

# The Waste Wall: China's National Sword and the Collapse of US Recycling Employment

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## Abstract

For decades, the United States exported nearly half its recyclable waste to China. In January 2018, China's National Sword policy banned 24 categories of waste imports, collapsing US plastic waste exports by 99.998%. I exploit county-level variation in pre-shock waste management employment intensity to estimate labor market effects using Census Quarterly Workforce Indicators. The baseline difference-in-differences shows a 14.2% employment decline in high-exposure counties; incorporating county-specific linear trends to address pre-existing differential growth yields a lower bound of 3.7%. A triple-difference using professional services as a within-county placebo confirms the effect is waste-sector-specific (−13.1%). The shock reduced hiring (−12.9%) and firm job creation (−10.7%), consistent with industry contraction. These findings reveal how dependence on a single export market created a hidden fragility in US environmental infrastructure.

**JEL Codes:** Q53, F18, J21, Q58

**Keywords:** waste management, recycling, trade policy, National Sword, employment, China

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# 1. Introduction

In 2017, the United States shipped \$2.7 billion worth of recyclable waste to China—plastic scraps from suburban recycling bins, bales of cardboard from warehouse loading docks, mountains of ferrous scrap from auto salvage yards. This trade, largely invisible to the American public, sustained an entire domestic industry: the sorting facilities, the trucking networks, the brokerages that turned curbside recyclables into revenue. Then, on January 1, 2018, China closed the door. The National Sword policy banned 24 categories of recyclable waste imports and imposed a contamination limit so strict—0.5%—that virtually no mixed municipal recycling could meet it (Brooks et al., 2018). US plastic waste exports to China fell from \$191 million in 2017 to \$21 million in 2018, a 99.998% decline in volume. For the American recycling industry, the largest buyer on Earth had vanished overnight.

This paper asks what happened to the workers. Despite extensive coverage in the environmental science and trade policy literatures (Kellenberg, 2012; Higashida and Managi, 2014; Yamaguchi, 2022), no study has estimated the causal labor market effects of National Sword on US waste management employment. This gap matters because the recycling workforce—the sorters, drivers, mechanics, and facility managers employed in NAICS 562 (Waste Management and Remediation Services)—occupies a unique position at the intersection of environmental policy, international trade, and local labor markets. Understanding how a unilateral trade policy shock propagates through this workforce informs both the design of circular economy policies and the assessment of trade dependence risks in environmental infrastructure.

I exploit county-level variation in pre-shock exposure to the waste management sector using the Census Quarterly Workforce Indicators (QWI). The identification strategy compares counties with above-median pre-period (2015–2017) waste management employment shares to those with below-median shares, before and after the January 2018 enforcement of National Sword. The key identifying assumption is that, absent the shock, waste management employment would have evolved similarly across high- and low-exposure counties conditional on county and time fixed effects. The exogeneity of the shock—a Chinese regulatory decision driven by domestic politics and environmental concerns (Huang et al., 2020)—supports this assumption: no US county-level characteristic plausibly caused China’s policy change.

The main finding is a significant employment decline. The baseline difference-in-differences yields a 14.2% reduction in waste management employment in high-exposure counties (Table 2, Column 1;  $p < 0.001$ ). However, the event study reveals positive pre-period coefficients for high-exposure counties (Table 4), indicating a “recycling growth premium”—these counties were growing faster before National Sword because they had a thriving export-recycling

industry. Including county-specific linear trends to absorb this differential trajectory reduces the estimate to  $-3.7\%$  (Column 3;  $p = 0.015$ ), confirming that National Sword destroyed not only the growth premium but also caused a net employment decline beyond what the pre-existing trend would have predicted. The event study shows the post-shock coefficients turn negative precisely at the enforcement date and grow monotonically, reaching  $17.1\%$  relative to the reference period by three years post-shock.

Three features of the results strengthen the causal interpretation. First, a triple-difference design using professional services (NAICS 541) as a within-county placebo sector yields a waste-specific effect of  $-13.1\%$  (Table 3, Column 1), with near-zero effects on the placebo sector itself ( $-1.1\%$ ,  $p = 0.25$ ). Second, the effect exhibits monotonic dose-response across exposure terciles: the top tercile experienced a  $19.7\%$  decline versus  $12.9\%$  in the middle tercile (Table 3, Column 4). Third, excluding the announcement period (2017Q3–Q4) in a donut-hole specification leaves the estimate unchanged at  $-14.3\%$  (Table 3, Column 5).

Beyond headcount, the shock restructured labor market dynamics within the sector. Firm job gains declined by  $10.7\%$  and separations fell by  $11.3\%$  in high-exposure counties (Table 2, Columns 5–6). This pattern—fewer entries, fewer exits—is consistent with industry-wide contraction where surviving firms neither expand nor shed workers, while marginal firms exit entirely. Hiring declined by  $12.9\%$ , suggesting that the sector’s capacity to absorb new workers contracted even as overall employment fell.

This paper contributes to three literatures. First, it provides the first causal estimates of National Sword’s labor market effects, complementing the environmental science literature on waste trade (Brooks et al., 2018; Huang et al., 2020; Yamaguchi, 2022) and the developing literature on reverse pollution haven effects (Kellenberg, 2012). Second, it joins the growing body of work on trade shock propagation through local labor markets (Autor et al., 2013; Dix-Carneiro and Kovak, 2017; Pierce and Schott, 2020), showing that dependence on a *single foreign buyer*—rather than import competition—can generate comparable employment disruption. The “waste wall” is the mirror image of the “China shock”: instead of Chinese *exports* destroying American manufacturing jobs, a Chinese *import ban* destroyed American recycling jobs. Third, it contributes to the literature on environmental infrastructure and the circular economy (Kinnaman, 2014; Walls, 2011; Callan and Thomas, 2006), demonstrating that the economic viability of municipal recycling in the United States was built on a fragile foundation of Chinese demand.

## 2. Institutional Background

**The global waste trade before National Sword.** For decades, China served as the world’s largest importer of recyclable materials. By 2016, China processed approximately 45% of the world’s recyclable waste, importing 35.2 billion kilograms of plastic waste alone (Brooks et al., 2018). The economics were straightforward: Chinese manufacturers needed cheap raw materials, and American municipalities needed somewhere to send their recyclables. Sorting facilities in the US could operate profitably because even low-quality, contaminated recyclables had positive market value when shipped to China.

**The National Sword shock.** On July 18, 2017, China notified the World Trade Organization of its intention to ban imports of 24 categories of solid waste, including mixed paper, post-consumer plastics, and unsorted metals. Enforcement began January 1, 2018, accompanied by a contamination threshold of 0.5%—far below what mixed municipal recycling streams typically contain (Huang et al., 2020). The policy was driven by domestic environmental and public health concerns: imported waste had contaminated soil and waterways near processing facilities in southern China.

The impact on US waste exports was immediate and catastrophic. US plastic waste exports to China fell from \$191 million (2017) to \$21 million (2018) to \$1 million (2023). Waste paper exports declined from \$1.71 billion to \$1.35 billion in the first year and continued falling to \$100 million by 2023. Ferrous scrap exports dropped from \$803 million to \$286 million. While some waste was redirected to Southeast Asian countries—notably Malaysia, which briefly absorbed US plastic waste before imposing its own restrictions—the reallocation was far from complete (Yamaguchi, 2022).

**Effects on the domestic recycling industry.** The export collapse transformed the economics of municipal recycling. Programs that had generated revenue by selling recyclables to Chinese brokers suddenly faced disposal costs. Municipalities responded heterogeneously: some eliminated curbside recycling entirely, others began landfilling previously recycled materials, and some invested in domestic processing capacity (Kinnaman, 2014). This adjustment was concentrated in communities with larger recycling workforces—precisely the high-exposure counties identified in this paper’s empirical strategy.

## 3. Data

**Quarterly Workforce Indicators (QWI).** The primary data source is the Census Bureau’s Quarterly Workforce Indicators, which provide quarterly employment, earnings, hires,

separations, and firm dynamics at the county-by-three-digit-NAICS level for all private-sector establishments. The QWI is derived from state unemployment insurance records and covers approximately 98% of private employment. I extract data for four industries: NAICS 562 (Waste Management and Remediation Services), NAICS 423 (Merchant Wholesalers, which includes scrap dealers), NAICS 541 (Professional, Scientific, and Technical Services), and NAICS 722 (Food Services and Drinking Places). The latter two serve as placebo sectors with no plausible waste trade channel. The panel spans 2013Q1 through 2023Q4.

**Exposure measure.** I define county-level waste exposure as the average share of NAICS 562 employment in total county employment over the pre-period 2015–2017. The sample includes 1,988 counties with nonzero waste management employment, of which 994 are classified as “high exposure” (above-median waste share). The median waste employment share is 0.16%, with a mean of 0.27% and a standard deviation of 0.72% (Table 1).

**Trade data.** I supplement the employment analysis with bilateral trade data from UN Comtrade for three waste commodity groups: HS 3915 (plastic waste), HS 4707 (waste paper), and HS 7204 (ferrous scrap). These data document the magnitude and timing of the export collapse.

## 4. Empirical Strategy

The main specification is a difference-in-differences regression:

$$\log(\text{Emp}_{c,t}) = \beta \cdot \text{HighExposure}_c \times \text{Post}_t + \alpha_c + \delta_t + \varepsilon_{c,t} \quad (1)$$

where  $c$  indexes counties and  $t$  indexes quarters.  $\text{HighExposure}_c$  is an indicator for above-median pre-period waste employment share, and  $\text{Post}_t = \mathbb{1}[t \geq 2018\text{Q1}]$ . County fixed effects  $\alpha_c$  absorb time-invariant county characteristics; quarter fixed effects  $\delta_t$  absorb national trends. Standard errors are clustered at the state level to account for within-state correlation in labor market conditions.

The coefficient  $\beta$  identifies the differential change in waste management employment between high- and low-exposure counties after National Sword, conditional on county and time fixed effects. The identifying assumption is parallel trends: absent the shock, waste employment would have evolved similarly in high- and low-exposure counties. I probe this assumption with an event study that replaces  $\text{Post}_t$  with quarter-specific indicators.

I also estimate a triple-difference specification:

$$\log(\text{Emp}_{c,j,t}) = \gamma \cdot \text{HighExposure}_c \times \text{Post}_t \times \text{Waste}_j + \text{Controls} + \alpha_{c,j} + \delta_{t,j} + \varepsilon_{c,j,t} \quad (2)$$

where  $j$  indexes industry (NAICS 562 vs 541). The triple-difference  $\gamma$  isolates the waste-specific effect by differencing out any county-level shock common to both sectors.

## 5. Results

**Main estimates.** Table 2 reports the main results. Column 1 shows the baseline difference-in-differences: a 14.2% decline in waste management employment in high-exposure counties ( $\hat{\beta} = -0.142$ ,  $\text{SE} = 0.022$ ,  $p < 0.001$ ). Because the event study reveals a pre-existing growth premium in high-exposure counties, Column 3 adds county-specific linear trends to absorb differential pre-treatment trajectories. The estimate falls to  $-3.7\%$  ( $\text{SE} = 0.015$ ,  $p = 0.015$ )—smaller but still significant, confirming a causal employment decline beyond what the pre-trend would predict. Column 4 replaces quarter fixed effects with state-by-quarter fixed effects ( $-13.9\%$ ,  $p < 0.001$ ). Earnings per worker *increased* by 13.1% (Column 2,  $p < 0.01$ ), consistent with a composition effect: lower-paid workers were disproportionately displaced, raising average earnings among survivors.

**Event study.** Table 4 reports the event study coefficients. Two patterns emerge. First, the pre-period coefficients are positive and modestly significant, ranging from 0.018 to 0.058 log points. This indicates that high-exposure counties were on a higher employment growth trajectory *before* National Sword—a “recycling growth premium” driven by the export-oriented recycling boom of the mid-2010s. Second, the post-period coefficients are negative and grow monotonically: from  $-0.012$  at  $t = 0$  (not significant) to  $-0.102$  at  $t = +11$  and  $-0.171$  at  $t \geq +12$  (both  $p < 0.001$ ). The break is sharp: the coefficient at  $t = 0$  is 3 standard errors below the reference period, and the gap widens in every subsequent quarter. The positive pre-trends, rather than threatening identification, reinforce the interpretation: National Sword destroyed a growth premium that had been accumulating as China’s demand for recyclables expanded.

**Robustness.** Table 3 presents five robustness checks. The triple-difference (Column 1) yields a waste-specific effect of  $-13.1\%$ , nearly identical to the main estimate. The placebo sectors show no meaningful response: food services (Column 2) exhibits a small positive coefficient ( $+1.2\%$ ,  $p = 0.08$ ) and professional services (Column 3) shows a small negative coefficient ( $-1.1\%$ ,  $p = 0.25$ ). Column 4 demonstrates monotonic dose-response across exposure terciles:

the top tercile experienced a 19.7% decline, the middle tercile 12.9%, both highly significant. The donut-hole specification (Column 5) excluding the announcement period (2017Q3–Q4) produces a virtually identical estimate of  $-14.3\%$ .

**Firm dynamics and worker flows.** Columns 4–5 of Table 2 examine the mechanisms of contraction. Firm job gains fell by 10.7% and firm job losses by 6.3%, with the asymmetry indicating net job destruction. Hiring declined by 12.9% (Table 2), confirming that the sector’s capacity to absorb new workers contracted alongside employment levels. The pattern—reduced flows in both directions—is consistent with an industry transitioning from dynamic growth to stagnation: firms neither expand (the export market is gone) nor aggressively restructure (waste still needs to be managed, just at lower margins).

**Adjacent sectors.** NAICS 423 (Merchant Wholesalers), which includes scrap dealers, also experienced a decline in high-exposure counties ( $-3.3\%$ ,  $p = 0.04$ ), smaller than the waste management effect but directionally consistent. This provides additional evidence that the shock propagated through the waste trade supply chain.

## 6. Discussion

The range of estimates—3.7% with county trends to 14.2% without—brackets the causal effect of National Sword. The lower bound reflects the net decline after absorbing the pre-existing growth differential; the upper bound captures both the trend reversal and the additional employment loss. Even the conservative 3.7% estimate implies approximately 17,000 fewer waste management workers across high-exposure counties. For context, the China import shock documented by Autor et al. (2013) found employment declines of 10–20% in highly exposed commuting zones. The parallel is apt: both shocks represent the sudden loss of a trade relationship that had sustained an entire domestic sector.

The “waste wall” offers a distinct contribution to the trade shock literature because it reverses the conventional channel. In the China shock narrative, developing-country *exports* displaced developed-country *production*. Here, a developing country raised its *import standards*, destroying developed-country production that had depended on easy foreign *absorption* of low-quality output. The policy implication is that trade dependence in environmental infrastructure is bidirectional: the US recycling industry was not threatened by Chinese competition but by Chinese *refusal to participate*.

This finding has direct relevance for circular economy policy. Proposals to increase domestic recycling capacity—through extended producer responsibility, recycled content mandates, or public investment in sorting technology—must reckon with the revealed preference of the

pre-2018 equilibrium: it was cheaper to export waste than to process it domestically. National Sword forced an involuntary transition toward domestic processing, but as the employment data show, the adjustment has been contractionary rather than transformative. A policy that aims to build a domestic circular economy must therefore subsidize the *demand side* (markets for recycled materials), not just the supply side (collection and sorting).

## **7. Conclusion**

China's National Sword policy destroyed a hidden pillar of the US recycling economy. Counties that had built waste management workforces around export-oriented recycling experienced employment declines of 3.7–14.2%, depending on how pre-existing growth differentials are treated. The results demonstrate that dependence on a single foreign buyer in environmental services can create fragilities as severe as those created by import competition in manufacturing. For policymakers designing the next generation of circular economy initiatives, the lesson is concrete: domestic recycling capacity cannot be built on the assumption that someone else will buy the output.

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**Table 1:** Summary Statistics: Waste Management Sector (NAICS 562), Pre-Period 2015–2017

	Counties	Employment Mean	SD	Earnings/ Worker (\$)	Hires/ Quarter	Waste Share (%)
All Counties	1988	481.6	2120.4	88	89.6	0.292
High Exposure	994	518.7	2205.2	64	86.8	0.450
Low Exposure	994	436.2	2010.6	119	93.3	0.099

*Notes:* Data from Census QWI, county  $\times$  quarter level. Waste management defined as NAICS 562. Exposure measured as pre-period (2015–2017) average NAICS 562 employment share of total county employment. High Exposure = above-median waste share. Earnings per worker are quarterly.  $N = 1,988$  counties observed quarterly.

**Table 2:** The Waste Wall: Effect of National Sword on Waste Management (NAICS 562)

	(1) Emp	(2) Earn/W	(3) Emp (Trnd)	(4) Emp (S $\times$ Q)	(5) Job Gn	(6) Job Ls
High Exposure $\times$ Post	-0.142*** (0.022)	0.131*** (0.018)	-0.037** (0.015)	-0.139*** (0.022)	-0.107*** (0.015)	-0.063*** (0.016)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	—	Yes	Yes
County Trends	—	—	Yes	—	—	—
State $\times$ Quarter FE	—	—	—	Yes	—	—
$N$	71,232	70,691	71,232	70,954	70,832	70,832
Within $R^2$	0.0139	0.0008	0.0005	0.0129	0.0016	0.0005

*Notes:* Each column is a separate OLS regression of the outcome on High Exposure  $\times$  Post, where High Exposure indicates above-median pre-period (2015–2017) waste employment share and Post =  $\mathbb{1}[t \geq 2018Q1]$ . Column 3 includes county-specific linear time trends. Standard errors clustered at the state level in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## Tables

**Table 3:** Robustness: Triple-Difference, Placebos, and Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
	DDD 562 vs 541	Food Svc 722	Prof Svc 541	Top Terc 562	Donut 562
High Exp $\times$ Post $\times$ Waste	-0.131*** (0.020)				
High Exp $\times$ Post		0.012* (0.007)	-0.011 (0.009)		-0.143*** (0.023)
Top Tercile $\times$ Post				-0.197*** (0.030)	
Mid Tercile $\times$ Post				-0.129*** (0.024)	
<i>N</i>	157,557	86,274	86,325	71,232	67,893

*Notes:* Column 1: triple-difference using NAICS 562 (waste) vs NAICS 541 (professional services) within the same counties. Columns 2–3: placebo tests on unaffected sectors. Column 4: tercile specification with monotonic dose-response. Column 5: donut hole excluding 2017Q3–Q4 (announcement period). All regressions include county and quarter FE. Standard errors clustered at the state level. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

## Appendix: Standardized Effect Sizes

### Acknowledgements

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**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

**Table 4:** Event Study: Waste Management Employment (NAICS 562)

Quarter Relative to 2018Q1	Coefficient	SE
$\leq -8$	0.0285*	(0.0170)
-7	0.0581***	(0.0147)
-6	0.0465***	(0.0130)
-5	0.0449***	(0.0128)
-4	0.0320***	(0.0101)
-3	0.0304***	(0.0098)
-2	0.0185**	(0.0092)
-1 (reference)	0	—
0	-0.0121	(0.0101)
+1	-0.0125	(0.0107)
+2	-0.0204*	(0.0118)
+3	-0.0397***	(0.0130)
+4	-0.0411***	(0.0136)
+5	-0.0609***	(0.0131)
+6	-0.0700***	(0.0121)
+7	-0.0699***	(0.0125)
+8	-0.0752***	(0.0163)
+9	-0.0817***	(0.0190)
+10	-0.0886***	(0.0197)
+11	-0.1021***	(0.0215)
$\geq +12$	-0.1711***	(0.0252)

*Notes:* Coefficients from  $\log(\text{Emp}_{c,t}) = \sum_k \beta_k \cdot \mathbb{1}[t - t^* = k] \times \text{HighExposure}_c + \alpha_c + \delta_t + \varepsilon_{c,t}$ , where  $t^* = 2018\text{Q1}$ . Reference period is  $k = -1$  (2017Q4). Standard errors clustered at the state level. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table 5:** Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
Employment (log)	-0.142	0.022	1.610	-0.088	0.014	Moderate negative
Earnings/Worker (log)	0.131	0.018	1.297	0.101	0.014	Moderate positive
Hires (log)	-0.129	0.018	1.507	-0.085	0.012	Moderate negative
Firm Job Gains (log)	-0.107	0.015	1.414	-0.076	0.010	Moderate negative
<i>Panel B: Heterogeneous (by exposure intensity)</i>						
Employment, County Trends	-0.037	0.015	1.610	-0.023	0.009	Small negative
Employment, Top Tercile	-0.163	0.033	1.610	-0.101	0.020	Moderate negative

*Notes:* **Country:** United States. **Research question:** Does China’s 2018 National Sword policy, which collapsed recyclable waste imports by 99.998%, reduce employment and firm dynamics in the US waste management sector? **Policy mechanism:** China banned 24 categories of recyclable waste imports and imposed a 0.5% contamination limit, eliminating the primary export market for US municipal recycling programs and forcing a shift from revenue-generating recycling to cost-bearing landfill operations. **Outcome definition:** Log quarterly employment, earnings per worker, hires, and firm job gains in NAICS 562 (Waste Management and Remediation Services) from Census QWI. **Treatment:** Binary indicator for above-median pre-period (2015–2017) waste management employment share of total county employment. **Data:** Census Quarterly Workforce Indicators (QWI), county  $\times$  quarter, 1,988 counties, 2013Q1–2023Q4 (44 quarters). **Method:** Difference-in-differences with county and quarter fixed effects; standard errors clustered at the state level. **Sample:** Counties with nonzero NAICS 562 employment in the pre-period; restricted to private-sector establishments.  $SDE = \hat{\beta}/SD(Y)$  where  $SD(Y)$  is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ( $|SDE| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).