency, we rely on monitor-level data from the Ministry of Ecology and Environment (MEE). As for water quality, we rely on the data compiled by Lin et al. (2024), which provide extensive and detailed water quality at the monitor level across China covering major water bodies.

Customs Enforcement Technology To measure regulatory capacity, we utilize the China Government Procurement (CGP) database. As the official repository for government tenders, the CGP provides detailed records on buyer identities, item descriptions, and transaction values. This dataset has been validated in the literature as a reliable source for tracking public sector activity in China

(Beraja et al., 2023). We used these records to construct a province-year index of enforcement-related technology procurement (e.g., container scanners, X-ray/CT systems) by customs agencies.

Table 1: Summary Statistics of Main Variables

Variables	Mean	Standard deviation	Minimum	Maximum	Obs.
Panel A: Product level					
ln(Reported Import Value)	16.567	2.978	1.386	26.164	12,717
ln(Reported Import Quantities)	14.526	3.670	-2.419	27.748	12,172
GapRatio in Value	0.105	0.428	-1.000	1.000	13,240
GapRatio in Quantity	0.172	0.487	-1.000	1.000	13,210
GapRatio in Unit Value	-0.055	0.319	-1.000	1.000	12,126
ln(Tariff)	0.068	0.047	0.000	0.300	13,240
Panel B: Exporter-product level					
GapRatio in Value	-0.038	0.799	-1.000	1.000	354,861
GapRatio in Quantity	-0.016	0.819	-1.000	1.000	346,646
ln(Tariff)	0.068	0.048	0.000	0.300	354,861
ln(Population-weighted distance)	8.683	0.763	6.071	9.854	354,861
Rule of Law Index	0.777	0.920	-1.831	2.019	354,679
Control of Corruption Index	0.698	1.015	-1.600	2.196	354,679
Government Effectiveness Index	0.833	0.861	-1.814	2.284	354,679
Political Stability Index	0.281	0.797	-2.703	1.937	354,679
Regulatory Quantity Index	0.851	0.871	-2.249	2.205	354,679
Voice and Accountability Idex	0.526	0.901	-1.796	1.720	354,617
Panel C: City level					
Smuggling cases	156.209	400.682	0.000	10253.000	2,982
Customs enforcement	33.927	79.006	0.000	455.000	2,982
Granted Quota	0.002	0.008	0.000	0.146	2,982
ln(Recycling firms)	5.375	1.270	0.693	9.306	2,982
ln(PM2.5), $\mu g/m^3$	3.664	0.516	2.147	4.894	17,160
Panel D: Firm level					
ln(Operating Revenue)	16.482	1.862	4.963	24.935	92,125
ln(Number of Employees)	5.416	1.374	0.693	8.747	56,677
EBIT margin, %	2.980	11.955	-100	97.560	64,466
ln(Labor Productivity)	11.629	1.052	8.383	14.659	56,677
Panel E: Monitoring-site level					
lnCODMn, mg/L	0.894	0.562	-2.303	2.910	2,861
Nighttime Light, standardized	0.239	1.408	-0.557	9.548	2,861

Notes: This table presents descriptive statistics for the main variables used in empirical analysis. The Gap in value and quantity is measured by $GapRatio = (ExportToChina - ChinaImports)/(ExportToChina + ChinaImports)$. Gap in unit value is measured by $GapRatioUnitValue = (UnitValue^X - UnitValue^M)/(UnitValue^X + UnitValue^M)$. $ln(Tariff)$ represents China's MFN tariff. Smuggling cases include both common-goods smuggling and waste-goods smuggling. Customs enforcement refers to the number of public procurement contracts handled by China's customs department. Recycling firms refer to the cumulative number of resource-recycling firms registered locally.

Firm and Customs Data To test whether import controls disrupt firm production activities, we used the Orbis database, assembled by Bureau van Dijk, for the period 2015-2021. Compared to the commonly used Annual Survey of Chinese Industrial Firms dataset, the Orbis database provides financial performance and company profiles of a wide range of Chinese companies over recent years, spanning from large to small companies. We merge firms from the China Customs and Orbis databases by firm name and focus on manufacturing firms that import intermediates.

Table 1 presents the summary statistics for the main variables.[1]

3 Reduced-Form Evidence: an Anatomy of the Waste Ban

This section presents reduced-form evidence on the impacts of the ban on waste imports. We first document the policy's effect on reported waste trade flows and the surge in evasion using both mirror trade statistics and criminal judgments data. We then examine the socioeconomic consequences of these restrictions, estimating their effect on local environmental quality and the performance of import-dependent manufacturing firms.

3.1 Effect on China's Reported Waste Imports

To examine the disruption to China's recorded imports induced by the waste ban, we examine the evolution of imports for targeted products relative to non-targeted ones using the following event-study specification:

$$Y_{pt} = \alpha + \sum_{k=-3,-2,0,1,2,3} \beta_k \times Treated_p \times D_t^k + \gamma \cdot ln(Tariff_{pt}) + \sigma_p + \sigma_t + \epsilon_{pt} \tag{1}$$

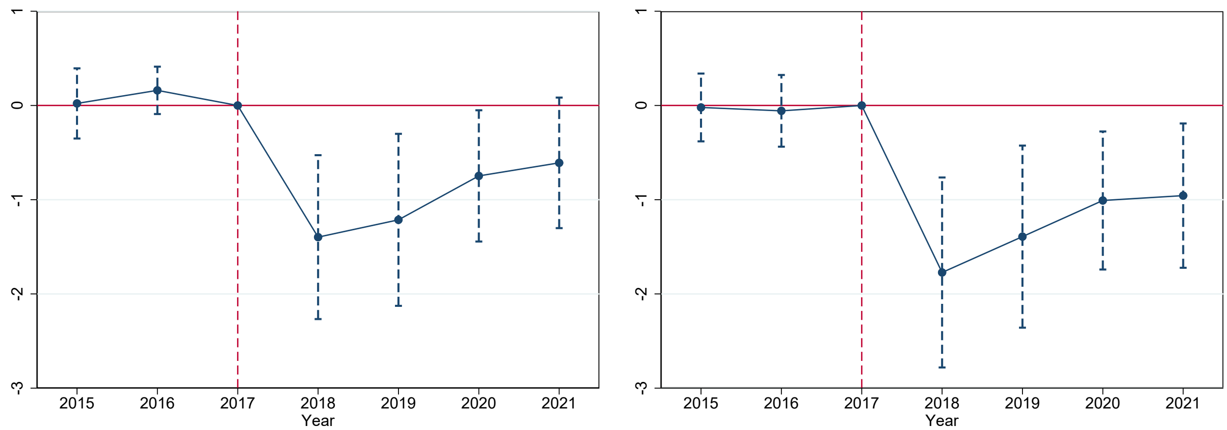
where Y_{pt} is the logarithm of reported import of product p in year t by China. $Treated_p = 1$ identifies products subject to the ban. D_t^k are event-time indicators relative to the implementation year, with $k = -1$ serving as the omitted reference period. The lead coefficients ($k < 0$) test for pre-existing trends, while the lag coefficients ($k \geq 0$) capture the dynamic response of imports. We include product (σ_p) and year (σ_t) fixed effects to account for unobserved heterogeneity and common shocks, and $\ln(Tariff_{pt})$ for changes in import tariffs.

The results in Figure 2 reveal no evidence of differential pre-trends: pre-policy coefficients are small and statistically insignificant. Upon implementation, however, legal imports collapse. The coefficient for the initial year is -1.397 for import value and -1.772 for import quantity,[2] with a persistent negative effect in subsequent years. By constraining legal access, the policy widens the

[1] More details on sources and cleaning process for each dataset can be found in Appendix B.

[2] These point estimates imply that reported waste imports fell by around 80% on impact.

gap between market demand and authorized supply, thereby increasing the relative payoff of illicit sourcing and incentivizing a shift toward smuggling, which we examine next.



(a) Import Value

(b) Import Quantity

Figure 2: The Effect on China's Reported Imports

Notes: This figure shows year-wise event-study coefficients with 95% confidence intervals, based on an HS 6-digit product-year panel. The dependent variable is the logarithm of legal imports; controls include MFN tariff rates and year- and product-fixed effects. The pre-policy period ($k = -1$, 2017) is normalized to zero. Standard errors are clustered at the HS 6-digit product level.

3.2 Effects on Waste Smuggling

3.2.1 Evidence From Mirrored Data

Empirical Specification Following Fisman and Wei (2004), we leverage mirror trade statistics from UN Comtrade to detect evasion through reporting discrepancies. Specifically, we employ a difference-in-differences (DID) design to test whether targeted waste products exhibit differential changes in reporting gaps relative to non-targeted goods. Crucially for our identification, the assignment of treatment status was determined by administrative assessments of environmental risk rather than by contemporaneous market conditions, ensuring that the policy shock provides plausibly exogenous variation in regulatory stringency. Our empirical specification is as follows:

$$GapRatio_{pt} = \alpha + \beta \cdot Treated_p \cdot Post_t + \gamma \cdot ln(Tariff_{pt}) + \sigma_p + \sigma_t + \epsilon_{pt} \tag{2}$$

where the dependent variable $GapRatio_{pt}$ is the discrepancy between partner-reported exports to China and China's own recorded imports, normalized by the total reported volume:

$$GapRatio_{pt} = \frac{ExportsToChina_{pt} - ChinaImports_{pt}}{ExportsToChina_{pt} + ChinaImports_{pt}}. \quad (3)$$

$Treated_p$ is an indicator equal to one if product p is targeted by the policy, while $Post_t$ equals one for 2018 and thereafter. We include $ln(Tariff_{p,t})$, China's MFN tariff, to control for tariff-driven misreporting incentives. σ_p denotes product fixed effects, which absorb time-invariant product attributes, such as intrinsic product value, detectability, or smuggling risk. Year fixed effect σ_t absorbs common aggregate shocks, such as changes in shipping costs, enforcement intensity, or data quality. The coefficient β quantifies the policy impact: a positive β indicates a relative widening of the gap between partner-reported exports and China's reported imports for treated goods, signaling a rise in evasion.

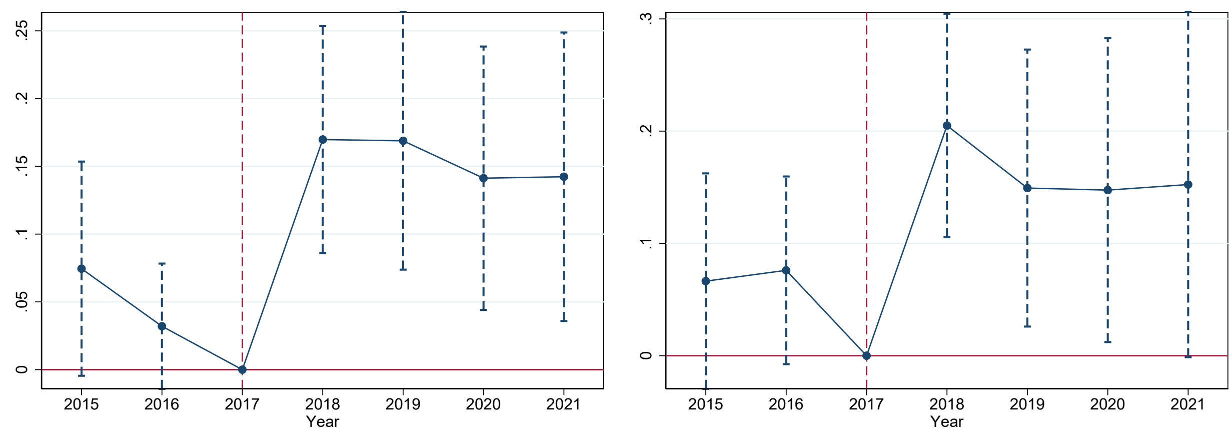
Table 2: Effect on the Missing Waste Trade

Dependent Variable	Gap Value			Gap Quantity			Gap Unit Value		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	0.141***	0.154***	0.138***	0.135***	0.153***	0.132**	0.0212	-0.0115	0.0217
	(0.0500)	(0.0402)	(0.0500)	(0.0520)	(0.0508)	(0.0520)	(0.0401)	(0.0658)	(0.0401)
Similar Product × Post			-0.0698**			-0.0878**			0.0104
			(0.0319)			(0.0404)			(0.0355)
ln(Tariff)	0.237	0.411**	0.261	-0.207	0.490	-0.177	0.501**	-0.222	0.497**
	(0.189)	(0.198)	(0.190)	(0.249)	(0.301)	(0.250)	(0.221)	(0.234)	(0.221)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Trend	No	Yes	No	No	Yes	No	No	Yes	No
Adjusted R^2	0.695	0.726	0.695	0.553	0.586	0.553	0.437	0.479	0.437
No. of observations	13,240	13,240	13,240	13,210	13,210	13,210	12,106	12,106	12,106

Notes: Each column represents separate regressions based on HS 6-digit product level data from 2015 to 2021. The control group includes other products under the same 2-digit HS categories as waste products. Treated products refer to the listed waste products as of 2018. *Post* represents the implementation of import controls on waste from 2018 onward. Dependent variable in Columns 1-6 is trade gap measure rescaled by the sum of reported values given by equation (3). In Columns 7-9, we measure the differences in exporter-reported and importer-reported unit value in ratio: $GapRatioUnitValue = (UnitValue^X - UnitValue^M)/(UnitValue^X + UnitValue^M)$. *SimilarProduct* equals 1 for products under the same 4-digit HS category to waste products. We have controlled for year FE, product FE, and MFN tariffs in all columns. Columns 2, 5, 8 add controls for HS 4-digit-level product trend. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5%, and 1% significance levels, respectively.

Baseline Results Column (1) of Table 2 shows the estimation results of our baseline specification in Equation 2. The estimated coefficient for $Treat \times Post$ is 0.141 and statistically significant at the 1% level. Column (2) further controls for product-specific trends; the estimate remains robust at 0.154. This magnitude implies that, relative to the control group, listed products experienced a post-ban increase in the trade value gap equivalent to 15.4% of the average reported trade values.[3]

[3] We further conducted a placebo test by reassigning treatment labels uniformly across products, and the results in Figure C2 suggest the false DID variable does not have an apparent impact on trade value gaps.



(a) Reported Value Gap Ratio

(b) Reported Quantity Gap Ratio

Figure 3: Effect on Reporting Gaps over Time

Notes: This figure presents event-study coefficients with 95% confidence intervals from a HS 6-digit product-year panel. The dependent variable is the reported trade gap measured by equation (3). The regression controls for year FE, product FE, product trend, and MFN tariff. The pre-policy year (2017, k = -1) is normalized to zero. Standard errors are clustered at the 6-digit product level.

Our identification assumption is that, absent the waste import ban, the growth patterns of the trade gap $GapRatio_{p,t}$ for control products would parallel those of treated products. We test this parallel trends assumption using an event-time specification following Equation (1). Figure 3 shows that pre-policy coefficients (2015–2016) are statistically insignificant, indicating no anticipatory divergence between listed and never-listed products. Conversely, coefficients rise significantly from 2018 onward. The absence of pre-trends confirms that the widened trade gap and the implied quota evasion were likely driven by the waste ban rather than omitted variables.

Mechanisms of Evasions Turning to channels, following Fisman and Wei (2009) and Che et al. (2025), we examine evasion through underreporting of unit values and quantities as well as misclassifications of product categories. Columns (4) and (5) of Table 2 present the results for physical quantities. The results show that the estimated coefficients of $Treat \times Post$ are positive and significant at the 1% level only for the gap in physical quantities. Columns (7) and (8) present the result on the gap in unit value, which shows an insignificant effect. Meanwhile, the estimated coefficient for gap quantity is quite close to our baseline results in columns (1) and (2). These findings suggest that discrepancies in waste products are primarily driven by under-reporting of quantities rather than unit values, consistent with the optimal evasion pattern under quota restrictions.[4]

[4] As modeled in Appendix A.2 following Ferrantino et al. (2012), tariffs incentivize price and quantity manipulation, whereas quotas only incentivize quantity misreporting.

As further evidence of misreporting during the importation process, we add a dummy variable "*similar product*," which equals 1 if a product belongs to the same HS 4-digit category as regulated waste, following Javorcik and Narciso (2017) and Che et al. (2025). Columns (3) and (6) show that the coefficient on $Similar\ product \times Post$ is negative and significant for gap value and gap quantity variables, but insignificant for gap unit value in column (9). Therefore, the reported trade gaps in value and quantity are attenuated for similar products, which suggests that importers exploit similar product categories to evade quotas.

3.2.2 Evidence from China Judgments Online

Reported trade gaps are a useful tool for detecting potential smuggling at scale (Ferrantino et al., 2012; Kee and Nicita, 2022; Tyazhelnikov and Romalis, 2024). However, enlarging discrepancies do not, by themselves, prove illegality but are best interpreted as an early warning signal of regulatory loopholes or illegal activity. Hence, reported trade gaps remain an indirect proxy, necessitating the use of complementary evidence that measures actual illegal conduct.

Court judgments provide direct, micro-level evidence of criminal activities (Ma et al., 2025; Zhang et al., 2025). These records provide details on the parties, charges, dates, locations, and adjudicative outcomes. We have shown above that the ban redirected activity in the treated HS lines from legal trade to concealment. Intuitively, cities that historically imported more of those products should exhibit a larger post-2018 rise in waste prosecutions. By testing this relationship, we can determine whether the reported trade gaps are accompanied by an increase in adjudicated crime. This alignment strengthens the causal interpretation of the ban's impact.

We apply text analysis to CJO case records (2015–2020) and classify city-level smuggling offenses into waste smuggling versus common-goods smuggling. To examine the ban's impacts on waste smuggling, we estimate a two-way fixed effects DID specification by Poisson Pseudo Maximum Likelihood (PPML), which accounts for the sparse nature of case count data:

$$SmuggleCases_{cst} = \alpha + \gamma \cdot TreatmentIntensity_{cs} \cdot Post_t + \sigma_{cs} + \sigma_t + \epsilon_{cst}, \tag{4}$$

where $SmuggleCases_{cst}$ denotes the number of smuggling cases of type $s \in \{waste, common\}$ in city c in year t. $TreatmentIntensity_{cs}$ is a city's case-type level exposure to the ban, calculated as $TreatmentIntensity_{cs} = E_c \times \mathbf{1}\{s = \text{waste}\}$. Here, $E_c = WasteImports_c / WasteImports_{China}$ is city c's pre-ban share in China's waste imports, and $\mathbf{1}\{s = waste\}$ is an indicator for waste smuggling. Crucially, we control for customs enforcement intensity, measured by the number of inspection-related procurement contracts awarded by the local customs bureau. City-case-type fixed effect (σ_{cs}) absorbs persistent differences in prosecution intensity across cities and case types, while σ_t captures nationwide time-varying shocks.

Table 3: Effect on City-level Smuggling Cases

	Smuggling cases				
	(1)	(2)	(3)	(4)	(5)
Treatment intensity × Post	0.186***	0.201***	0.229**	1.533***	-0.167
	(0.0530)	(0.0531)	(0.102)	(0.413)	(0.157)
Customs Enforcement		-0.0646*	-0.0639	-0.0579	-0.0696*
		(0.0371)	(0.0400)	(0.0372)	(0.0371)
Treatment intensity × Post × Granted Quota			-13.65**		
			(6.139)		
Treatment intensity × Post × Two Control Zones				-1.336***	
				(0.416)	
Treatment intensity × Post × ln(Recycling Firms)					0.0680*
					(0.0357)
Year FE	Yes	Yes	Yes	Yes	Yes
City-case FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.931	0.931	0.931	0.931	0.931
No. of observations	2,982	2,982	2,982	2,982	2,982

Notes: PPML regressions on balanced city–case–year panels (2015–2020). Columns (3)–(5) include all lower-order interactions from the triple-differences specification; estimates for these auxiliary terms are omitted for space. $Treatment\ Intensity$ measures the intensity of exposure to the waste ban. $Post$ indicates the post-treatment period beginning in 2018. $Customs\ Enforcement$ is the standardized number of customs procurement contracts. $Granted\ Quota$ captures a city's pre-ban share in the national quota allocation, interacted with the degree of national quota tightening. $Recycling\ firms$ means the log count of cumulative registered resource-recycling firms. Standard errors are clustered at the city level (in parentheses). *, **, and *** denotes 10%, 5%, and 1% significance levels, respectively.

The coefficient γ in Equation (4) captures the extent to which the post-ban rise in waste smuggling intensifies with a city's pre-ban exposure to waste imports. Table 3 reports the PPML estimates. The baseline specification in Column (1) yields $\hat{\gamma} \approx 0.186$ (significant at 1%), implying that greater exposure leads to a larger spike in waste smuggling cases relative to common smuggling. Figure 4 tests the parallel trends assumption by extending specification (4) with an event-study design. We find that the divergence in waste-related smuggling cases relative to common goods smuggling emerges significantly after 2019.[5] These results support a causal interpretation, confirming that divergence is unique to the treated group and occurs after policy enactment. Column (2) adds customs enforcement, yielding a similar estimate and confirming the robustness of the exposure-driven surge. The negative coefficient indicates that restrictive border measures induce concealment (Kee and Nicita, 2022).

The positive relationship between $TreatmentIntensity$ and waste-smuggling cases may vary across cities. First, a tighter contraction of licensed quota access raises the returns to evasion. Second, stronger local enforcement increases detection risk, deterring smuggling or shifting it toward weaker jurisdictions. Third, higher local demand for scrap inputs amplifies the incentive to

[5]The one-year lag is consistent with the mean value of litigation duration in China (Zhu, 2024).

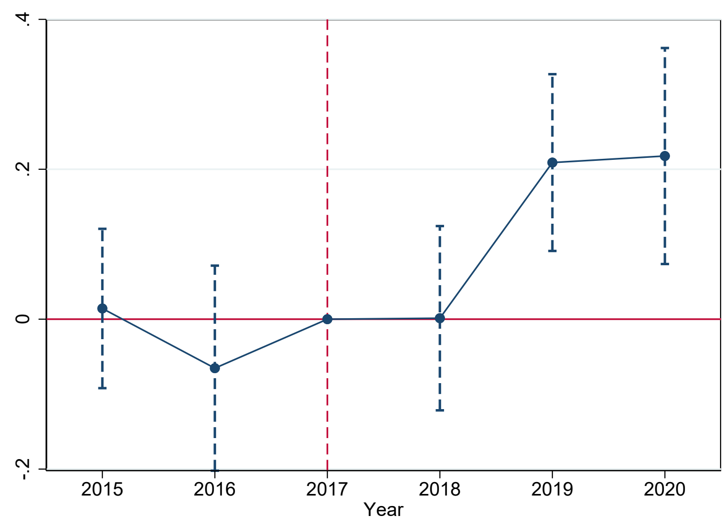


Figure 4: Effect on Smuggling Cases of waste Relative to Common Goods

Notes: This figure presents event-study coefficients with 95% confidence intervals from a city-case-year panel. The dependent variable is the number of smuggling cases. We estimate dynamic effects by interacting the time-invariant $Treatment\ Intensity$ measure with year indicators. The regression controls for year FE, city-case FE, and customs enforcement. The pre-policy year (2017, k = -1) is normalized to zero. Standard errors are clustered at the city level.

substitute from legal imports to illicit imports when the ban is in effect.

To examine the legal-access channel, we construct a shift-share measure of quota allocation: $Granted\ Quota = PreShare_c \times Q_t/Q_{2015}$. Here, $PreShare_c$ is the city's pre-shock (2015–2016) share of national quotas, and Q_t/Q_{2015} captures national quota tightening over time. Column (3) of Table 3 reveals a negative and significant triple interaction with $Granted\ Quota$, indicating that greater legal access attenuates the post-ban rise in smuggling. Therefore, relaxing licensed channel constraints reduces the marginal return to evasion, encouraging compliance.

We use China's "Two Control Zones" (TCZ) designation as a proxy for systematically stricter environmental enforcement in certain areas. Established in 1998 to combat SO_2 and acid rain, the TCZ policy imposes concrete abatement mandates based on ambient conditions (Chen et al., 2025b). In Column (4) of Table 3, the triple interaction with $Two\ Control\ Zones$ is -1.336 and significant at the 1% level. This supports a deterrence channel: in jurisdictions with historically tighter enforcement, exposure-induced incentives to smuggle are less likely to translate into observed cases. In other words, TCZ status appears to raise the expected cost of waste trafficking, thereby suppressing the shift from legal imports to concealment.

To test the demand channel, we interact $TreatmentIntensity \times Post$ with local dependence on recycled resources, proxied by $ln(Recycling\ Firms)$, the log count of registered local resource-recycling firms. Column (5) of Table 3 shows that this interaction is positive (0.068) and significant at the 10% level. This indicates that cities more reliant on the recycling industry experienced a larger post-ban increase in waste smuggling. These results align with Che et al. (2025), highlighting how demand-side factors amplify the impact of restrictive policies. More specifically, local governments in regions more dependent on waste recycling can be more tolerant of evasion (Du and Li, 2023), and central government enforcement exposes such crimes.

3.3 Environmental Consequences

The waste ban aims to mitigate pollution from the processing of imported scrap. Here, we assess environmental performance along two dimensions: air quality and water quality.

Air Quality Using air quality data from the MEE, we compute average $PM_{2.5}$ for each city (c) in month (m) and year (t) and estimate the following DID specification:

$$lnPM_{2.5cmt} = \alpha + \beta_{air} \cdot Treated_c \cdot Post_t + \lambda Z_c f(t) + \theta X_{cmt} + \sigma_{cm} + \sigma_{mt} + \epsilon_{c,t}, \quad (5)$$

where $Treated_c = 1$ if any firms in city c had imported waste. $Post_t$ takes the value 1 post 2018. Following Shi and Zhang (2023), we include pre-determined control variables (Z_c) and then interact them with a third-order polynomial function of year $f(t)$. X_{cmt} represents a set of standardized climatic variables, including wind speed, relative humidity, air pressure, precipitation, and air temperature. Further fixed effects include city-month (σ_{cm}) and year-month (σ_{mt}).

Panel A of Table 4 presents the estimation result. The estimate of β_{air} in Column (1) is -0.049 and significant at 5% level, indicating that exposure to the ban led to a 4.9% reduction in $PM_{2.5}$ concentration relative to unexposed cities, consistent with the findings of Shi and Zhang (2023). Column (2) adds controls for customs enforcement intensity. The estimate remains similar, alleviating concerns that differential enforcement drives the observed effects. To validate the parallel trends assumption underlying the DID specification, Appendix Figure C4 (a) plots the event-study estimates. As shown, there is no significant difference in air quality trends between treated and control cities prior to the ban.

We next examine whether the improvement in air quality varies with pre-existing smuggling activity. If the ban diverts imports into illicit channels, pollution reductions should be weaker in areas where smuggling was more prevalent. To test this, we add a triple-difference term with $Preban\ Waste\ Smuggling$ (defined as the pre-2018 share of waste cases in total smuggling) to Equation (5) and include all lower-order interactions to form a saturated triple-DID design. In Column (3) of Table 4, the triple-interaction coefficient is positive and significant, indicating that cities with higher smuggling intensity experienced smaller $PM_{2.5}$ reductions. Column (4) adds control for customs enforcement, yielding a similar positive estimate.

Table 4: Effect on Environmental Outcomes

	(1)	(2)	(3)	(4)
Panel A: Effect on Air Pollution – $\ln PM_{2.5}$				
Treated × Post	-0.0490**	-0.0495**	-0.0577***	-0.0581***
	(0.0195)	(0.0195)	(0.0205)	(0.0204)
Treated × Post × Preban Waste Smuggling			0.0956*	0.0958*
			(0.0527)	(0.0527)
Post × Preban Waste Smuggling			-0.0736	-0.0740
			(0.0520)	(0.0519)
Customs Enforcement		0.00368		0.00371
		(0.00979)		(0.00978)
Year-month FE	Yes	Yes	Yes	Yes
City-month FE	Yes	Yes	Yes	Yes
City-level controls	Yes	Yes	Yes	Yes
City-year trend	Yes	Yes	Yes	Yes
Ajusted R^2	0.884	0.884	0.884	0.884
No. of observations	17,160	17,160	17,160	17,160
Panel B: Effect on Water Pollution – $\ln COD_{Mn}$				
Treated × Post	-0.158***	-0.161***	-0.177***	-0.179***
	(0.0495)	(0.0499)	(0.0570)	(0.0568)
Treated × Post× Preban Waste Smuggling			0.500*	0.493*
			(0.255)	(0.253)
Post× Preban Waste Smuggling			-0.489*	-0.484*
			(0.251)	(0.248)
Customs Enforcement		0.0233		0.0210
		(0.0563)		(0.0582)
Year-month FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
River-month trend	Yes	Yes	Yes	Yes
Site-level Controls	Yes	Yes	Yes	Yes
City-year trend	Yes	Yes	Yes	Yes
Adjusted R^2	0.662	0.661	0.662	0.662
No. of observations	2,861	2,861	2,861	2,861

Notes: 1) Panel A reports regression using city-month panel data (2015–2019) with $\ln PM_{2.5}$ as the dependent variable. $Treated = 1$ is a dummy for cities importing waste during 2015–2016. $Post$ indicates the implementation of import controls (from January 2018). Controls include predetermined city characteristics (industry share, logged GDP, logged imports, logged $PM_{2.5}$) interacted with a flexible time trend, plus climatic variables (wind speed, temperature, humidity, precipitation, pressure). ***Pre-ban Waste Smuggling*** is the share of waste cases in total smuggling (2015–2017). ***Customs Enforcement*** counts the number of customs procurement contracts. Standard errors are clustered at the city level.
2) Panel B reports regressions using monitoring site-month data (2015–2018) with $\ln COD_{Mn}$ as the dependent variable. In Panel B, $Treated = 1$ for sites downstream of waste-importing firms within a 10-km buffer. The control group consists of monitoring sites with no upstream waste-importing firms and is further restricted to sites with pre-ban water pollution levels below the median and low nearby firm density. Site-level controls include standardized precipitation, temperature, and nightlight radiance. Standard errors are clustered at the site level.
3) *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Water Quality Untreated wastewater from waste processing entering waterways can impair water quality. We use the Permanganate Index (COD_{Mn}) as the primary water quality metric.[6] Employing a DID specification parallel to Equation (5), we analyze the ban's effects on water quality using monitoring site-month data from 2015 to 2018. As illustrated in Appendix Figure C3, we define the treatment group as monitoring sites located downstream of waste-importing firms within a 10-km buffer zone; the control group comprises monitoring sites without upstream waste-importing firms.[7] To limit contamination from other local pollution sources, we further restrict the control group to sites with pre-ban pollution levels below the median and low firm density nearby. The regression controls for site-level covariates (precipitation, temperature, and nightlight radiance), as well as monitoring-site, year-month, and river-by-month fixed effects to absorb time-invariant site characteristics, common temporal shocks, and time-varying river-specific factors.

Panel B of Table 4 presents the results. Column (1) indicates that treatment sites experienced a statistically significant decline in COD_{Mn} of approximately 15.8% relative to controls after the ban. Since a higher COD_{Mn} indicates poorer water quality, this estimate implies a meaningful improvement at exposed sites. The result remains robust when controlling for provincial customs enforcement intensity in Column (2). Appendix Figure C4 (b) supports the parallel trends assumption, showing no significant differential pre-policy trend. Post-implementation, water quality gains emerge gradually, becoming pronounced approximately 9–10 months later. Given a pre-ban average COD_{Mn} of 4.06 mg/L, the estimated 15.8% decline in Column (2) implies an absolute reduction of 0.64 mg/L, lowering the concentration to approximately 3.42 mg/L. This shift is sufficient to improve water quality classification from Class III to Class II on the COD_{Mn} scale.

Columns (3) and (4) use a triple-difference design to test whether the environmental gains are attenuated by evasion via smuggling. The DID effect remains negative and significant, and the triple-interaction term is positive and is marginally significant. This suggests that reductions in water pollution are attenuated where illicit trade incentives are strong. The result mirrors the air quality heterogeneity in Panel A, supporting a smuggling-driven pollution rebound.

3.4 Firm Performance

Environmental regulations often impose high economic costs, including losses in productivity, output, and employment (Gollop and Roberts, 1983; Hazilla and Kopp, 1990; Greenstone, 2002). As an import policy, the waste ban may affect domestic industries that rely on imported scrap. Variation in firms' import bundles allows us to implement a DID strategy to evaluate firm performance.

[6] COD_{Mn} measures the oxygen required to oxidize organic matter; higher values indicate greater pollution. Missing values for this indicator are filled using linear interpolation at each monitoring site. More details on variable construction are presented in Appendix B.2.3.

[7] Following He et al. (2020), we define upstreamness based on the relative elevation of monitoring sites and firms.

Table 5: Impact on Firm Performance

Dependent Variable	log(Operating Revenue)		log(Employees)		EBIT margin		log(Labor Productivity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	-0.106**	-0.112**	0.0625	0.0509	-1.443**	-1.403**	-0.105**	-0.0945**
	(0.0539)	(0.0538)	(0.0468)	(0.0467)	(0.706)	(0.708)	(0.0469)	(0.0471)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-industry trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.909	0.909	0.894	0.895	0.559	0.559	0.767	0.767
No. of observations	92,125	92,125	56,677	56,677	64,466	64,466	56,677	56,677

Notes: OLS regression results on unbalanced firm-year panels (2015–2021). $Treated$ is a dummy for firms that imported waste during the pre-shock period. $Post$ indicates the implementation of import controls starting in 2018. Controls include predetermined firm characteristics (share of intermediate imports and share of capital goods from developed economies) interacted with a linear time trend. Standard errors clustered at the firm level are reported in parentheses. *, **, and *** denotes 10%, 5%, and 1% significance levels, respectively.

The treatment group includes firms that imported listed waste before the policy, and the control group includes firms in the same 2-digit NACE sectors. The estimation equation is:

$$y_{it,s} = \alpha + \beta_f \cdot Treated_i \cdot Post_t + \lambda Z_i \times t + \sigma_i + \sigma_t + \sigma_{i,s} \times t + \epsilon_{it}, \tag{6}$$

where $y_{it,s}$ represents performance for firm i in sector s and year t, $Treated_i$ identifies pre-ban waste importers and $Post_t$ indicates the post-2018 period. The specification controls for predetermined firm characteristics (Z_i) interacted with a linear time trend t, and includes firm (σ_i), year (σ_t), and city-industry-specific trends ($\sigma_{i,s}$).

Table 5 presents the estimation results. Column (1) shows a coefficient of -0.106 on log operating revenue, implying a 10.6% decline for treated firms relative to controls. This estimate is robust to controlling for trends in imports of intermediates and capital goods (Column 2). We next turn to labor market outcomes. Columns (3) – (4) show positive but insignificant coefficients on employment, indicating no significant change in workforce size due to the ban. Columns (5) – (6) assess profitability via the EBIT margin (Earnings Before Interest and Taxes relative to revenue). The negative and significant coefficients suggest a decline of approximately 1.4 percentage points in profit margins for treated firms relative to controls. Finally, Columns (7) – (8) document a 9.45% decline in labor productivity. This aligns with evidence that input access restrictions harm productivity (Amiti and Konings, 2007; Singh and Chanda, 2021).

3.5 Robustness Checks and Heterogeneity Analysis

To strengthen the causal interpretation, we conduct a battery of robustness checks on the above baseline smuggling results and a rich set of heterogeneity analyses.

Is It Due to Exporter-Side Policy? Exporter-side misreporting could contaminate the trade discrepancy measure. A salient threat to identification is that, contemporaneously with China's ban, several source countries (e.g., EU and ASEAN members, and Turkey) tightened export regulations, including stricter quality standards and enhanced environmental enforcement. Such shocks would also affect the mirrored trade gap even if nothing changed at China's border.

To address this potential confounder, we use reporter–product–year NTM data, focusing on restrictions where the partner jurisdiction is China or the World. The data reveal that waste exports to China face substantial regulatory barriers, including licensing requirements (P33), export prohibitions (P22), and technical authorizations (P11, P12). We construct a product-level export restriction index. For each product p in year t, we define an indicator, $\mathbf{1}\{\text{Export NTM}_{jpt}\}$, equal to 1 if exporter j imposes NTMs relevant to waste export, and aggregate these across exporting countries, weighted by their shares of China-bound exports:

$$Export\ Restriction_{pt} = \sum_j \left(\frac{ExportsToChina_{jpt} \cdot \mathbf{1}\{\text{Export NTM}_{jpt}\}}{\sum_k ExportsToChina_{kpt}} \right),$$

which increases when a larger share of China's suppliers adopt export-side NTMs. Columns (1)–(2) of Table D4 show that the $Treat \times Post$ coefficient remains significantly positive, even after controlling for the export restriction index or excluding the top 20 percentiles of products most affected by such restrictions. Our results remain robust in Columns (3)–(4), which further include the interaction between the export restriction index and the treatment indicator. Results in Columns (5)–(8) confirm that the quantity underreporting channel remains robust.

Transportation Process and Timing One potential confounding factor is mechanical measurement error stemming from shipping delays and port congestion. Waste is primarily transported by container ships, a journey that typically lasts several weeks. Hence, exports recorded abroad in year $t-1$ may not appear in China's import data until year t. Such temporal mismatches could bias the baseline gap if the ban coincides with unusual customs backlogs. To rule out this factor, we reconstruct the dependent variable by lagging partner-country export data by one year:

$$GapRatio_{p,t} = \frac{ExportToChina_{p,t-1} - ChinaImports_{p,t}}{ExportToChina_{p,t-1} + ChinaImports_{p,t}}.$$

Table D5 confirms that our results are robust to this timing adjustment. The $Treat \times Post$ coefficients remain positive and significant, even with controls for export restrictions. This confirms that maritime delays or recording timing do not drive our results.

Alternative Measure of Trade Gap As a further robustness check, we employ a logarithmic transformation of the trade gap: $Gap = log(1 + ExportsToChina) - log(1 + ChinaImports)$. While this approach is conventional in the literature (Fisman and Wei, 2004, 2009; Ferrantino et al., 2012) and alleviates concerns about extreme observations, we acknowledge recent methodological discussions about its limitations in dealing with zero-valued trade flows (Chen and Roth, 2024). For this reason, our baseline specification uses the ratio measure. Nevertheless, results using the log-based gap, presented in Table D9 and Figure C1, are consistent with our main findings. These conclusions are also robust to controlling for exporter policies and transport delays (Tables D10 and D5, respectively).

Non-randomness of Missing Trade Statistics A final concern is selective non-reporting of imports under tightened controls. If missing observations correlate with evasion, OLS estimates are biased. To correct for this, we follow Kee and Nicita (2022) and implement a Heckman selection model with a log trade gap measure $Gap = log(ExportsToChina) - log(ChinaImports)$. Column (1) of Table D6 reports the first-stage estimates, showing that restricted products are significantly less likely to be reported. Using the fitted probabilities from the first stage, we construct the Inverse Mills Ratio (IMR) and include it in the second-stage regressions. Columns (2) – (6) show that our core findings are robust to this correction.

Exporter Features To examine whether exporter characteristics amplify or dampen the policy's impact, we extend our analysis to an exporter–product–year panel using the following specification, which interacts the treatment effect with exporter features predetermined in 2015:

$$\begin{aligned} GapRatio_{jpt} = \alpha &+ \beta_1 \cdot Treated_{jp} \cdot Post_t + \beta_2 \cdot Feature_{j,2015} \cdot Treated_{jp} \cdot Post_t \\ &+ \gamma \cdot ln(Tariff_{pt}) + \theta \cdot ln(PopDist_{pt}) + \sigma_p + \sigma_{jp} + \sigma_t + \epsilon_{jpt}, \end{aligned} \tag{7}$$

where $GapRatio_{jpt}$ measures the reported gap between country j exports and Chinese imports of product p in year t, as defined in equation (3). $Treated_{jp}$ is an indicator equal to 1 if China had imported waste product p from country j, and $Post_t$ equals 1 for years after 2018. $Feature_{j,2015}$ represents country characteristics measured prior to the policy shock. We include a rich set of fixed effects: σ_{jp} absorbs persistent exporter-product characteristics, σ_p controls for global product-specific factors, and σ_t captures annual global shocks. Controls include China's MFN tariff, $Tariff_{pt}$, and the population-weighted distance to China, $PopDist_{pt}$. The coefficient of interest β_2 captures the moderating role of exporter characteristics on the post-policy gap.

Table 6 reports the estimation results for trade value gaps. Column (1) replicates our baseline results. The $Treat \times Post$ coefficient is positive and significant, confirming that the effect on

Table 6: Moderating Effects of Exporter Features

Dependent Variable	GapRatio Value								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	0.127*	0.199**	0.105	0.155**	0.152**	0.155*	0.140**	0.160**	0.156**
	(0.0683)	(0.0970)	(0.0677)	(0.0768)	(0.0737)	(0.0793)	(0.0700)	(0.0789)	(0.0717)
Income level × Treat × Post		-0.0886							
		(0.0566)							
SoutheastAsia × Treat × Post			0.144***						
			(0.0463)						
Rule of law × Treat × Post				-0.0408*					
				(0.0226)					
Control of corruption × Treat × Post					-0.0408**				
					(0.0190)				
Government Effectiveness × Treat × Post						-0.0368			
						(0.0269)			
Political Stability × Treat × Post							-0.0645***		
							(0.0246)		
Regulatory quality × Treat × Post								-0.0425*	
								(0.0245)	
Voice and accountability × Treat × Post									-0.0630***
									(0.0231)
ln(Tariff)	0.507***	0.508***	0.508***	0.507***	0.507***	0.507***	0.507***	0.507***	0.507***
	(0.0890)	(0.0890)	(0.0889)	(0.0884)	(0.0884)	(0.0884)	(0.0884)	(0.0884)	(0.0885)
ln(Pop-weighted distance)	-0.532**	-0.522**	-0.524**	-0.516**	-0.518**	-0.517**	-0.509**	-0.509**	-0.531**
	(0.243)	(0.243)	(0.243)	(0.242)	(0.243)	(0.242)	(0.243)	(0.242)	(0.243)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567
No. of observations	354,861	354,861	354,861	354,679	354,679	354,679	354,679	354,679	354,617

Notes: Regressions on country-product-year panels (2015–2021). The control group comprises products under the same 2-digit HS categories as waste products and countries that have a waste trade relationship with China. Treated products are waste products on the 2017 plan list. *Post* equals 1 from 2018 onward. The dependent variable is the bilateral reported gap ratio. The income level indicates that the country is high- or upper-middle-income. *SoutheastAsia* is an indicator for 11 Southeast Asian countries, including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Vietnam. Standard errors clustered at the 6-digit product level are in parentheses. *, **, and *** denotes 10%, 5%, and 1% significance levels, respectively.

reported trade value gaps persists at the exporter–product level. Column (2) interacts the treatment with income level; the coefficient is negative but insignificant, suggesting no clear evidence that income mitigates the gap. Column (3) explores geographic proximity, a factor known to facilitate transshipment and document fraud (Tyazhelnikov and Romalis, 2024). The positive and significant interaction coefficient with the Southeast Asia indicator implies that these countries' proximity to China facilitates smuggling, thereby amplifying the trade gap.

Columns (4) – (9) employ World Governance Indicators to test the role of institutions. Interactions with the rule of law, corruption control, political stability, regulatory quality, and voice and accountability are all negative and significant, while government effectiveness is not (Column 6). These results align with the literature, which highlights that strong enforcement increases the cost of documentation fraud, re-routing, and misclassification, thereby reducing the reported gap (Fisman and Wei, 2009; Javorcik and Narciso, 2017).[8]

[8]Robustness checks using a quantity-based gap measure, reported in Table D7, confirm our findings.

4 Theoretical Framework

The previous section documents the ban's effects, but these reduced-form facts are insufficient to quantify aggregate welfare. This section bridges that gap by deriving a sufficient statistic welfare formula and developing a structural model to estimate the shadow costs required to implement it.

4.1 Aggregate Welfare Implications

We use a sufficient statistics framework to evaluate the ban's welfare impact. This approach expresses welfare changes in terms of aggregate elasticities and policy wedges, connecting our reduced-form estimates of behavioral responses to the welfare analysis.

Consider an economy importing a good at the given world price P^* subject to an import quota Q.[9] The market is characterized by several distortions: an ad valorem import tariff τ, an ad valorem quota rent (license fee) t_q, and a per-unit environmental externality λ. In addition, unlike standard quota models that assume perfect enforcement (e.g., Baqaee and Sangani, 2025), we allow for leakage via illicit channels when policies tighten. Total imports M comprise legal quota imports Q and smuggled imports S, such that $M = Q + S$. Smuggling incurs a real resource cost τ_s, representing an "iceberg" cost of evasion that includes expenses for circuitous transshipment, repackaging, concealment, and shipment fragmentation to avoid detection. To capture customs enforcement, we assume that with probability $\rho \in [0, 1)$, smuggled imports are confiscated. Hence, for each unit successfully smuggled, $(1 + \tau_s)/(1 - \rho)$ units must be shipped.

The social welfare W derived from imports is the utility $U(M)$, minus real resource costs and environmental externalities:

$$W = U(M) - P^*Q - \frac{1 + \tau_s}{1 - \rho} P^*S - \lambda M. \tag{8}$$

The real cost to the economy for a legal unit is the world price P^*. For the smuggled unit, it is $P^*(1 + \tau_s)/(1 - \rho)$. Total environmental cost is λM. Although importers pay tariffs to the government and quota rents to quota owners, they are transfer payments within the domestic economy. Therefore, they do not represent real resource costs in the welfare equation. Their impact arises from the distortions on imports.

We define the leakage rate as the increased smuggling in response to a tightening quota $dQ < 0$:

$$\mu = -\frac{dS}{dQ}. \tag{9}$$

We note that $\mu \in [0, 1]$. If $\mu = 0$, substituting legal imports with smuggling is impossible; if $\mu = 1$,

[9] Following the classical analysis in Bhagwati and Hansen (1973), we assume away the terms-of-trade effect.

they are perfect substitutes. The marginal welfare impact of tightening the quota or legal imports Q is characterized by the following proposition.

Proposition 1. *The first-order change in social welfare resulting from a tightening of the import quota is given by:*

$$\frac{\Delta W}{|\Delta Q|} = \underbrace{\lambda(1-\mu)}_{\textit{Environmental Gain}} \underbrace{- P^*(t_q+\tau)(1-\mu)}_{\textit{Distortion Loss}} - \underbrace{P^*\mu\left(\frac{\rho+\tau_s}{1-\rho}\right)}_{\textit{Smuggling Resource Cost}} . \tag{10}$$

Proof. See Appendix A.1.

Equation (10) decomposes the welfare effect of quota tightening into three distinct economic forces. The first term, $\lambda(1-\mu)$, represents the gross environmental benefit of the policy: society avoids pollution costs λ on the *net* reduction in imports. The ban's efficacy is dampened by the leakage rate μ; if leakage is complete ($\mu = 1$), environmental gains are entirely nullified.

The second term, $P^*(t_q + \tau)(1-\mu)$, captures the welfare loss from policy-induced distortions. Consistent with Baqaee and Sangani (2025), in frictionless environments without externality, leakage, or pre-existing distortions ($\lambda = \mu = \tau = 0$), the entire welfare cost of tightening quotas is summarized by the quota rents, P^*t_q. The component $P^*\tau$ reflects the compounding effect of pre-existing tariffs. In the limit, where leakage is complete ($\mu = 1$), the distortion loss vanishes because the reduction in legal imports is fully offset by smuggling.

The third term, $P^*\mu(\rho + \tau_s)/(1-\rho)$, measures the welfare loss from the real resource cost of evasion. It reflects the fact that smuggling dissipates real resources. It vanishes if there is no leakage ($\mu = 0$), and increases with the smuggling cost (τ_s) and the probability of confiscation (ρ).

Figure 5 illustrates the welfare decomposition derived in Proposition 1. The area of rectangle *ABCD* measures the environmental gain $\lambda(1-\mu)$, while *HICD* represents the distortion loss from fewer legal imports, $P^*(t_q + \tau)(1-\mu)$. Both effects decrease with the leakage rate μ. In contrast, the resource cost of evasion $P^*\mu(\rho + \tau_s)/(1-\rho)$, represented by *EFDG*, is increasing in μ. Net welfare gains are captured by the difference between areas *ABIH* and *EFDG*.

Although Equation (10) offers a clear theoretical benchmark, its empirical application is hindered by the difficulty of identifying key parameters. We can directly observe the world price P^* and tariffs τ, and estimate the leakage rate μ from the reduced-form behavioral elasticities. However, two critical parameters remain unobserved: the quota rent t_q and the smuggling cost τ_s. Since import licenses were not auctioned, the shadow value of the quota is private information. Likewise, the cost structure of the illicit sector is inherently hidden from administrative records. To overcome these challenges, the following subsection develops a model of heterogeneous firms facing an endogenous choice of sourcing mode. This structural model allows us to recover the unobserved shadow costs (t_q and τ_s), thereby fully operationalizing the sufficient statistics formula.

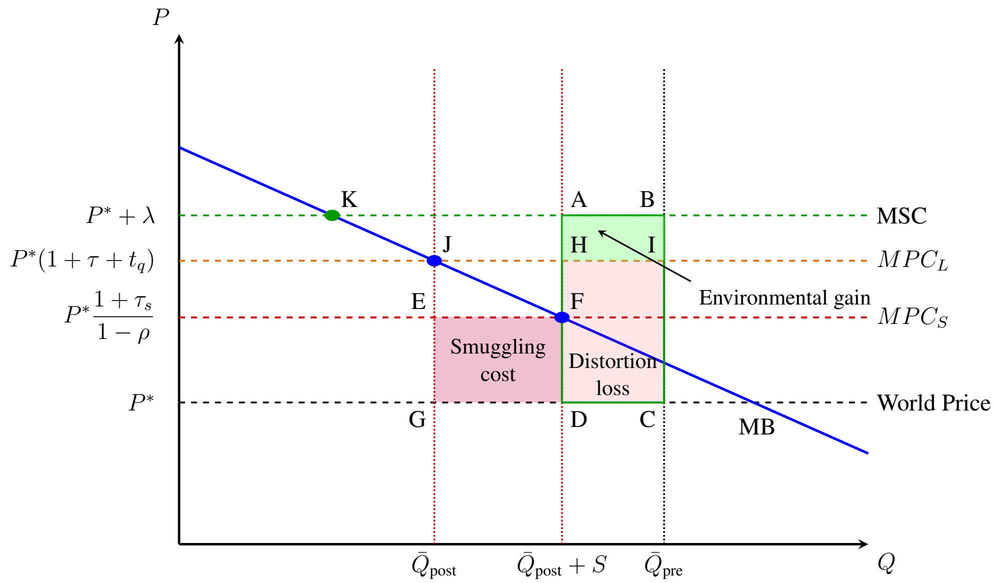


Figure 5: Welfare Decomposition

Notes: This figure shows the welfare effect of quota tightening from $\overline{Q}_{pre}$ to $\overline{Q}_{post}$ and an S amount is smuggled. P^* is the world price. $P^*(1+\tau+t_q)$ is the price of legal import inputs, inclusive of tariffs τ and quota rent t_q. Smuggled inputs cost $P^*(\rho+\tau_s)/(1-\rho)$, reflecting iceberg costs τ_s and confiscation risk ρ. The per-unit environmental externality is λ. The areas represent: environmental gain (*ABCD*), distortion loss (*HICD*), and the smuggling cost (*EFDG*).

4.2 Modeling the Shadow Costs

To structurally estimate the unobserved shadow costs, we model heterogeneous firms that source inputs either legally or through smuggling. We adopt the monopolistic competition framework of Chaney (2008), assuming a continuum of firms with a fixed total measure N. These firms produce non-tradable differentiated final goods. The demand for each variety ω is:

$$q(\omega) = Ap(\omega)^{-\sigma}, \tag{11}$$

where $\sigma > 1$ is the constant elasticity of substitution and A is an aggregate demand shifter. Firms are indexed by productivity φ, drawn from a cumulative distribution function $G(\varphi)$. Each firm chooses one of three sourcing modes for inputs: domestic sourcing (D), legal importing (L), or smuggling (S). Firms operate under constant returns to scale, with total output satisfying

$$y_j(\varphi) = \varphi q_j(\varphi), \tag{12}$$

where $q_j(\varphi)$ is the amount of inputs and $j \in \{D, L, S\}$.

Each sourcing mode is characterized by a specific cost structure affecting both marginal and fixed costs. Firms sourcing domestically incur a marginal cost $c_D(\varphi) = P_D/\varphi$ and a fixed cost f_D, where P_D is the price of domestic inputs. Firms choosing legal imports pay the exogenous world price P^* plus an ad valorem tariff τ and a quota rent t_q, in addition to a fixed cost f_L. This yields a marginal cost of $c_L(\varphi) = P_L/\varphi$, where $P_L = P^*(1 + \tau + t_q)$. Alternatively, firms may smuggle. This mode avoids tariffs and quota rents but incurs a fixed cost f_S, an iceberg cost τ_s, and a confiscation risk of ρ. To get one unit of input, a smuggler must ship $(1 + \tau_s)/(1 - \rho)$ units, implying an effective marginal cost of $c_S(\varphi) = P_S/\varphi$, where $P_S = P^*(1 + \tau_s)/(1 - \rho)$.

Assumption 1: Input prices and fixed costs of sourcing satisfy $P_S < P_L < P_D$ and $f_D < f_L < f_S$.

Assumption 1 posits that smuggled input prices are lower than legal imports and domestic inputs, albeit with a higher fixed cost. This cost structure ensures an interior equilibrium in which all three sourcing modes coexist in equilibrium.

Figure 6: Sorting Pattern in Firm Sourcing

Firms choose the sourcing mode that maximizes profit. The profit function for a firm with productivity φ choosing mode j is:

$$\pi_j(\varphi) = \frac{r_j(\varphi)}{\sigma} - f_j = B\, P_j^{1-\sigma}\, \varphi^{\sigma-1} - f_j, \tag{13}$$

where $r_j(\varphi)$ denotes revenue and $B = \frac{A}{\sigma}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$. Firms self-select into the optimal mode based on productivity cutoffs, as shown in Figure 6. Firms with low productivity ($\varphi < \varphi_L^*$) source domestically. Firms with intermediate productivity ($\varphi_L^* \leq \varphi < \varphi_S^*$) choose legal imports to access cheaper foreign inputs. The most productive firms ($\varphi \geq \varphi_S^*$) opt for smuggling despite its higher fixed costs and risks. The cutoffs φ_L^* and φ_S^* are determined by the indifference conditions:

$$\pi_D(\varphi_L^*) = \pi_L(\varphi_L^*),\ \pi_L(\varphi_S^*) = \pi_S(\varphi_S^*),$$

combining the indifference conditions with Equation (13) yields:

$$\varphi_L^* = \left(\frac{f_L - f_D}{B\left(P_L^{1-\sigma} - P_D^{1-\sigma}\right)}\right)^{\frac{1}{\sigma-1}},\ \varphi_S^* = \left(\frac{f_S - f_L}{B\left(P_S^{1-\sigma} - P_L^{1-\sigma}\right)}\right)^{\frac{1}{\sigma-1}}. \tag{14}$$

Legal and smuggled import volumes Q and S satisfy:

$$Q = N \int_{\varphi_L^*}^{\varphi_S^*} q_L(\varphi) dG(\varphi), \tag{15}$$

$$S = N \int_{\varphi_S^*}^{\infty} q_S(\varphi) dG(\varphi), \tag{16}$$

respectively. Equation (15) is a market-clearing condition for the import quota that links the observed aggregate quota to the unobserved shadow price t_q, since for $\varphi \in [\varphi_L^*, \varphi_S^*)$, we have

$$q_L(\varphi) = \frac{r_L(\varphi)}{p_L(\varphi) \cdot \varphi} = (\sigma - 1) B [P^*(1 + \tau + t_q)]^{-\sigma} \varphi^{\sigma - 1}. \tag{17}$$

Everything else equal, equations (15) and (17) together imply that a higher import quota Q reduces the quota rent t_q. Likewise, for a firm with productivity $\varphi \geq \varphi_S^*$, the smuggled input demand is

$$q_S(\varphi) = \frac{r_S(\varphi)}{p_S(\varphi) \cdot \varphi} = (\sigma - 1) B [P^* \frac{1 + \tau_s}{1 - \rho}]^{-\sigma} \varphi^{\sigma - 1}. \tag{18}$$

Equations (16) and (18) together imply that smuggling cost τ_s reduces smuggled imports. These conditions form the basis for the structural estimation of shadow costs.

5 Quantitative Analysis

5.1 Estimation of the Shadow Costs

We apply the model to China's restrictions on waste imports. The main goal is to estimate the unobserved shadow costs, thereby enabling the assessment of the policy's welfare implications.

Parameterization and Calibration Our calibration proceeds in three steps. First, we fix standard primitives and impose normalizations that remove pure scale. Second, we calibrate parameters that map directly from observables. Third, we estimate the remaining structural parameters by matching model-implied legal and illicit imports to their data counterparts.

We set $B = 1$ and normalize the domestic input price to $P_D = 1$. Productivity draws follow a Pareto distribution with $G(\varphi) = 1 - (\varphi_{min}/\varphi)^k$. Following Melitz and Redding (2015), we set the elasticity of substitution to $\sigma = 4$, the Pareto shape parameter to $k = 4.25$, and the lower bound of productivity to $\varphi_{min} = 1$. We set the fixed cost of domestic sourcing to $f_D = 0$. From the data, we calibrate an ad valorem tariff of $\tau = 0.019$, the average of China's tariffs on listed products, weighted by exporters' reported trade values. The relative world price is measured at

$P^*/P_D = 0.63$, where we compute P^* as the average of FOB prices of wastes from UN Comtrade data, and P_D, the average price of domestic waste, is sourced from *China's Recycling Industry Report on Renewable Resources Development (2015-2016)*. Firm mass $N = 22435$ is calibrated to match the number of manufacturing importers in our sample. Finally, we calibrate the enforcement parameter, ρ, as the ratio of the smuggling value recorded in court documents to the reduced-form estimates of the trade value gap of waste, which yields $\rho = 0.028$.

We let $\Theta \equiv (\tau_s,\ f_S,\ f_L)$ denote the remaining structural parameters and estimate them using the method of moments given by:

$$\hat{\Theta} = \arg\min_{\Theta} \left\{ w_L\left(\frac{Q(\Theta) - Q^{\text{data}}}{Q^{\text{data}}}\right)^2 + w_S\left(\frac{S(\Theta) - S^{\text{data}}}{S^{\text{data}}}\right)^2 + w_\chi\left(\frac{\chi_L(\Theta) - \chi_L^{\text{data}}}{\chi_L^{\text{data}}}\right)^2 \right\}.$$

Here, $Q(\Theta)$, $S(\Theta)$, and $\chi_L(\Theta)$ are model-implied quantities of legal imports, smuggling, and legal importer share, respectively, and Q^{data}, S^{data} and χ_L^{data} represent their data counterparts. w_L, w_S, and w_χ are the weights assigned to each moment. Under the Pareto assumption, the share of legal importers $\chi_L \equiv \Pr(\varphi_L^* \leq \varphi \leq \varphi_S^*) = G(\varphi_S^*) - G(\varphi_L^*)$ is given by:

$$\chi_L = \frac{\varphi_L^{*\,-k} - \varphi_S^{*\,-k}}{\varphi_{min}^{-k}}, \tag{19}$$

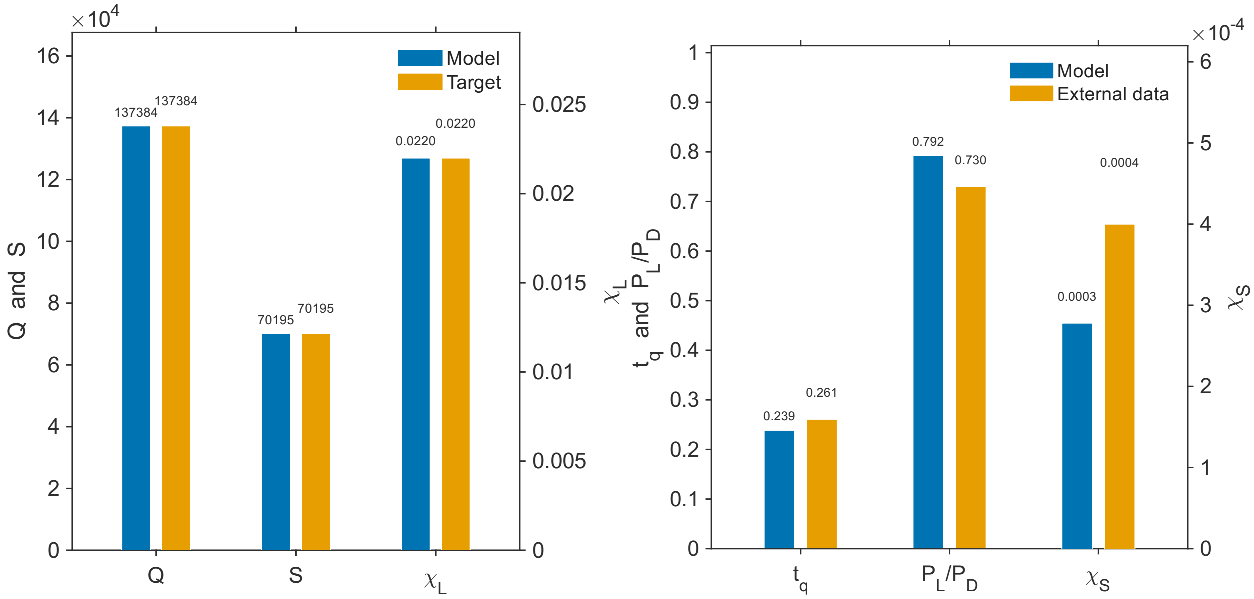
where φ_L^* and φ_S^* satisfy Equation (14).

We target the post-ban average legal import quantity $Q^{\text{data}} = 137383.5$ (in 100-tonne units), the reduced-form estimates of smuggled quantity $S^{\text{data}} = 70195.5$ (in 100-tonne units), and a pre-ban legal importer share of $\chi_L = 0.022$.[10] We normalize each moment by its mean and set equal weights $w_L = w_S = w_\chi$ to ensure comparability. With three parameters and three moments, the model is exactly identified. The estimates are $\widehat{\tau}_s = 0.143$, $\widehat{f}_S = 159.7$, and $\widehat{f}_L = 14.8$. Given these estimates, the quota market-clearing condition (Equation 15) implies a quota rent of $\widehat{t}_q = 0.239$. Figure 7a shows that the calibrated model matches the target moments almost exactly.

To validate the estimated model, we compare three non-targeted moments against external data in Figure 7b. Absent direct measures, we rely on approximate measures. First, using UN Comtrade data for CIF import prices (P_L) and FOB export prices (P^*), and the relationship $P_L = P^*(1+\tau+t_q)$, we calculate the quota rent as $t_q = P_L/P^* - 1 - \tau = 0.261$, which is slightly above the model estimate.[11] Second, using average CIF prices from UN Comtrade to measure P_L, we find $P_L/P_D = 0.730$, which is in the ballpark of the model estimate of 0.792. Finally, we calculate the smuggler share by dividing the number of firms involved in smuggling by the total number of

[10] We lack access to post-ban Chinese customs data, which prevents us from identifying post-ban waste importers. Later, we conduct a robustness check with respect to this moment.

[11] This is a rough approximation, as the price ratio may also capture other non-tariff barriers.



(a) Model Fit

(b) External Validation

Figure 7: Model Fit and Validation

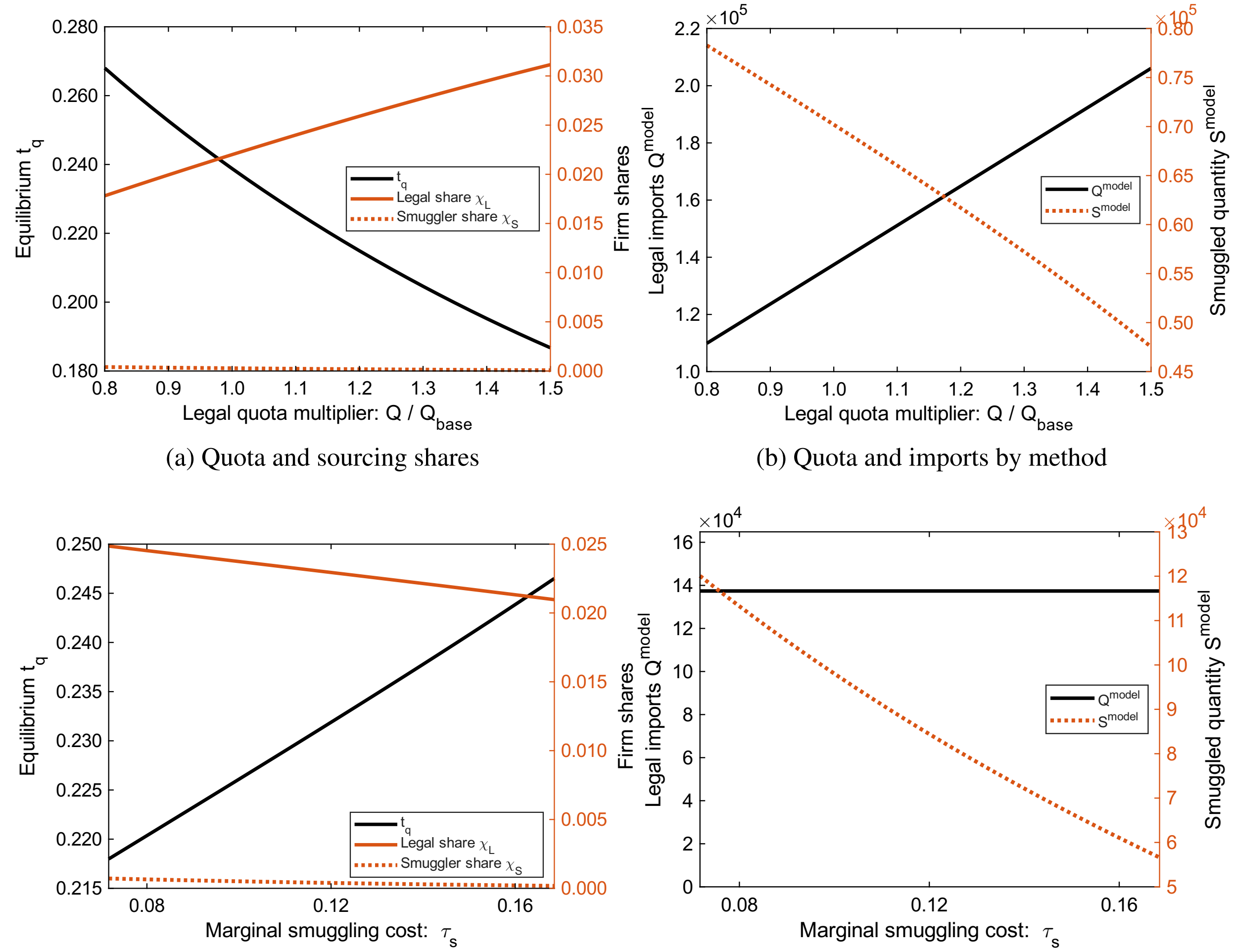
Notes: Panel (a) shows the fit for targeted moments. Panel (b) validates model predictions against external data for the quota rent (t_q), the relative import prices (P_L/P_D), and the smuggler share (χ_S).

manufacturing importers, yielding 0.0004, close to the model estimate of 0.0003.[12]

Counterfactual Analysis To better understand the model mechanism and policy effects, we consider several counterfactual exercises. As shown in Figure 8a and 8b, a tighter quota $\bar{Q}$ raises the quota rent t_q. This drives selection effects: as t_q rises, marginal legal importers exit, while high-productivity firms shift into smuggling. A counterfactual 20% reduction in $\bar{Q}$ raises t_q to 0.268 (a 12% increase) and expands smuggled inflows by 12% to 7.83 million tonnes. Conversely, increasing the quota by 50% suppresses t_q and substantially reduces smuggling. These are consistent with our reduced-form evidence that tighter quotas induce more smuggling.

The other key parameter is the marginal cost of operating outside the formal system, captured by τ_s. As shown in Figure 8c and 8d, our model predicts that halving the calibrated τ_s to 0.072 reduces the shadow price t_q to 0.218 and significantly expands the illicit margin: the share of smugglers rises from 0.0003 to 0.0007, driving a 71% surge in smuggled inflows from 7.02 million to 12 million tonnes. A lower quota rent would draw in firms that previously found legal channels too expensive, thus raising the legal-importer share χ_L.

[12]These statistics warrant caution. Undetected smugglers likely lead to an underestimation of the true share, while unregistered waste-using firms in Orbis/customs data likely lead to an overestimation.



(a) Quota and sourcing shares

(b) Quota and imports by method

(c) Smuggling cost and sourcing shares

(d) Smuggling cost and imports by method

Figure 8: Policy Counterfactual on Smuggling

Notes: This figure presents the comparative statics of model responses to policy adjustments. The left panels (a and c) plot the shares of firms by sourcing method. The right panels (b and d) plot the aggregate import quantity by method (units, 100 tonnes). We simulate the effect of a varying quota $\bar{Q}$ (a and b) and variable smuggling costs τ_s (c and d).

5.2 Welfare Analysis

This subsection quantifies the welfare effects of China's waste import restriction using Equation (10). It captures both the environmental benefits from curbing waste processing and associated pollution, as well as the welfare loss arising from distortions and smuggling.

Welfare Input Parameters Three additional parameters are needed for welfare computation in Equation (10). First, we estimate the leakage rate $\mu = dS/|dQ|$, which measures how much illicit inflow increases per unit reduction in legal imports. Empirically, we estimate dS and dQ using the baseline DID specification in Equation (2), replacing the dependent variable with (i) legal import quantity and (ii) the quantity gap (our proxy for illicit inflows). Let $\hat{\beta}_Q$ and $\hat{\beta}_S$ denote the corresponding treatment effects. We then construct $\mu = \hat{\beta}_S/|\hat{\beta}_Q|$ and obtain inference via the delta method, yielding $\hat{\mu} = 0.28$ (p-value $= 0.014$).

Second, we monetize the environmental externality using the marginal social disutility from waste processing, λ. We anchor the monetized benefits of air quality improvement using the back-of-the-envelope valuation in Shi and Zhang (2023), which report \$6.67 billion in health benefits attributable to the air-quality improvement induced by the ban. For water quality, we rely on Ge et al. (2025), who estimate that a 0.352 standard deviation improvement in water quality increases housing prices by 5.4% within 500 meters of the nearest treated river. To monetize this effect, we proxy the exposed housing market by the share of pre-policy nightlight intensity within the 500-meter river buffer of treated cities relative to the national total. With \$1001.97 billion national total residential sales in 2015, this implies an exposed housing value of \$23.35 billion (\$1001.97 billion $\times$ 2.33% = \$23.35 billion, where 2.33% is the share of exposed houses). Using our standardized COD_{Mn} estimate in Table D8, the implied housing capitalization gain is \$0.74 billion (\$23.35 billion $\times (0.206/0.352) \times$ 5.4% = \$0.74 billion). Dividing the total environmental gains (\$6.67 + \$0.74 = \$7.41 billion) by our estimated pre-post decline in legal waste imports (76 million tonnes) yields $\hat{\lambda} = 97.5$ \$/tonne.[13]

Finally, we set $P^* = 407.89$ \$/tonne, the average pre-ban waste FOB price measured from the UN Comtrade data.[14] Table 7 summarizes the parameters in the baseline economy.

Welfare Accounting Figure 9a reports the welfare accounting implied by Equation (10), which reports the overall welfare effect and its decomposition. The status quo baseline estimate yields a net welfare cost of $\$25.6$ per tonne: While the environmental gain is sizable (\$$70.2$, offsetting about 73% of the gross losses), it is outweighed by the smuggling cost (-\$20.1) and the dominant distortion loss (-\$75.7).

To see the role of smuggling, we evaluate the scenario with perfect enforcement ($\mu = 0$), which affects welfare through the following adjustments. On the one hand, total inflows fall one-for-one with legal imports, so the environmental gain rises from 70.2 to 97.5. On the other hand, as the policy is strictly enforced, the distortion loss intensifies, rising from -75.7 to -105.2, and smuggling costs vanish with its elimination. Net welfare therefore improves from -\$25.6 to -\$7.6 per tonne.

Conversely, under no enforcement ($\mu = 1$), every unit reduction in legal imports is fully offset

[13] The social disutility from air pollution is close to the estimation of \$87 per tonne for waste in suburban US by the minimum-externality solution according to Martinez-Sanchez et al. (2017). As far as we know, monetized estimates of water quality improvements remain scarce, especially in the Chinese context. We therefore treat this housing capitalization measure as an approximation of the benefits from improved water quality.

[14] While the structural estimation normalizes prices relative to domestic waste, welfare effects are reported in dollar terms per tonne (\$/tonne).

Table 7: Baseline Parameters for the Structural Model

Parameter	Definition	Value	Source
1. Calibrated Primitives			
B	Demand shifter	1	Normalization
$\phi_{\min}$	Lower support of productivity	1	Normalization
P_D	Domestic price	1	Normalization
f_D	Fixed cost of domestic sourcing	0	Normalization
σ	Elasticity of substitution	4	Melitz and Redding (2015)
k	Pareto shape parameter	4.25	Melitz and Redding (2015)
τ	Ad-valorem tariff	0.019	Post-ban weighted average (2018–2020)
N	Mass of firms	22,435	Pre-ban average (2015–2016)
P^*/P_D	Relative world price	0.63	Pre-ban average (2015–2016)
P^*	World price	407.89	Pre-ban average (2015–2016)
ρ	Detection risk	0.028	Post-ban average (2018–2020)
μ	Leakage rate	0.28	Reduced-form regression
λ	Social disutility	97.5	See the main text
2. Estimated Parameters			
f_L	Fixed cost of legal import	14.8	Method of moment estimator
f_S	Fixed cost of smuggling	159.7	Method of moment estimator
τ_s	Variable cost of smuggling	0.143	Method of moment estimator

Notes: This table presents the baseline values we use for model calibration.

by smuggling ($dS = dQ$). Therefore, total inflows remain unchanged, nullifying both the environmental gain and the distortion loss. Welfare is then driven solely by smuggling costs (-71.9).

These simulations underscore the dual cost of leakage μ: it attenuates the environmental gain by shrinking $1 - \mu$, and imposes a direct deadweight loss proportional to μ.

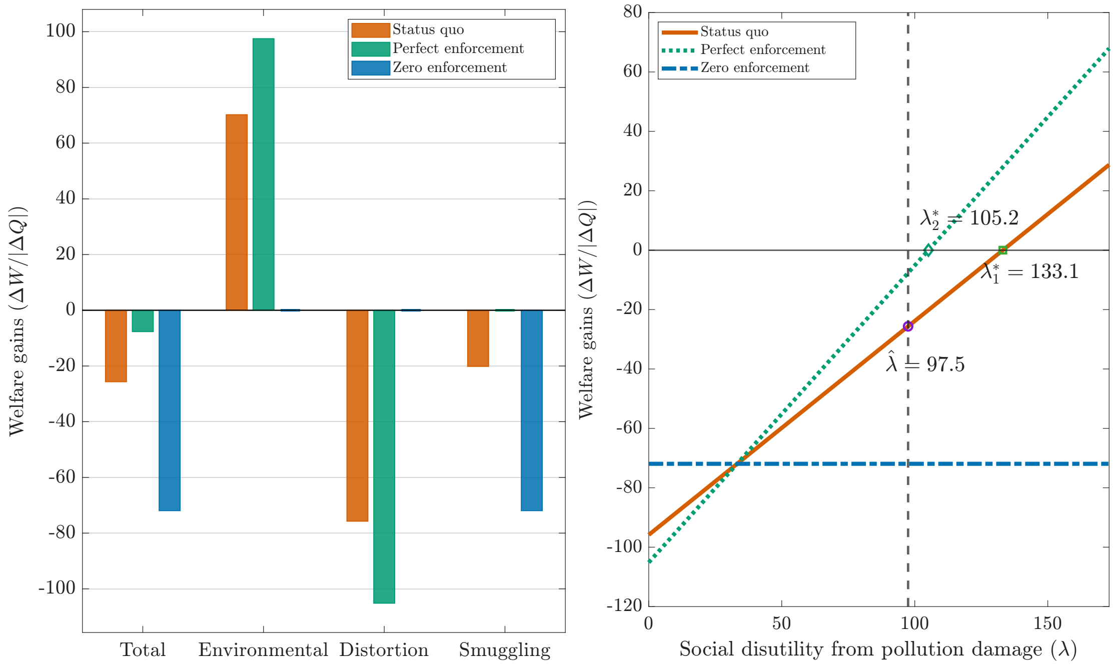
The Break-Even Social Disutility Rather than taking λ as given, we solve for the marginal social disutility required to render the ban welfare-neutral ($\Delta W/|\Delta Q| = 0$). From Proposition 1, this break-even threshold is:

$$\lambda^* = P^*\big(t_q + \tau + \frac{\mu}{1-\mu}\frac{\rho + \tau_s}{1-\rho}\big).$$

Under the status quo ($\mu = 0.28$), the implied valuation is $\lambda^* = 133.1$, roughly 1.4 times our benchmark estimate ($\hat{\lambda} = 97.5$). This suggests the policy is currently welfare-reducing unless environmental damages are substantially larger than estimated.[15]

Figure 9b illustrates how the welfare effect varies with λ under alternative scenarios. Perfect enforcement ($\mu = 0$) lowers the threshold to 105.2 by ensuring that reduced legal imports trans-

[15]This threshold is below the \$161 per-tonne carbon-reduction benefits estimated by Chen et al. (2025a), who concluded China's energy conservation program could be justified at this rate.



(a) Welfare Decomposition

(b) Welfare Gains with Varying Social Disutility

Figure 9: Welfare Analysis

Notes: Panel (a) presents the welfare decomposition with estimated leakage rate $\hat{\mu} = 0.28$ and social disutility from pollution $\hat{\lambda} = 97.5$. Panel (b) shows the aggregate welfare under different values of social disutility and alternative regulations. The vertical, long-dashed line represents the baseline estimate. λ_1^* denotes break-even social disutility under status quo, while λ_2^* for the scenario of perfect enforcement.

late one-for-one into fewer waste inflows and eliminating the deadweight loss from smuggling. Intuitively, enforcement improves the policy's "exchange rate" between legal contraction and environmental gains, making the policy viable at lower damage valuations.

Conversely, under the complete-leakage scenario ($\mu = 1$), we have $\Delta W/|\Delta Q| = -P^*(\rho + \tau_s)/(1-\rho)$. The welfare profile flattens below zero for all λ, as the policy yields no environmental gain. In addition, there is also no distortion loss from reduced imports. The ban merely dissipates resources through smuggling. Therefore, without enforcement to prevent displacement, the ban cannot be welfare-improving for any level of social disutility.

5.3 Robustness Checks and Discussions

This subsection first presents several robustness checks to further validate our baseline quantitative results. We then discuss potential extensions to our framework and acknowledge its limitations.

Robustness Checks Table 8 examines model sensitivity by varying one parameter at a time, with the baseline reproduced in the first row. First, replacing the product-weighted tariff ($\tau = 0.019$) with a simple average ($\tau = 0.055$) leaves results virtually unchanged. Second, due to the lack of post-ban firm-level customs data, we proxy χ_L using pre-ban importer and firm counts. An alternative that divides the pre-ban importer count by the post-ban firm count yields $\chi_L = 0.018$. The lower legal importer share implies a higher fixed cost for legal imports and a lower smuggling cost, which slightly reduces the welfare loss. Finally, we recalibrate the seizure probability ρ from a value-based measure to a quantity-based measure. This updated higher $\rho = 0.064$ is offset by a lower estimated smuggling cost τ_s, leaving the overall welfare effect largely unchanged.[16]

Table 8: Robustness Checks for the Structural Model

Specification	Model Parameters			Model Predictions			Welfare Effect
	f_L	τ_s	f_S	t_q	P_S/P_L	χ_S	$\Delta W/\lvert\Delta Q\rvert$
Baseline	14.806	0.1434	159.67	0.239	0.935	0.00028	-25.6
$\tau = 0.055$	14.803	0.1433	160.02	0.203	0.935	0.00028	-25.6
$\chi_L = 0.018$	18.837	0.1340	159.98	0.217	0.944	0.00025	-18.3
$\rho = 0.064$	14.655	0.1059	159.49	0.241	0.938	0.00026	-26.9

Notes: Sensitivity tests vary one parameter at a time: (1) simple average of tariff $\tau = 0.055$, (2) post-ban share of legal importers $\chi_L = 0.018$, and (3) alternative seizure probability, $\rho = 0.064$. The estimated parameters (f_L, τ_s, and f_S) and model-predicted of quota rent t_q, smuggling prices relative to legal import P_S/P_L, and the share of smugglers χ_S, and welfare effect are reported.

Additive Trade Costs We have so far assumed that variable trade costs and quota rents are ad valorem. This is not a crucial assumption. It is easy to verify that if these wedges are additive, the welfare effect of a tightening quota is given by

$$\frac{\Delta W}{|\Delta Q|} = \lambda(1-\mu) - (t_q + \tau)(1-\mu) - \mu\left(\frac{\rho P^* + \tau_s}{1-\rho}\right), \tag{20}$$

which closely resembles the baseline result of Equation (10).

General Equilibrium Effects Our analysis focuses on the partial equilibrium effects in the waste import market rather than broader general equilibrium repercussions. Given that waste processing represents a tiny share of China's production and trade volume (see Appendix Table D3), it is unlikely to generate significant economy-wide price effects or terms-of-trade changes. However, to

[16] From the 2018 official reports, the seizure amount is 1.55 $million\ tonnes$ and the legal imported amount is 22.63 $million\ tonnes$. We calibrate $\rho = 1.55/(22.63 + 1.55) = 0.064$.

the extent that the import restriction may have induced technological changes or expanded domestic waste recycling capacity, these dynamics fall outside the scope of our current framework. We leave the exploration of these channels to future research.

6 Conclusion

Governments are increasingly using trade policy to achieve environmental objectives. However, the efficacy of such measures depends crucially on enforcement and market responses. This paper evaluates China's ban on waste imports, one of the most significant environmental trade interventions in recent history. We find a stark trade-off: while the ban reduced local environmental pollution, it triggered a surge in illicit activity and imposed substantial costs on firms.

We demonstrate that the policy-induced scarcity of imported waste did not merely suppress legal imports but drove the market underground, fostering the emergence of organized crime. Evasion primarily occurred through underreporting of quantities and misclassification, rather than through transfer pricing. Such illicit trade significantly dampened the intended environmental gains, and was most pronounced in regions with weak institutional oversight and high demand for recycled inputs.

Our central contribution is to quantify these distortions using a hybrid framework that combines reduced-form elasticities, structural modeling, and sufficient statistics. We find that the welfare costs arising from smuggling frictions and distortion loss outweigh the monetized benefits of cleaner air and water. This result cautions that unilateral import bans that ignore the shadow value of resources may replace visible pollution with invisible, inefficient, and costly black markets. Effective environmental trade policy requires not only border controls but also complementary measures to address domestic resource demand and enforcement capacity.

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Evading the Ban: Smuggling, Pollution, and the Welfare Effects of China's Waste Import Restrictions

(Online Appendix)

by

Hanwei Huang Yuyuan Yu

Appendix A Proofs and Additional Theoretical Results

Appendix A.1 Proofs of Proposition 1

Totally differentiating W given by equation (8) with respect to the quota Q:

$$\frac{dW}{dQ} = U'(M)\frac{dM}{dQ} - P^* - P^*\frac{1+\tau_s}{1-\rho}\frac{dS}{dQ} - \lambda\frac{dM}{dQ} \tag{A1}$$

When the legal import amounts Q vary, firms equate the marginal benefit of legal imports to their *private marginal cost*. For legal imports Q, the private cost comprises the world price, the tariff τ, and the quota license price t_q:

$$U'(M) = P^*(1 + t_q + \tau) \tag{A2}$$

This condition reveals that the social value of the marginal unit ($U'(M)$) is higher than the world price due to the combined wedge of the tariff and the quota. Using the leakage definitions: $dS/dQ = -\mu$ and $dM/dQ = 1 - \mu$, and substituting (A2) into (A1), we obtain:

$$\frac{dW}{dQ} = [P^*(1 + t_q + \tau)](1-\mu) - P^* - P^*\frac{1+\tau_s}{1-\rho}(-\mu) - \lambda(1-\mu) \tag{A3}$$

Grouping the terms with coefficients of P^*:

$$P^*\left[(1 + t_q + \tau)(1-\mu) - 1 + \mu\frac{1+\tau_s}{1-\rho}\right] = P^*\left[(t_q + \tau)(1-\mu) + \mu\frac{\rho+\tau_s}{1-\rho}\right]$$

Substituting back into the derivative:

$$\frac{dW}{dQ} = -\lambda(1-\mu) + P^*(t_q+\tau)(1-\mu) + \mu P^*\frac{\rho+\tau_s}{1-\rho} \tag{A4}$$

Expressing the change for a quota reduction (where $|\Delta Q| = -dQ$):

$$\frac{\Delta W}{|\Delta Q|} = \lambda(1-\mu) - P^*(t_q+\tau)(1-\mu) - P^*\mu\frac{\rho+\tau_s}{1-\rho}. \tag{A5}$$

Appendix A.2 Firms' Reporting Incentives: Tariffs vs Quotas

Here, we develop a simple model to analyze firms' smuggling and reporting incentives, building on the work of Ferrantino et al. (2012) and Kee and Nicita (2022). In these models, traders optimize the level of smuggling by weighing the benefits of under-reporting against the expected costs. It predicts that import quotas and tariffs induce distinct reporting behaviors. While both policies generate discrepancies in official trade statistics, tariff evasion drives gaps in both quantity and unit price, whereas quota evasion drives gaps only in quantity, leaving unit prices stable.

To illustrate these distinct effects, we consider a common modeling environment. Let E represent the exporter and I the importer. Exporters and importers each submit customs declarations for a given shipment, potentially reporting different quantities to their respective customs authorities Q_E and Q_I, corresponding to the export price (FOB) P_E and importer price (CIF) P_I, respectively.

Given that exports are largely unregulated in most source countries, we assume exporters truthfully report the quantity actually exported, i.e., $Q_E = Q$. Conversely, importers may under-report to evade restrictions. We define the smuggled quantity as $Q_S = Q - Q_I$. Smugglers face a risk of detection: with probability of $\delta \in (0, 1)$, they are apprehended and incur a fine; with probability of $1 - \delta$, they evade detection. Hence, δ reflects the intensity of customs enforcement of import regulations.

Tariff Evasions First, consider the case where importers face an ad valorem tariff t but no quantity constraint. The importer chooses a reported quantity Q_I and imports an actual quantity Q. The residual $Q_S \equiv Q - Q_I \geq 0$ is smuggled. The expected total cost comprises five parts. First, the purchase cost $P_E Q$ is paid on the full physical shipment Q, independent of reporting. Second, the tariff on legal reported units adds $tP_I Q_I$. Third, any under-reporting Q_S exposes the importer to an expected penalty $\delta t P_I Q_S$, where penalties equal the evaded tariff. Fourth, operational evasion costs are modeled as $cQ_S + \frac{\gamma}{2} Q_S^2$ with $c > 0$ capturing per-unit outlays (e.g., document forgery, off-manifest logistics) and $\gamma > 0$ capturing the rising marginal difficulty of smuggling larger volumes. Finally, the price misreporting costs are $\frac{\lambda}{2}(P_E - P_I)^2$, with $\lambda > 0$, reflecting the cost of falsifying invoices and audit risk. Therefore, the importers' problem under tariffs is given by:

$$\min_{Q_S, P_I} C_T = \underbrace{P_E Q}_{\text{purchase}} + \underbrace{tP_I Q_I}_{\text{tariff on legal units}} + \underbrace{\delta t P_I Q_S}_{\text{expected penalty}} + \underbrace{cQ_S + \frac{\gamma}{2} Q_S^2}_{\text{operational smuggling cost}} + \underbrace{\frac{\lambda}{2}(P_E - P_I)^2}_{\text{price misreporting cost}} . \tag{A6}$$

The first-order condition with respect to Q_S, $\partial C_T / \partial Q_S = 0$, implies that

$$Q_S = Q - Q_I = \frac{tP_I(1 - \delta) - c}{\gamma}. \tag{A7}$$

Equation (A7) suggests that if the expected net saving per smuggled unit is positive ($tP_I(1-\delta) > c$), the firm will under-report quantity ($Q_S > 0$). Higher tariffs or lower detection rates incentivize larger smuggling volumes. The first-order condition with respect to P_I, $\partial C_T/\partial P_I = 0$, implies:

$$P_E - P_I = \frac{t}{\lambda}[Q - (1-\delta)Q_s]. \tag{A8}$$

Since $Q \geq Q_S$ and $\delta \in (0,1)$, Equation (A8) implies $P_E > P_I$. Thus, under ad valorem tariffs, the importer under-reports the unit price to lower the tax base on both legal and smuggled units. This price gap increases with the tariff rate t. The resulting reporting gap in trade value is:

$$ValueGap_T = P_E Q - P_I Q_I = Q(P_E - P_I) + P_I Q_S, \tag{A9}$$

This gap consists of a price gap component $Q(P_E - P_I)$ and a quantity gap component $P_I Q_S$, both of which rise with import tariffs. These results are summarized in the following proposition.

Proposition 2. *Under ad valorem import tariffs, reporting gaps in quantity, price, and import value all tend to rise with the tariff rate.*

This result is consistent with Ferrantino et al. (2012) and Kee and Nicita (2022). We next show that importers exhibit different reporting behavior under quota constraints.

Quota Evasions Next, consider a binding import quota where the importer can legally declare at most $\bar{Q}$ units. Compliance requires paying a per-unit quota rent r (the shadow price of the quota). We assume the quota is binding, so demand $Q > \bar{Q}$. The importer chooses a legal quantity $Q_I \leq \bar{Q}$ and smuggles the residual $Q_S = Q - Q_I$. Detection occurs with probability of $\delta \in (0,1)$. If smuggling is detected, the importer must pay the evaded per-unit rent r on Q_S. Smuggling also entails operational costs captured by a linear term cQ_S and a convex term $\frac{\gamma}{2}Q_S^2$ with $c > 0$ and $\gamma > 0$. The importer's expected total cost therefore consists of: (i) the purchase cost $P_E Q$ on the full physical flow, (ii) the rent on legal units rQ_I, (iii) the expected penalty $\delta r Q_S$ on smuggled units, and (iv) smuggling technology costs $c\,Q_S + \frac{\gamma}{2}Q_S^2$, and (v) price misreporting costs $\frac{\lambda}{2}(P_E - P_I)^2$. The importers' problem is summarized as follows:

$$\min_{Q_S, P_I} C_Q = \underbrace{P_E Q}_{\text{purchase}} + \underbrace{rQ_I}_{\text{shadow price on legal units}} + \underbrace{\delta r Q_S}_{\text{expected penalty}} + \underbrace{cQ_S + \tfrac{\gamma}{2}Q_S^2}_{\text{operational smuggling cost}} + \underbrace{\frac{\lambda}{2}(P_E - P_I)^2}_{\text{price misreporting cost}}.$$

$$\text{s.t. } Q_I \leq \bar{Q} \tag{A10}$$

The first-order condition with respect to Q_S, $\partial C_Q/\partial Q_S = 0$, implies that

$$Q_S = \frac{r(1-\delta) - c}{\gamma}. \tag{A11}$$

Hence, if the expected net saving per smuggled unit is positive $r(1-\delta)-c > 0$, it is always optimal for the importing firm to under-report, such that $Q_S > 0$. In addition, a tighter quota (lower $\bar{Q}$) that increases the shadow price r, or a lower detection risk (smaller δ), increases the incentive to smuggle quantity Q_S. The first-order condition with respect to P_I, $\partial C_Q/\partial P_I = 0$, implies

$$P_E = P_I. \tag{A12}$$

Therefore, importers report the unit price of imports truthfully. Intuitively, manipulating the reported unit price (P_I) does not relax the quantity constraint ($Q_I \leq \overline{Q}$) nor does it reduce the quota rent, which is based on quantity. Since misreporting price entails a cost without providing any savings, the importer reports the price truthfully. Hence, the reporting gap in trade value is

$$ValueGap_Q = P_E Q - P_I Q_I = P_E(Q - Q_I), \tag{A13}$$

which depends on the reporting gap in quantity. These results are summarized as:

Proposition 3. *A tightening quota constraint increases reporting gaps in quantity and import value, but the gap in reported unit price remains unaffected.*

Table A1: Tariff Evasion Versus Quota Evasion

Reported outcomes by exporters and importers	Tariff Evasion	Quota Evasion
Price gap	✓	×
Quantity gap	✓	✓
Value gap	✓	✓

Table A1 summarizes the different patterns in the reported outcomes under tariff evasion and quota evasion. We expect to see reported gaps in price, quantity, and trade value between exporters and importers under tariff evasion, but only gaps in quantity and value under quota evasion.

Appendix B Data Sources and Processing

Appendix B.1 Cleaning of Main Variables

Appendix B.1.1 UN Comtrade Database

The disaggregated trade data at the country-product level were retrieved from the UN Comtrade Database from 2015 to 2021. Before analysis, we convert all observations to the HS 2012 classification using the official correspondence tables provided by the United Nations Statistics Division. We focus on annual rather than monthly aggregates to minimize distortions from reporting delays, shipping lags, and irregular transaction-level shocks. In addition, the sample is restricted to HS six-digit product codes belonging to the same two-digit HS chapters as listed waste. This refinement reduces noise from unrelated product classes, ensuring that the dataset captures trade flows most relevant for examining waste-related discrepancies.

Before aggregating data to product-year level, we exclude some countries or regions to ensure consistent matching across datasets: 1) countries that adopt older version of HS code than HS2012 because we cannot properly map HS2002 or HS2007 to later code like HS2012 due to n:1 relationship, including AFG, ATG, BRB, CAF, DJI, DMA, GAB, GMB, GNB, GUY, KNA, LBY, MOZ, MRT, MSR, PHL, SDN, SLE, STP, SUR, SYC, TJK, TLS, TTO, VCT. 2) Unknown regions classified as R4, A59, A79, E19, F19, O19, _X and S19. 3) We further drop China's self-export.

Appendix B.1.2 Tariff Data

All customs codes in tariff data are harmonized to the HS 2012 classification system using the official UN correspondence tables to ensure within-product comparability over time. When multiple tariff lines map into a single HS6 product within a year, we compute the simple average across those lines. Let $MFN_{p,t}$ denote the statutory ad valorem rate (percent) for HS6 product p in year t. We convert this to a price wedge: $ln(Tariff) = ln(1 + MFN_{p,t}/100)$.

Appendix B.1.3 Criminal Records of Smuggling

Building on the semi-structured features of court documents, we implement a reproducible text-analysis pipeline that first parses structured headers for the charge, court, and judgment date, and then applies constrained keyword rules to the narrative only when the charge field is missing. Cases are classified as *waste smuggling* when the charge or narrative indicates *smuggling of solid waste* (*zou si gu ti fei wu*), and as *common-goods smuggling* when charged as (*zou si pu tong huo wu wu pin zui*). When an incident address is available, we geocode it to the city level; otherwise, we assign the court's city. Appeals and related documents are de-duplicated to a single first-instance case.

Appendix B.1.4 Government Procurement Database

To measure the capability of customs enforcement, we utilize the government procurement database and filter out records whose buyer is a sub-national customs bureau across the 42 customs administrative regions, excluding the central customs bureau. Public procurement contracts by customs administrations are often related to border inspection and risk control, such as container scanners, X-ray/CT systems, handheld spectrometers, radiation detectors, or anomaly-detection software. We then aggregate the number of qualifying contracts to the province–year level, using the buyer's registered location. We focus on contract counts rather than values because monetary amounts are frequently absent in award notices, and missing price fields vary over time and across regions, potentially biasing expenditure aggregates.

Appendix B.2 Additional Data

Appendix B.2.1 Exporter Feature

We proxy exporter governance and state capacity using the World Bank's Worldwide Governance Indicators (WGI), a cross-country panel that aggregates information from surveys and expert assessments into comparable annual measures. We use six indicators to capture different dimensions of institutional features, which are plausibly related to documentation integrity and the feasibility of illicit cross-border trade. We use the predetermined values of these indicators to mitigate the potential reverse causality problem.

Besides, we draw standard gravity covariates from the CEPII database. Our main geography control is the population-weighted average between China and the exporter's most populous city. This measure summarizes systematic variation in transport costs and market access that affects both baseline shipment patterns and the scope for re-routing or concealment.

Appendix B.2.2 City-level Variables

Number of Recycling Firms We measure local recycling and waste-processing capacity using China's Administrative Registration Database, which records establishments' registered locations, industry classifications, and business scopes. We classify an establishment as recycling-related if either (i) its registered name or business scope contains keywords associated with renewable resources (e.g "renewable resources") or (ii) it is registered under the industry category "comprehensive utilization of waste resources." We then aggregate by city and registration year to construct

$ln(RecyclingFirms)$, the cumulative count of newly registered recycling firms.

Granted Quota We assemble quota-license issuance data from the Center of China Waste and Chemicals Management, which publishes official approval bulletins listing license holders, approved import quantities, and product codes/descriptions for regulated waste (2015–2020). We match license-holder firm names to the Administrative Registration Database to assign each license to a city, and we aggregate approved quantities to the city-year level. Since realized quota allocations may respond to enforcement and compliance concerns (e.g., suspensions following detected misuse), we avoid using contemporaneous city quotas as a direct regressor. Instead, we construct a shift-share measure that anchors cross-city exposure in the pre-period: $GrantedQuota = PreShare_c \times \frac{Q_t}{Q_{2015}}$, where $PreShare_c$ is city c's pre-shock share of the national quota allocation and $\frac{Q_t}{Q_{2015}}$ captures the national tightening of quota issuance over time.

Air Quality and Climatic Conditions We measure ambient pollution using PM2.5 readings from the Ministry of Ecology and Environment's real-time monitoring platform, which reports hourly concentrations at the monitoring-site level. We compute monthly averages for each site and then average across sites within a city to obtain a city-month PM2.5 series. To reduce sensitivity to extreme readings and data anomalies, we winsorize the city-month PM2.5 distribution at the 1st and 99th percentiles. To net out weather-driven variation in pollution, we use the China Meteorological Forcing Dataset compiled by He et al. (2025), which provides monthly gridded meteorological variables. We extract precipitation, air pressure, relative humidity, and wind speed for 2015–2020, map them to cities, and standardize each variable prior to estimation.

Appendix B.2.3 Monitoring Site-level Water Quality

The data collection and matching process follows a series of steps outlined in He et al. (2020) and Agarwal et al. (2023), as illustrated in Fig. C3. Treated sites are those within a 10-km buffer of upstream waste import firms. Following Agarwal et al. (2023), we focus on control sites that do not have waste import firms upstream and are positioned below the median in both upstream firm density and average water quality levels.

Water Quality Data We draw on the extensive and detailed water quality dataset compiled by Lin et al. (2024). This high-frequency dataset covers the weekly water quality data provided by the China National Environmental Monitoring Center (CNEMC) from 2007 to 2018. We aggregate it into monthly data by taking simple averages to improve data usability and comparability while preserving key temporal trends.

Surrounding Economic Activities The for COD_{Mn} levels recorded at each monitoring site reflect the overall discharge of pollutants from nearby industrial firms and other sources. Therefore, we use the 2017 points of interest (POIs), categorized as companies (excluding service and trading companies), to account for surrounding pollution sources. To determine the relative upstream and downstream positions of monitoring sites and surrounding firms, we compare their elevations using high-resolution topographic data, following He et al. (2020). Specifically, the elevation information is extracted from the 1 arc-second resolution (approximately 30-m) Digital Elevation Model (DEM) provided by NASA's Shuttle Radar Topography Mission (SRTM). Then we count the number of upstream firms based on a 10km search radius of each monitoring site. Table 1 shows a significant variation in upstream firm density across monitoring sites.

Another proxy for surrounding economic activities is the average nightlight radiance. The advantage of this dataset is that it suffers less from manual manipulation and provides high-frequency information that varies over time and across monitoring sites (Chor and Li, 2024). Besides, agriculture has replaced industry as the most significant source of water pollution in China since 2005, which generated about 44% of national COD emissions and 57% of nitrogen demand (Li et al., 2017). We calculate the average nightlight radiance within the 10-km radius buffer of each monitoring site. The monthly cloud-free nightlight data with 15 arc second resolution (approximately 500 m) were downloaded from the global VIIRS nighttime lights (Elvidge et al., 2013, 2017, 2021).

Climate Conditions Climate conditions near monitoring sites are essential when studying water quality due to their significant influence on physical, chemical, and biological processes in aquatic systems. Temperature influences reaction kinetics, solubility, and dissolved oxygen dynamics, which are key water quality parameters. Precipitation, including extreme events like floods and droughts, alters water quality by driving dilution, pollutant transport, and organic matter flushing. Therefore, we also calculate the monthly climate conditions near the monitoring sites. The 1-km monthly precipitation and temperature grid data for China were accessed from the National Tibetan Plateau Data Center (Shouzhang, 2024a,b).

Appendix B.2.4 Firm-level Variables

China Customs Database The latest transactional-level customs database extends to 2015 and 2016, which helps us to effectively identify firms in the treatment group. According to customs data, we identified 2,714 firms and 2,951 firms that imported at least one listed waste product in 2015 and 2016, respectively. In total, 3,953 unique firms were involved in waste imports before the policy's implementation.

Orbis Database Financial information of Chinese firms in the broadly defined manufacturing sector was retrieved from the Orbis database, assembled by Bureau van Dijk, over the period 2015-2021. Before matching, we address duplicated firm-year observations in the Orbis database, following Li and Su (2022). First, we consider only unconsolidated statements to avoid double-counting. Consolidated statements are reported by the parent company and incorporate the financial performance of its subsidiaries. Therefore, we keep samples with conation codes U1 and U2 and extend them to code LF to incorporate firms with limited financial statement data. Second, we closely follow the remaining steps of Li and Su (2022) in dealing with firm-year duplicates by keeping the entry with the highest flow variable, operating revenue.

Then we match the Orbis database with the China Customs Database. Following Tian and Yu (2012), we preprocess firms' Chinese names in two databases by removing non-essential keywords, such as "limited company" and "group". Then, we link entities in both databases by using these refined native names as identifiers.

In the above-mentioned matched dataset, we drop two-digit NACE manufacturing sectors without any waste import firms to control for unobserved sector heterogeneity because only a few sectors use recyclable waste as production inputs. The further data cleaning process partly follows the practices of Li and Su (2022) and Fons-Rosen et al. (2021).

First, we drop observations with basic reporting mistakes in the following steps: (1) We drop firm-year observations that have missing values simultaneously in total assets, operating revenues, sales, and employment. (2) We drop the entire firm if there are negative values in these variables in any year: total assets, employment, sales, or fixed assets are negative in any year. (3) We drop firm-year observations with missing or non-positive values for operating revenue, total assets, and costs of goods sold. (4) We drop firms that have an incorporation date later than the closing date. (5) We drop firms that have abnormal employment growth: below the 0.1 percentile or above the 99.9 percentile of the sample.

Second, we exclude observations with inconsistent balance sheet information. Specifically, we drop observations that are below 0.1 percentile or above 99.9 percentile of the distribution of each ratio: (1) The sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of total fixed assets; (2) The sum of stocks, debtors, and other current assets as a ratio of total current assets; (3) The sum of fixed assets and current assets as a ratio of total assets.

Table B2: List of Waste Products under Import Restrictions

HS Code	Description
Panel A: Products subject to an Import Ban	
0501	Human hair; unworked, whether or not washed or scoured; waste of human hair
0502	Pigs', hogs' or boars' bristles and hair; and waste thereof
0505	Skins and other parts of birds with feathers, down; feathers, down and parts thereof; not further worked than cleaned, disinfected, treated for preservation; powder, waste and parts of feathers
0506	Bones and horn-cores, unworked, defatted, simply prepared (but not cut to shape), treated with acid or degelatinised; powder and waste of these products
0507	Ivory, tortoise-shell, whalebone and whalebone hair, horns, antlers, hooves, nails, claws and beaks unworked or simply prepared, not cut to shape; waste and powder of these products
0511	Animal products not elsewhere specified or included; dead animals of chapter 1 or 3, unfit for human consumption
1522	Degras; residues resulting from the treatment of fatty substances or animal or vegetable waxes
1703	Molasses; resulting from the extraction or refining of sugar
2517	Pebbles, gravel, crushed stone for concrete aggregates for road or railway ballast, shingle or flint; macadam of slag, dross etc tarred granules, chippings, powder of stones of heading no. 2515 and 2516
2525	Mica, including splittings; mica waste
2530	Mineral substances not elsewhere specified or included
2620	Slag, ash and residues; (not from the manufacture of iron or steel) containing metals, arsenic or their compounds
2621	Slag and ash n.e.c. in chapter 26; including seaweed ash (kelp) and ash and residues from the incineration of municipal waste
2710	Petroleum oils and oils from bituminous minerals, not crude; preparations n.e.c, containing by weight 70% or more of petroleum oils or oils from bituminous minerals; these being the basic constituents of the preparations; waste oils
2713	Petroleum coke, petroleum bitumen; other residues of petroleum oils or oils obtained from bituminous minerals
2804	Hydrogen, rare gases and other non-metals
3006	Pharmaceutical goods
3804	Residual lyes from the manufacture of wood pulp, whether or not concentrated, desugared or chemically treated, including lignin sulphonates, but excluding tall oil of heading no. 3803
3825	Residual products of the chemical or allied industries, not elsewhere specified or included; municipal waste; sewage sludge; other residual products.
3915	Waste, parings and scrap, of plastics

Continued on next page

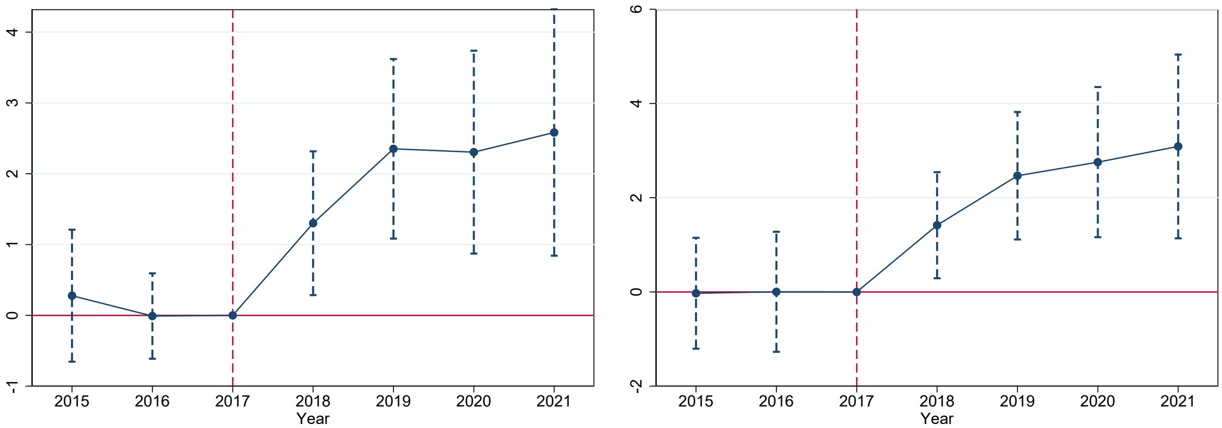
HS Code	Description
4004	Waste, parings and scrap of rubber (other than hard rubber) and powders and granules obtained therefrom
4017	Hard rubber (e.g. ebonite) in all forms, including waste and scrap; articles of hard rubber
4115	Composition leather with a basis of leather or leather fibre, in slabs, sheets or strip, in rolls or not; parings and other waste of leather or of composition leather, not suitable for the manufacture of leather articles; leather dust, powder and flour
5103	Waste of wool or of fine or coarse animal hair, including yarn waste but excluding garnetted stock
5104	Wool, or fine or coarse animal hair; garnetted stock
5202	Cotton waste (including yarn waste and garnetted stock)
5505	Waste (including noils, yarn waste and garnetted stock), of man-made fibres
6309	Textiles; worn clothing and other worn articles
6310	Rags; used or new, scrap twine, cordage, rope and cables and worn out articles of twine, cordage, rope or cables, of textile materials
7001	Glass; cullet and other waste and scrap of glass, glass in the mass
7112	Waste and scrap of precious metal or of metal clad with precious metal; other waste and scrap containing precious metal compounds, of a kind uses principally for the recovery of precious metal
7401	Copper mattes; cement copper (precipitated copper)
7802	Lead; waste and scrap
8102	Molybdenum; articles thereof, including waste and scrap
8105	Cobalt; mattes and other intermediate products of cobalt metallurgy, cobalt and articles thereof, including waste and scrap
8107	Cadmium; articles thereof, including waste and scrap
8110	Antimony; articles thereof, including waste and scrap
8111	Manganese; articles thereof, including waste and scrap
8112	Beryllium, chromium, germanium, vanadium, gallium, hafnium, indium, niobium (columbium), rhenium and thallium; and articles of these metals, including waste and scrap
8548	Waste and scrap of primary cells, primary batteries and electric accumulators; spent primary cells, spent primary batteries and spent electric accumulators; electrical parts of machinery or apparatus, n.e.c. or included elsewhere in chapter 85
Panel B: Products subject to an Import Quota	
2618	Granulated slag (slag sand) from the manufacture of iron or steel
2619	Slag, dross; (other than granulated slag), scalings and other waste from the manufacture of iron or steel
4707	Waste and scrap of paper and paperboard

Continued on next page

HS Code	Description
7602	Aluminium; waste and scrap
8101	Tungsten (wolfram); articles thereof, including waste and scrap
8104	Magnesium; articles thereof, including waste and scrap
8106	Bismuth; articles thereof, including waste and scrap
8108	Titanium; articles thereof, including waste and scrap
8109	Zirconium; articles thereof, including waste and scrap
8113	Cermets; articles thereof, including waste and scrap
8908	Vessels and other floating structures; for breaking up
Panel C: Non-restricted Products	
4401	Fuel wood, in logs, billets, twigs, faggots or similar forms; wood in chip or particles; sawdust and wood waste and scrap, whether or not agglomerated in logs, briquettes, pellets or similar forms
4501	Natural cork, raw or simply prepared; waste cork; crushed, granulated or ground cork
7204	Ferrous waste and scrap; remelting scrap ingots of iron or steel
7404	Copper; waste and scrap
7503	Nickel; waste and scrap
7902	Zinc; waste and scrap
8002	Tin; waste and scrap
8103	Tantalum; articles thereof, including waste and scrap

Notes: This table lists the 4-digit customs codes for solid waste products covered by the 2017 *Catalog of Import Waste Management*. All customs codes are converted to the 2012 Harmonized System (HS) classification.

Appendix C Additional Figures



(a) Trade Gap in Value

(b) Trade Gap in Quantity

Figure C1: Parallel Trend Test with Trade Gap Measured in Log Differences

Notes: This figure presents event-study coefficients with 95% CI from a 6-digit product-year panel (2015–2021). The dependent variable is expanded trade gap $Gap = log(1 + ExportsToChina_{p,t}) - log(1 + ChinaImports_{p,t})$. The regression controls for year FE, product FE, product trend, and MFN tariff. The pre-policy year (2017, k = -1) is normalized to zero. Standard errors are clustered at the 6-digit product level.

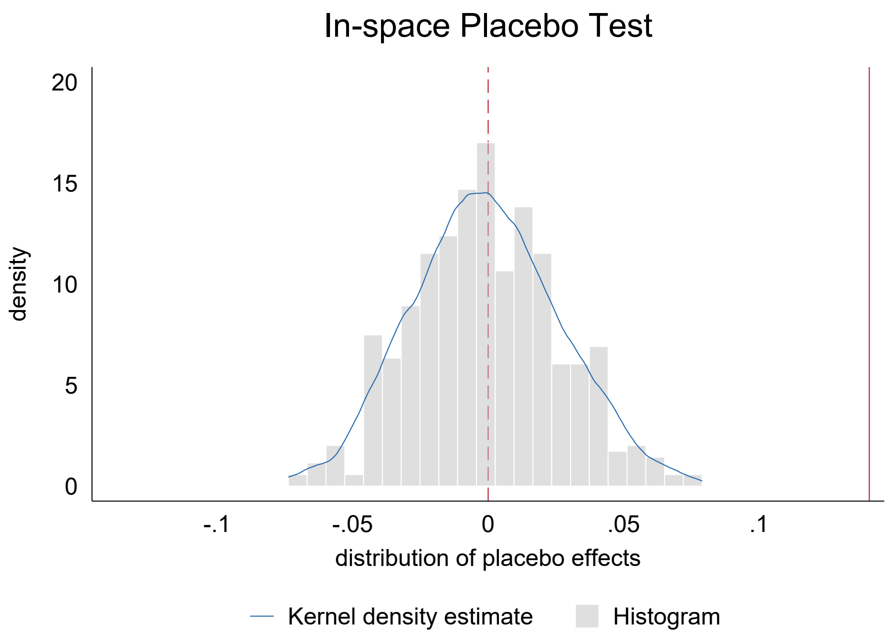


Figure C2: Placebo Test

Notes: This figure presents the in-space placebo test result. The vertical line denotes the baseline estimated coefficients. Following the literature (Chen et al., 2025b), we conduct a permutation test by randomly reassigning treatment labels across products ($Treated_{fake}$) while holding the overall treated share fixed. For each of the 500 iterations, we re-estimate the baseline regression (Equation 2) using the placebo DID variable and store the coefficient. The distribution of these placebo estimates is tightly centered around zero, indicating that the false DID variable has no systematic effect on trade value gaps. Crucially, the benchmark estimate of 0.141 (indicated by the red vertical line) lies far outside the upper tail of this distribution, confirming that the waste ban caused an unusual increase in trade gaps.

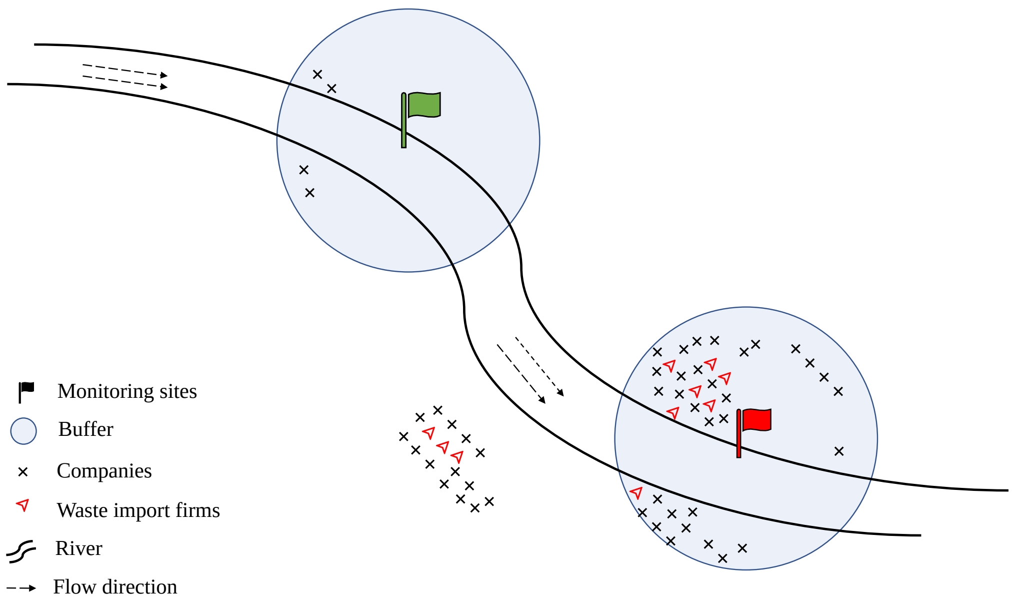
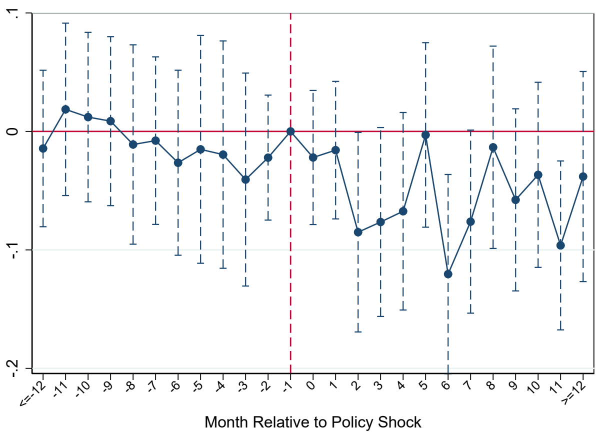


Figure C3: Identification of Treatment and Control Water Monitor Sites

Notes: This figure illustrates the definition of treatment and control water quality monitoring stations. Treated sites are defined as those located downstream of waste-importing firms within a 10-km buffer; control sites are those without upstream waste-importing firms.



(a) Air Pollution

(b) Water Pollution

Figure C4: Parallel Trends Test for Environmental Outcomes

Notes: 1) This figure presents the point estimates of month-wise dummies in the event-study specification with 95% confidence intervals. The coefficient for the baseline period before policy implementation (December 2017), $k = -1$, is normalized to zero. 2) In Panel (a), regression is based on city-month panel data (2015–2019) with $lnPM_{2.5}$ as the dependent variable. The treatment group includes cities importing waste during 2015–2016. We have also incorporated year-month FE, city-month FE, city-year trend, city-level controls, and customs enforcement. Standard errors are clustered at the city level. 3) Panel (b) uses a sample of monitoring site-month panel from January 2015 to December 2018. The dependent variable is $lnCODMn$. The treatment group is monitoring sites located downstream of waste-importing firms and within a 10-km buffer zone. The control group consists of monitoring sites with no upstream waste-importing firms and is further restricted to sites with below-median pre-ban water pollution levels and low nearby firm density. The regression incorporates year-month FE, site FE, river-month FE, city year trend, site-level controls, and customs enforcement. Standard errors are clustered at the site level.

Appendix D Additional Tables

Table D3: Waste Sector in the Chinese Economy

	2002	2005	2007	2012	2015	2017	2018	2020
Panel A: Gross output								
Waste Utilization sector	84.18	122.76	436.60	422.26	441.62	660.14	856.61	988.24
Total economy	31343.05	54676.47	81885.90	160162.71	208144.65	225773.35	249549.83	269902.78
Share	0.27%	0.22%	0.53%	0.26%	0.21%	0.29%	0.34%	0.37%
Panel B: Value added								
Waste Utilization sector	84.18	122.76	353.09	326.57	78.31	552.42	720.07	817.61
Total economy	12185.89	18625.61	26604.38	53680.02	68025.41	82321.57	92205.72	101642.20
Share	0.69%	0.66%	1.33%	0.61%	0.12%	0.67%	0.78%	0.80%
Panel C: Total Imports								
Waste Utilization sector	3.02	76.70	140.86	230.01	140.51	153.18	124.27	59.42
Total economy	2694.25	5939.85	7402.06	12202.70	12515.31	14926.84	16863.42	16265.92
Share	0.11%	1.29%	1.90%	1.88%	1.12%	1.03%	0.74%	0.37%

Notes: Source data: Input Output Tables from the National Bureau of Statistics of China. Values are in billion CNY.

Table D4: Impacts of Exporter-Side Restrictions

Dependent Variable	GapRatio Value				GapRatio Quantity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	0.140***	0.155**	0.140***	0.155**	0.134***	0.154**	0.134***	0.151**
	(0.0500)	(0.0610)	(0.0499)	(0.0605)	(0.0520)	(0.0630)	(0.0518)	(0.0626)
ln(Tariff)	0.233	0.285	0.233	0.285	-0.212	-0.198	-0.211	-0.200
	(0.190)	(0.182)	(0.190)	(0.182)	(0.249)	(0.267)	(0.249)	(0.267)
Export restriction	0.0255	-0.299***	0.0272	-0.299***	0.0372	-0.169***	0.0337	-0.153**
	(0.0247)	(0.0467)	(0.0269)	(0.0457)	(0.0263)	(0.0601)	(0.0282)	(0.0598)
Export restriction × Treat			-0.0157	0.000739			0.0328	-0.253
			(0.0610)	(0.289)			(0.0724)	(0.337)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Sample	No	Top20	No	Top20	No	Top20	No	Top20
Adjusted R^2	0.695	0.704	0.695	0.704	0.553	0.554	0.553	0.554
No. of observations	13,240	10,531	13,240	10,531	13,210	10,506	13,210	10,506

Notes: Each column represents separate regressions based on 6-digit product-level data from 2015 to 2021. The control group is products under the same 2-digit HS categories as waste products. Treated products are the listed waste in 2018. $Post$ represents the implementation of import controls on waste from 2018 onward. The dependent variable is $GapRatio = (ExportToChina - ChinaImports)/(ExportToChina + ChinaImports)$ in Columns 1-8. $ExportRestriction$ is a weighted average index on whether product p faces export-related NTM restrictions in exporting country j. We drop observations with export restrictions at the top 20% percentile in the even columns. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D5: Impacts of Transportation Process

	WasteGapRatio Value		WasteGap Value		WasteGapRatio Quantity		WasteGap Quantity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	0.184***	0.184***	2.626***	2.622***	0.177***	0.175***	2.739***	2.715***
	(0.0537)	(0.0538)	(0.605)	(0.606)	(0.0539)	(0.0540)	(0.699)	(0.699)
ln(Tariff)	0.138	0.136	-0.208	-0.234	-0.529*	-0.538**	-1.878	-2.032
	(0.198)	(0.198)	(0.872)	(0.880)	(0.270)	(0.270)	(1.773)	(1.771)
Export restriction		0.00706		0.114		0.0400		0.675**
		(0.0256)		(0.166)		(0.0305)		(0.287)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.669	0.669	0.744	0.744	0.516	0.516	0.458	0.459
No. of observations	11,283	11,283	11,287	11,287	11,264	11,264	11,287	11,287

Notes: Each column represents separate regressions based on 6-digit product level data from 2015 to 2021. The control group includes other products under the same 2-digit HS categories as waste products. Treated products refer to the listed waste products as of 2018. $Post$ represents the implementation of the import control over waste starting from 2018. The dependent variable is $GapRatio_{p,t} = (ExportsToChina_{p,t-1} - ChinaImports_{p,t})/(ExportsToChina_{p,t-1} + ChinaImports_{p,t})$ in Columns 1-2 and Columns 5-6. Column 3-4 and 7-8 use an extended measure of waste gap $Gap_{p,t} = log(1 + ExportToChina_{p,t-1}) - log(1 + ChinaImports_{p,t})$. $ExportRestriction$ is a weighted average index on whether product p faces export-related NTM restrictions in exporting country j. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D6: Effects on Missing Waste Trade with Heckman Selection Model

	Prob. of Report	logGap Value			logGap Quantity			logGap Unit Value		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat × Post		0.760**	0.570*	0.753**	1.034**	0.767*	1.027**	-0.269	-0.178	-0.269
		(0.370)	(0.318)	(0.370)	(0.468)	(0.419)	(0.468)	(0.207)	(0.214)	(0.207)
Similar Product × Post				-0.176*			-0.188			0.0168
				(0.0993)			(0.138)			(0.111)
ln(Tariff)		0.504	0.989	0.563	-0.464	1.695*	-0.401	0.903	-0.555	0.897
		(0.621)	(0.628)	(0.622)	(0.766)	(0.937)	(0.767)	(0.671)	(0.676)	(0.671)
Inverse Mills Ratio		-13.76***	0.298	-13.77***	-21.10***	-10.86	-21.11***	7.410**	10.92***	7.411**
		(4.406)	(4.302)	(4.406)	(6.335)	(6.795)	(6.335)	(3.552)	(3.932)	(3.552)
Treat	-1.018***									
	(0.382)									
Restriction type	0.480***									
	(0.144)									
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Trend		No	Yes	No	No	Yes	No	No	Yes	No
Adjusted R^2		0.654	0.684	0.654	0.575	0.609	0.575	0.428	0.459	0.428
No. of observations	13,240	12,656	12,656	12,656	12,106	12,106	12,106	12,106	12,106	12,106

Notes: Sample: 6-digit product-year panel from 2015-2021. Each column represents a separate regression based on 6-digit product-level data from 2015 to 2021. We focus only on products under the same 2-digit HS categories to waste products. The dependent variable in Column (1) is the probability of reporting positive import values. The dependent variable is $Gap = log(ExportsToChina_{p,t}) - log(ChinaImports_{p,t})$ in Columns (2)-(7). Columns (8)-(10) use $GapUnitValue = log(UnitValue^X) - log(UnitValue^M)$ as the dependent variable. $Treated$ refers to the listed waste products as of 2018. $Post$ represents the implementation of the import control over waste starting from 2018. $SimilarProduct$ equals 1 for products under the same 4-digit HS category to waste products. We have controlled for MFN tariffs in all columns. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D7: Moderating Effects of Exporter Features on the Gap in Quantity

	WasteGapRatio Quantity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	0.102	0.184**	0.0772	0.131*	0.127*	0.132*	0.114*	0.135*	0.131*
	(0.0654)	(0.0926)	(0.0642)	(0.0726)	(0.0703)	(0.0745)	(0.0671)	(0.0745)	(0.0683)
Income level × Treat × Post		-0.102*							
		(0.0551)							
SoutheastAsia × Treat × Post			0.160***						
			(0.0458)						
Rule of law × Treat × Post				-0.0431**					
				(0.0209)					
Control of corruption × Treat × Post					-0.0423**				
					(0.0177)				
Government Effectiveness × Treat × Post						-0.0393			
						(0.0245)			
Political Stability × Treat × Post							-0.0634***		
							(0.0231)		
Regulatory quality × Treat × Post								-0.0429*	
								(0.0225)	
Voice and accountability × Treat × Post									-0.0639***
									(0.0214)
ln(Tariff)	0.306**	0.306**	0.307**	0.306**	0.306**	0.306**	0.306**	0.306**	0.306**
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)
ln(Pop-weighted distance)	2.005***	2.016***	2.013***	2.023***	2.020***	2.022***	2.029***	2.030***	2.005***
	(0.328)	(0.328)	(0.328)	(0.328)	(0.328)	(0.328)	(0.328)	(0.327)	(0.328)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.521	0.521	0.521	0.521	0.521	0.521	0.521	0.521	0.521
No. of observations	345,806	345,806	345,806	345,639	345,639	345,639	345,639	345,639	345,577

Notes: Each column represents separate regressions based on unbalanced panel data at the country-product-year level from 2015 to 2021. The control group includes products under the same 2-digit HS categories as waste products and countries that have waste trade with China. Treated products refer to the listed waste products as of 2018. $Post$ represents the implementation of import controls on waste from 2018 onward. Columns 1-8 use $GapRatio = (ExportsToChina_{p,t} - ChinaImports_{p,t})/(ExportsToChina_{p,t} + ChinaImports_{p,t})$ as the dependent variable. The income level is a dummy variable indicating whether the exporter is a high- or upper-middle-income country. $SoutheastAsia$ is an indicator for 11 commonly defined Southeast Asian countries, including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Vietnam. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D8: Effect on Water Quality with Replaced Measure

	Standardized CODMn			
	(1)	(2)	(3)	(4)
Treated × Post	-0.214**	-0.206**	-0.256**	-0.250**
	(0.0857)	(0.0782)	(0.104)	(0.0965)
Treated × Post× Preban Waste Smuggling			0.587**	0.607**
			(0.293)	(0.302)
Post× Preban Waste Smuggling			-0.505*	-0.519*
			(0.272)	(0.274)
Customs Enforcement		-0.0475		-0.0582
		(0.108)		(0.117)
Year-month FE	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes
River-month trend	Yes	Yes	Yes	Yes
Site-level Controls	Yes	Yes	Yes	Yes
City-year trend	Yes	Yes	Yes	Yes
Adjusted R^2	0.741	0.741	0.742	0.742
No. of observations	2,861	2,861	2,861	2,861

Notes: Regressions are based on monitoring site-month data (2015–2018) with standardized value of COD_{Mn} as the dependent variable. $Treated = 1$ for sites downstream of waste-importing firms within a 10-km buffer. $Post$ indicates the implementation of import controls (from January 2018). The control group consists of monitoring sites with no upstream waste-importing firms and is further restricted to sites with pre-ban water pollution levels below the median and low nearby firm density. Site-level controls include standardized precipitation, temperature, and nightlight radiance. Standard errors are clustered at the site level. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table D9: Effect on Missing Waste Trade with Replaced Gap Measure

	log1Gap Value			log1Gap Quantity			log1Gap Unit Value		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	2.076***	1.632***	2.058***	2.084***	1.753***	2.040***	0.0540	-0.00717	0.0547
	(0.562)	(0.525)	(0.562)	(0.613)	(0.610)	(0.613)	(0.116)	(0.185)	(0.116)
Similar Product × Post			-0.410**			-1.006***			0.0165
			(0.188)			(0.332)			(0.111)
ln(Tariff)	0.180	2.388**	0.318	0.0554	3.497*	0.395	0.949	-0.506	0.944
	(0.943)	(1.073)	(0.944)	(1.599)	(1.937)	(1.600)	(0.671)	(0.676)	(0.671)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Trend	No	Yes	No	No	Yes	No	No	Yes	No
Adjusted R^2	0.734	0.779	0.734	0.482	0.531	0.483	0.428	0.458	0.428
No. of observations	13,240	13,240	13,240	13,240	13,240	13,240	12,106	12,106	12,106

Notes: Sample: 6-digit product-year panel from 2015-2021. Each column represents a separate regression based on 6-digit product-level data from 2015 to 2021. We focus only on products under the same 2-digit HS categories to waste products. Treated products refer to the listed waste products as of 2018. $Post$ represents the implementation of import controls on waste from 2018 onward. $SimilarProduct$ equals 1 for products under the same 4-digit HS category to waste products. The dependent variable is $Gap = log(1 + ExportsToChina_{p,t}) - log(1 + ChinaImports_{p,t})$ in Columns (1) to (6). In Columns (7)-(9), we measure the differences in exporter-reported and importer-reported unit value: $GapUnitValue = log(ExportsToChina^V/ExportsToChina^Q) - log(ChinaImports^V/ChinaImports^Q)$. $SimilarProduct$ equals 1 for products under the same 4-digit HS category to waste products. We have controlled for MFN tariffs in all columns. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D10: Impacts of Exporter-Side Restrictions with replaced gap measure

	log1Gap Value				log1Gap Quantity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	2.065***	1.911***	2.074***	1.879***	2.057***	1.913***	2.057***	1.829***
	(0.561)	(0.642)	(0.559)	(0.627)	(0.611)	(0.702)	(0.609)	(0.690)
ln(Tariff)	0.119	-0.0876	0.146	-0.106	-0.0867	0.168	-0.0860	0.120
	(0.945)	(0.920)	(0.939)	(0.920)	(1.580)	(1.749)	(1.576)	(1.746)
Export restriction	0.378**	-0.820***	0.310**	-0.670***	0.893***	0.248	0.891***	0.646
	(0.169)	(0.270)	(0.153)	(0.218)	(0.246)	(0.445)	(0.250)	(0.424)
Export restriction × Treat			0.627	-2.381			0.0165	-6.331**
			(0.918)	(2.826)			(0.988)	(3.084)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Sample	No	Top20	No	Top20	No	Top20	No	Top20
Adjusted R^2	0.734	0.725	0.734	0.725	0.484	0.487	0.484	0.488
No. of observations	13,240	10,531	13,240	10,531	13,240	10,531	13,240	10,531

Notes: Each column represents separate regressions based on 6-digit product-level data from 2015 to 2021. The control group is products under the same 2-digit HS categories as waste products. Treated products are the listed waste in 2018. $Post$ represents the implementation of import controls on waste from 2018 onward. The dependent variable is $Gap = log(1 + ExportsToChina_{p,t}) - log(1 + ChinaImports_{p,t})$ in Columns 1-8. $ExportRestriction$ is a weighted average index on whether product p faces export-related NTM restrictions in exporting country j. We drop observations with export restrictions at the top 20% percentile in the even columns. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D11: Moderating Effects of Exporter Features with replace gap measure in value

Dependent Variable	WasteGap Value								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	1.249**	2.088**	0.981*	1.549**	1.501**	1.528**	1.377**	1.568**	1.543**
	(0.616)	(0.969)	(0.588)	(0.740)	(0.701)	(0.768)	(0.643)	(0.761)	(0.688)
Income level × Treat × Post		-1.043*							
		(0.588)							
SoutheastAsia × Treat × Post			1.713***						
			(0.477)						
Rule of law × Treat × Post				-0.442*					
				(0.264)					
Control of corruption × Treat × Post					-0.425*				
					(0.220)				
Government Effectiveness × Treat × Post						-0.370			
						(0.304)			
Political Stability × Treat × Post							-0.669**		
							(0.268)		
Regulatory quality × Treat × Post								-0.414	
								(0.280)	
Voice and accountability × Treat × Post									-0.657**
									(0.264)
ln(Tariff)	3.989***	3.993***	3.997***	3.997***	3.997***	3.997***	3.993***	3.997***	4.000***
	(0.731)	(0.731)	(0.729)	(0.726)	(0.726)	(0.726)	(0.726)	(0.726)	(0.727)
ln(Pop-weighted distance)	13.84***	13.96***	13.94***	14.01***	13.99***	13.99***	14.08***	14.07***	13.85***
	(3.101)	(3.097)	(3.099)	(3.092)	(3.095)	(3.091)	(3.091)	(3.089)	(3.102)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.610	0.610	0.610	0.610	0.610	0.610	0.610	0.610	0.610
No. of observations	354,861	354,861	354,861	354,679	354,679	354,679	354,679	354,679	354,617

*Notes:*Each column represents separate regressions based on unbalanced panel data at the country-product-year level from 2015 to 2021. The control group includes products under the same 2-digit HS categories as waste products and countries that have waste trade with China. Treated products are listed as waste products in 2018. $Post$ represents the implementation of the import control over waste starting from 2018. Columns 1-8 use $Gap = log(1 + ExportsToChina) - log(1 + ChinaImports)$ as the dependent variable. The income level is a dummy variable indicating whether the exporter is a high- or upper-middle-income country. $SoutheastAsia$ is an indicator for 11 commonly defined Southeast Asian countries, including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, and Vietnam. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

Table D12: Moderating Effects of Exporter Features with replace gap measure in quantity

	WasteGap Quantity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × Post	1.167*	2.177**	0.862	1.521*	1.450*	1.508*	1.302*	1.542*	1.500**
	(0.678)	(1.032)	(0.646)	(0.799)	(0.763)	(0.826)	(0.704)	(0.823)	(0.748)
Income level × Treat × Post		-1.255*							
		(0.646)							
SoutheastAsia × Treat × Post			1.948***						
			(0.474)						
Rule of law × Treat × Post				-0.522*					
				(0.284)					
Control of corruption × Treat × Post					-0.478**				
					(0.241)				
Government Effectiveness × Treat × Post						-0.454			
						(0.324)			
Political Stability × Treat × Post							-0.711**		
							(0.290)		
Regulatory quality × Treat × Post								-0.487	
								(0.307)	
Voice and accountability × Treat × Post									-0.745***
									(0.286)
ln(Tariff)	0.552	0.556	0.560	0.581	0.581	0.581	0.577	0.581	0.583
	(0.811)	(0.811)	(0.810)	(0.812)	(0.812)	(0.812)	(0.812)	(0.812)	(0.812)
ln(Pop-weighted distance)	29.75***	29.90***	29.87***	29.96***	29.92***	29.94***	30.01***	30.02***	29.77***
	(2.977)	(2.971)	(2.974)	(2.966)	(2.968)	(2.965)	(2.963)	(2.961)	(2.978)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559
No. of observations	354,861	354,861	354,861	354,679	354,679	354,679	354,679	354,679	354,617

*Notes:*Each column represents separate regressions based on unbalanced panel data at the country-product-year level from 2015 to 2021. The control group includes products under the same 2-digit HS categories as waste products and countries that have waste trade with China. Treated products refer to the listed waste products as of 2018. $Post$ represents the implementation of import controls on waste from 2018 onward. Columns 1-8 use $Gap = log(1 + ExportsToChina) - log(1 + ChinaImports)$ as the dependent variable. The income level is a dummy variable indicating whether the exporter is a high- or upper-middle-income country. $SoutheastAsia$ is an indicator for 11 commonly defined Southeast Asian countries, including Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Vietnam. Standard errors clustered at the 6-digit product level are reported in parentheses. *, **, and *** denotes 10%, 5% and 1% significance levels.

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