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ABSTRACT

Navigating Cleaner Waters: Waste Import and Water Pollution

This paper examines the causal impacts of reducing solid waste imports on water quality in China, which was the world's largest importer of waste until recently. We focus on the National Sword policy, introduced at the end of 2017, which abruptly banned the import of plastics, textiles, vanadium slag, and paper, reducing waste imports from 1.25 million tons per month to nearly zero. Using administrative data on waste imports and daily water quality readings from real-time automated monitoring stations across China, we exploit the sudden reduction in imported waste to identify significant improvements in dissolved oxygen levels in prefectures that previously imported the banned waste. These positive effects vary by the type of waste imported and are smaller in prefectures where the main importers are multinational firms. Our results are supported both by the Regression Discontinuity Design and the Difference-in-Differences framework. The magnitude of the effect is strongest immediately after the ban and gradually declines over time.

JEL Classification: Q53, Q56, Q58, F18, O13

Keywords: import waste, waste reduction, water pollution

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1 Introduction

Global solid waste management poses a significant challenge, with the World Bank projecting annual waste generation to rise from 2.01 billion tons today to 3.4 billion tons by 2050. Over the past two decades, the rapid increase in waste exports from developed to developing countries, propelled by lower costs, lenient regulations, and the demand for raw materials, has exacerbated global environmental challenges. Despite the urgency, there is limited understanding of the broader environmental impacts of large-scale policies that aim at reducing solid waste. Specifically, research on how waste reduction and improper recycling practices affect water resources in waste-importing developing countries remains particularly scarce (Greenstone et al., 2021).

In this paper, we provide causal evidence on the environmental impacts of waste imports in emerging economies, particularly those recognized as pollution havens. This paper estimates the causal environmental impacts of solid waste on water pollution by exploring the drastic policy shift known as the "National Sword Policy" in China. Enacted in January 2018, this policy banned 24 categories of waste imports across four main types: plastics, textiles, vanadium slag,[1] and paper, which accounted for 89% of the China's total waste imports. The policy reduced imports of these types of waste from 1.25 million tons per month following its announcement in August 2017, dropping to zero at the end of the year (see Figure 1).[2] This ambitious and stringent import waste ban policy, which effectively ended China's role as a major destination for global waste imports, offers a rare opportunity to study the environmental effects of substantial waste reduction.

The primary challenge in assessing the causal environmental impacts of reduced waste imports is the non-random distribution of waste volumes across regions over time. Provinces that imported more waste before the policy change may have had weaker local environmental regulations or little public concern for the environment, confounding the results. We utilize the sudden and significant decrease in waste imports to China following the National Sword policy to implement a Regression Discontinuity Design (RDD) in our analysis. This approach explores

[1] Vanadium slag is a byproduct generated during the production of steel or ferrovanadium alloys.

[2] We exclude data from the transition period (September-December 2017), or add a transition period dummy in our analysis because the reduction in waste imports during this time was likely influenced by the upcoming waste ban policy. Additionally, shipments received during this period likely included waste dispatched before the policy announcement.

the differences in water quality indicators before and after the policy change within a sufficiently short period of time. The strategy not only minimizes the effects of typical confounding factors, such as selection in waste import, but also eliminates concerns about the use of long-term data during this period, when policy initiatives targeting waste imports were frequent, such as Operation Green Fence in 2013 (Balkevicius et al., 2020) and the import license system in 2015 (Shang et al., 2020). Our analysis uses real-time readings of water quality published by automated water monitoring stations that encompass major rivers in China, which are considered more reliable due to their limited scope for data manipulation (Greenstone et al., 2022; Hu et al., 2023). Additionally, our administrative data on waste imports, detailed by eight-digit HS codes and destination prefectures, further enhance the precision of our analysis.

Our study reveals that the ban on waste import has led to an increase in dissolved oxygen levels, a key water quality indicator, by 2.65 mg/L (about one standard deviation) in prefectures that imported banned waste before import ban policy. While all waste types show some improvement in water quality, areas that imported vanadium slag experience the most significant gains. In contrast, we find that paper recycling, primarily carried out by large-scale facilities to produce low-grade paperboard, has a relatively limited impact on water quality. Our findings further suggest that the estimated environmental benefits are likely driven by reduced landfill use and lower industrial wastewater discharges following the policy change. In addition, we find that the improvement in water quality is largest in prefectures where the main waste importers were privately owned firms, and much smaller in prefectures where foreign-owned or multinational firms were the main importers.

In contrast to the significant before-after differences observed in prefectures that imported banned waste, we find no changes in water oxygen levels in prefectures that did not import banned waste, suggesting that our results are unlikely to be driven by unobserved confounding factors. However, a small spillover effect was observed in prefectures that did not import waste but are geographically located downstream of those that did, consistent with the flow of water bodies in China (He et al., 2020). No such spillover effect was observed in upstream prefectures.

Building on this finding, we further use those upstream prefectures that did not import waste as a control group to implement a Difference-in-Differences (DinD) framework. Compared to the RD estimates, which capture the immediate policy effect, the DinD estimates quantify the average effect over the post-policy period (2018-2019). The DinD estimation results align with our RD estimates. However, we find that the immediate effect (RDD) is larger than the average effect over the two-year post-policy period (DinD), suggesting that the impact of the National Sword policy diminishes over time.

Despite the scale of China's waste imports, as the world's largest waste importer until the implementation of the National Sword Policy, the environmental impact on water resources remains largely understudied, even as it becomes increasingly critical. The recycling and disposal of large amounts of solid waste require extensive water usage for cleaning, sorting, bleaching, and breaking down materials, leading to a significant water footprint. For example, recycling one ton of vanadium product from vanadium slag results in the generation of 30-50 tons of ammonia-contaminated water (Li et al., 2017). Waste and recycling residues can contaminate water through wastewater, landfill leachate, or improper dumping. These pollutants deplete dissolved oxygen by fueling decomposition, blocking sunlight needed for photosynthesis, and releasing toxins that harm oxygen-regulating organisms.

Although these significant water-related concerns exist, most research on solid waste management has focused primarily on air quality impacts (Tanaka et al., 2022; Guo et al., 2023; Li and Takeuchi, 2023; Shi and Zhang, 2023; Unfried and Wang, 2024), leaving the impacts on water quality largely unexplored. Water pollution has unique dynamics and mechanisms compared to air pollution, as pollutants originate from different sources and disperse through ecosystems in diverse ways (Keiser and Shapiro, 2019; Greenstone et al., 2021). In addition to its harmful effects on marine life and ecosystems, increasing evidence indicates that water quality is crucial for human health, affecting both drinking water safety and nutritional quality through its influence on agriculture (Ebenstein, 2012; Wang et al., 2022; Lin and Qian, 2024).[3]

[3]Previous research has documented the detrimental effects of surface water pollution on various health outcomes, including infant mortality, digestive cancer deaths and the health of older populations (Ebenstein, 2012; He and Perloff, 2016; Lai, 2017). Additionally, studies focusing on the roll-out of piped water in rural China have demonstrated significant improvements in both children's and adults' health outcomes, children's educational achievements, and reductions in infant mortality rates (Zhang, 2012; Zhang and Xu, 2016). Our research further adds to the growing body of literature on environmental regulations and water pollution, with a particular focus on developing countries (Cai et al., 2016; Chen et al., 2018; He et al., 2020; Greenstone et al., 2021; Hu et al., 2023).

To address the lack of empirical evidence on how waste management policies affect water quality in waste-importing developing countries, we exploit high frequency daily monitoring data to examine the impact of the National Sword Policy. Similar to Greenstone (2022), our regression discontinuity design compares outcomes before and after the policy using "day" as the running variable.[4] Specifically, we use daily panel data from 126 automated water monitoring stations across China in our analysis. The high frequency of our data ensures a large enough sample around the policy cut-off, reducing the need to widen the estimation window beyond around 200 days for credible identification.

Further, we observe that immediately following the announcement of the policy in mid-August 2017, waste imports to China sharply declined and virtually reduced to zero when the policy came into effect on January 1, 2018. During this four-month transition period, all water oxygen indicators steadily improved. This transition period provided sufficient time for adjustments in waste management practices, revealing its impact on water body. Our estimation results remain unchanged whether we drop the data from the transition period or include a dummy variable to account for the effect during the transition period.[5]

Our RD estimates essentially compare water quality in August 2017(policy announced) with January 2018(policy implemented). One concern is that the results may be driven by seasonality differences (August vs. January). We mitigate this concern by filter our water quality data using both month- and day-fixed effects. Furthermore, the absence of effects in upstream control prefectures during the same period suggests that our results are unlikely to be driven by seasonality. The absence of effects in placebo tests (e.g., comparing water quality in August 2015 with January 2016), further supports the robustness of our identification strategy.

This paper is closely related to the literature on the environmental effects of solid waste and waste management practices, where the empirical evidence is relatively sparse and largely focuses on developed countries (Akbulut-Yuksel and Boulatoff, 2021). Using a DinD framework, Shi and Zhang (2023), Li and Takeuchi (2023) and Unfried and Wang (2024) were the first

[4] Greenstone (2022) implements an RD design with "day" as the running variable using data from 654 air monitoring stations in China.

[5] We exclude data from the transition period (September-December 2017), or add a transition period dummy in our analysis because the reduction in waste imports during this time was likely influenced by the upcoming waste ban policy. Additionally, shipments received during this period likely included waste dispatched before the policy announcement.

to study the impact of China's NS Policy. Our paper makes several distinct contributions to this literature. First, while existing studies focus exclusively on the impact of the policy on air quality, this paper examines its impact on water—a key resource used in recycling and disposal—and highlights its unique impact, including spillover effects on downstream prefectures. Second, leveraging administrative data on waste imports by HS code, we differentiate the impact across waste types, whereas prior studies primarily examine the impact of plastic waste (Li and Takeuchi, 2023; Unfried and Wang, 2024) or overall all waste reductions (Shi and Zhang, 2023). Our heterogeneous results by banned waste types—showing a strong effect for slag but an insignificant effect for paper—raise important policy implication regarding whether a uniform ban on all waste imports is optimal. Third, utilizing high-frequency water quality data at daily level, we are able to analyze the immediate short-term effects by essentially comparing water quality in Aug 2017 (policy announced) with Jan 2018 (policy implemented). Combining RDD results with DinD results, we find that the impact on water quality is strongest immediately after the ban and gradually decreases over time. Fourth, we show that water quality steadily improved during the transition period (Sept-Dec 2017) as waste import gradually declined to zero (Figure 3).

This paper also contributes to the literature on the pollution-haven hypothesis, which suggests that stringent environmental regulations in developed countries may lead to the relocation of polluting industries to countries with weaker regulations. For example, environmental regulations such as Clean Air Act in the US led to an increase in outbound foreign direct investment, particularly involving polluting industries (Hanna, 2010; Tanaka et al., 2022).[6] Moreover, lower tariff and non-tariff barrier rates on polluting goods compared to cleaner goods are found to further facilitate the international trade of polluting products (Shapiro, 2021). This paper adds novel empirical evidence to the existing research on the relocation of polluting industries, focusing on one of the dirtiest types of products: solid waste.

The rest of the paper proceeds as follows. Section 2 provides a brief background on solid waste management in China and Operation National Sword. Section 3 describes the data, and

[6]Studies by Copeland and Taylor (2004); Levinson (2010); Cherniwchan et al. (2017) and Copeland et al. (2022) provide detailed support for this hypothesis.

the identification strategy is discussed in Section 4. Main results and robustness checks are reported in Section 5. Section 6 reports mechanisms and Section 7 concludes the paper.

2 Background

2.1 Waste Import in China and the National Sword Policy

Beginning in the 1990s, China's rapid industrial expansion led to a substantial demand for raw materials, often met by importing significant quantities of foreign waste for recycling. Consequently, China became the leading global importer of solid waste, with imports surging from 4 million tonnes annually in 1995 to over 45 million tonnes by 2016. Among these waste imports, 89% comprised wastepaper, plastic, textiles, and metal products. By the mid-2010s, half of the world's plastic scrap and wastepaper were imported into China (Tran et al., 2021; Xia, 2018). Recycling raw materials extracted from imported waste has been crucial for the growth and development of China's manufacturing industry (Chen et al., 2010; Shang et al., 2020).

Besides the large demand for raw materials, several other factors also made the waste importing and recycling process economically attractive, such as low labor and shipping costs. Additionally, environmental regulations in China, like in many other waste-importing countries, were less stringent compared to waste-exporting nations, further contributing to increased waste imports.

The large volumes of waste imports have been accompanied by significant challenges in waste management and widespread illicit waste trafficking (Tran et al., 2021; Katz et al., 2019). For example, Jambeck et al. (2015) reported that in 2010, China was the leading contributor to mismanaged plastic waste, with 76% of its 8.82 million metric tons of plastic waste improperly handled. Furthermore, the prevalence of small-scale, privately owned recyclers in China's recycling industry exacerbated waste management and hindered regulatory enforcement (Xia, 2018).

In response to growing concerns over waste contamination, illegal trafficking, and mislabeling, the Chinese government introduced regulations to improve the quality of imported waste and reduce its environmental impact. In February 2013, Operation Green Fence (OGF), a ten-month campaign, was launched to combat illegal imports and improve the quality of recyclables through stricter inspections. By the end of 2014, the Ministry of Ecology and Environment moved several categories of solid waste to restricted imports,[7] and in 2015, China further tightened controls with import quotas and a licensing system(Shang et al., 2020).

On July 18, 2017, China notified the WTO of its intention to permanently ban 24 categories of waste imports, classified into four specified types. The formal announcement of the waste ban to the public was made on August 10, 2017, through Decree No. 39, 2017 by the Ministry of Ecology and Environment (MEE) (see Appendix A for the Decree), with the ban scheduled to take effect after December 31, 2017. This policy is commonly referred to as the National Sword (NS) (Vedantam et al., 2022; Li and Mu, 2024). The four types of banned waste include unsorted wastepaper, post-consumer plastics, waste textile materials, and vanadium slag from metal production, covering 24 waste categories. Each of these 24 categories is specified by 10-digit HS codes by the MEE, and the complete list can be found in Appendix Table A1.

Figure 1a illustrates the monthly total import of banned waste from 2014 to 2019, while Figure 1b further breaks down the total amount into each of the four types of banned waste. These figures reveal that prior to the import waste ban announcement in August 2017, China imported around 1 to 1.5 million tons of these wastes every month. Following a sharp decline in the transition period of September to December 2017, the amount of imported waste virtually reached zero by January 2018. This underscores the effectiveness of the policy in curbing banned waste imports from the beginning of 2018, while also pointing out the transition period between the announcement of the policy in mid-August, 2017 and its full implementation in January 2018, allowing sufficient time for adjustment and gradual transition.

2.2 Dissolved Oxygen in Water

Dissolved Oxygen is the amount of oxygen gas that is dissolved in water. In our study, we primarily utilize daily measurements of dissolved oxygen (mg/L) as an indicator to assess water quality. This is motivated by the well-documented use of dissolved oxygen as a critical measure

[7] The policy is announced in Decree No. 80, 2014.

for evaluating the general health of aquatic environments and the quality of water for human use (U.S. EPA, 2023). Dissolved oxygen is not only vital for supporting a range of ecological processes but also is considered crucial for the overall well-being of aquatic ecosystems (Rounds et al., 2013; Wetzel and Likens, 2000; Behar et al., 1996). Further, dissolved oxygen levels in water serve as a reliable indicator for detecting water contaminants, which are potentially hazardous to human health (Bozorg-Haddad et al., 2021).

The optimal level of dissolved oxygen in the water bodies varies based on local environmental factors, such as atmospheric pressure and water temperature. Typically, warm water dissolves less amount of oxygen. However, water is generally classified as healthy if the dissolved oxygen concentration falls within 80 to 120 percent saturation and maintains a minimum value of 6.5 mg/L (U.S. Environmental Protection Agency, 2023; Behar et al., 1996).

2.3 How Waste Recycling Can Affect Water Oxygen Levels

There are three primary ways that waste and recycling residuals can end up in water bodies. First, the recycling process, notably for vanadium slag and textiles, demands substantial water use for cleaning, sorting, bleaching, and breaking down materials into smaller particles, inherently suggesting a significant water footprint. For example, in China, recycling one ton of vanadium product from vanadium slag results in the generation of 30-50 tons of ammonia-contaminated water (Li et al., 2017). The release of insufficiently treated wastewater into natural water bodies can introduce a variety of pollutants, such as chemical residues, suspended solids, and organic materials. Second, recycling residuals and contamination in the imported waste often end up in landfills. This can lead to the production of leachate, a liquid that, when not properly managed, can contaminate surrounding soil and water bodies. The composition of leachate varies based on the type of waste and can include hazardous substances harmful to aquatic ecosystems. Third, waste processing centers, especially small-scale privately owned facilities sometimes dump the waste into the water body, when waste exceeds their processing capacity.[8]

[8] For example, the Borgen Project once reported that 24 kilograms of floating debris, 88.7% of which is plastic, were found per 1,000 square meters of surface water in China (Jambeck et al., 2015).

When waste, residuals, and wastewater from recycling processes enter a water body, they can significantly impact dissolved oxygen levels in several ways. First, organic matter and chemicals in the waste can deplete oxygen as they break down. Microbes consume oxygen while decomposing the organic matter attached to the waste. Similarly, chemicals such as nitrogen-based compounds from recycling textiles and vanadium slag undergo nitrification, a process that also uses up oxygen. As a result, oxygen levels in the water can drop, sometimes to the point where they are completely depleted. These conditions can also lead to excessive algae growth, which further consumes oxygen and creates "dead zones"—areas where aquatic life cannot survive due to hypoxia (lack of oxygen). Second, waste materials that block sunlight can hinder photosynthesis in aquatic plants. Since photosynthesis is a key source of oxygen in water, this reduction further depletes oxygen levels. Third, toxic chemicals from waste, although they may not directly consume oxygen, can harm aquatic life. This reduction in the number of organisms that naturally help regulate oxygen levels can further disrupt the oxygen balance in the water. Appendix B further provides descriptions of how recycling each type of banned waste — plastic, textile, slag, and paper — could potentially reduce the water oxygen level.

3 Data Source and Descriptive Statistics

3.1 Water Quality Data

Our empirical analysis utilizes daily surface water quality data provided by the China National Environmental Monitoring Centre (CNEMC). The CNEMC publishes real-time surface water quality readings on its website, collected directly from its automated water quality monitoring stations across China. We collected the water quality readings for our analysis covering the period from January 1, 2015, to December 31, 2019. This dataset includes information from 126 automated water monitoring stations that consistently reported water quality data throughout our study period. These stations are distributed across 93 prefectures. Among these prefectures, 72 have only 1 station, 13 prefectures have 2 stations, and the remaining 8 have 3 to 5 stations. These automated stations cover major rivers in China that are deemed important by the CNEMC. The spatial distribution of these stations is illustrated in Figure 2, highlighting their coverage across Chinese prefectures.[9]

Over our study period, the CNEMC consistently reported dissolved oxygen, ammonia nitrogen, permanganate index, and pH levels from its automated stations. We primarily utilize daily measurements of dissolved oxygen as an indicator to assess water quality in our study, since it is regarded as a major indicator used to measure water pollution (Greenstone et al., 2021). We also present our main estimation results using ammonia nitrogen, permanganate index and pH levels in Appendix Table A2. Real-time water quality data is automatically updated every four hours, resulting in six readings per day. To evaluate daily water quality, we focused on the mode of dissolved oxygen from these six readings. This approach provides a more accurate and representative analysis of water quality.[10]

China started publishing real-time water quality readings from its automated water monitoring stations in the early 2010s. The advantage of using data published from automated stations is that it is likely to be more reliable than data from non-automated stations, due to the limited scope for data manipulation (Hu et al., 2023). However, the number of these automated stations is smaller than the total number of non-automated water monitoring stations, which exceeded 1000 in the mid-2010s.[11] One consideration related to the installation of automated water stations is that officials in prefectures with automated stations may be more vigilant about the public's environmental concerns (Axbard and Deng, 2024). Thus, it is important to note that the implementation of the National Sword Policy in 2018 does not coincide with the introduction of automated stations, which occurred several years earlier. Therefore, the likelihood of a discontinuity in 2018 being attributed to the introduction of automated stations is minimal.[12] We further investigate the continuity assumption related to this potential concern in Section 4.

[9] Note that due to data limitation, we only focus on mainland China. Taiwan is not included in this study.

[10] Our results remain virtually unchanged when we use the mean of the water quality readings.

[11] In early 2020,the CNEMC publishes real-time readings from more than 1000 water monitory stations.

[12] To further investigate this concern, we regress the presence of automated stations in each prefecture on the prefecture-level waste importing status in 2017. This analysis reveals no significant correlation between these two variables, providing additional evidence that such concerns are unlikely to have a substantial impact.

3.2 Waste Import Data

Our study also employs detailed firm-level annual trade data from 2015 to 2017, sourced from the China Customs Statistics (CCS) database. This database, maintained by the General Administration of Customs of China, provides a comprehensive record of all goods imported into China. It includes detailed information on trade products, identified by an eight-digit HS code, along with data on product quantity, unit, category, and value. Additionally, it offers granular firm-level details, such as the geographical location of importers at the prefecture level. Using the CCS data and HS code classifications, we identified the Chinese prefectures that were importing each banned waste category (i.e., plastics, textiles, paper, and vanadium slag), along with their corresponding trade volumes before the launch of the ban policy.[13]

3.3 Other Data

To provide a more comprehensive analysis of the factors influencing our results, we focus on two potential mediators: industrial waste and municipal solid waste (MSW). Data onindustrial waste, specifically the volume of industrial wastewater discharged, is compiled from the China City Statistical Yearbooks spanning from 2015 to 2019. This dataset includes information from 296 prefectures and details the total volume of wastewater discharged by industrial enterprises. For municipal solid waste, we use data from the China Urban Construction Statistical Yearbooks for the same period. This data provides county-level information on the volume of waste managed through landfills. This dataset is available for 644 counties, which we collapsed and merged into 325 prefectures using their census codes. Finally, we also compile a battery of time-variant prefecture-level indicators such as total GDP, population, number of post-secondary schools in the city, and the number of large firms. All control variables are collected from various China City Statistical Yearbooks available in the China City Database. The descriptive statistics of all these variables are reported in Appendix Table A3.

[13]The trade volume for banned waste is identified by matching the first 8 digits of the 10-digit HS code reported in the ban list with the 8-digit HS code reported in CCS. A potential concern is that CCS may include trade volumes of waste not covered by the ban due to differences in the last two digits of the HS code. However, the impact of this issue is likely to be limited. For instance, Figure 1 computed using the first 8 digits of the waste items' HS code, shows that the quantities have all dropped to near zero after the end of 2017, suggesting that the inclusion of non-banned waste is unlikely.

3.4 Summary Statistics and Descriptive Evidence of the Waste Ban Impact

Table 1 provides a detailed summary of our water quality indicator—dissolved oxygen. In addition to the level of dissolved oxygen, measured as mg of O_2 per liter of water (mg/L), denoted as DO, we also report the summary statistics for two dummy variables: Suboptimal DO and Extremely Low DO. Suboptimal DO equals 1 if dissolved oxygen is less than or equal to 6.5, indicating a healthy water oxygen level according to international standards (Section 2). Extremely Low DO equals 1 if DO is less than or equal to 3, a threshold used to define category 4 pollution levels by the Chinese Government, indicating severe pollution.[14]

Table 1 also includes both unadjusted (raw) outcomes and filtered outcomes. The filtered outcomes are generated by regressing each of the raw outcomes on month-fixed effects and day-fixed effects. The residuals from these regressions, representing deviations after accounting for these fixed effects are defined as the filtered outcomes. By construction, the filtered outcomes have a mean of zero. These filtered outcomes are used in all our regression analyses to account for within-year variations commonly influenced by seasonal weather patterns and human activities, factors that routinely affect water oxygen levels (Xu et al., 2020; Duan et al., 2018). For example, the average water oxygen level in the month of August is about 6 mg/L, whereas this number exceeds 9 mg/L in the month of January.[15]

Table 1 compares water quality indicators before and after the waste import ban policy in China. Notably, there is a visible increase in DO levels and a marked reduction in Suboptimal DO and Extremely Low DO following the waste ban policy. The DO level rose from 7.6 to 8.1, the proportion of Suboptimal DO decreased from 30.7% to 24.9%, and the proportion of Extremely Low DO decreased from 4.9% to 3%, respectively. Overall, the data in Table 1 provides preliminary evidence of the potential positive environmental effects of the waste ban policy, particularly regarding its impact on water quality in China.

Turning to waste import data, Appendix Table A4 reveals that within the 93 prefectures with automated water monitoring stations in our sample, 32 prefectures imported any type of banned

[14] Our results remain quantitatively and statistically robust when using alternative categories, such as a dummy indicating if DO level is less than or equal to 5 (category 3 in water quality) or DO level less than 6 (category 2 in water quality).

[15] Fail to account for such differences in seasonality violates the RD assumption, which requires that the policy treatment be the only factor causing differences in the outcome variable before and after the cutoff.

waste in 2017. Among these, 26 imported plastic, 14 imported textile, 2 imported slag, and 9 imported paper waste. This amounted to a total of 5,168 thousand tons of imported waste. Appendix Figure A.1 provides a detailed breakdown of the prefectures that imported waste in 2017, categorizing them according to the type of banned waste imported during this period (i.e., plastics, textiles, paper, and slag) conditional on the prefectures having automated water monitory systems. Notably, these maps reveal a significant overlap in the prefectures importing plastic and textile waste. In contrast, the importation of paper and, to an even greater extent, slag, appears to be more geographically dispersed.

In our main analysis, the waste import status of prefectures is determined by their waste import statistics in the year 2017 due to its proximity to our cut-off point in the RD design. Observations that are within the optimal bandwidth (before the cut-off) are almost all in 2017. In the robustness check, we also report the results where we use the import volume during 2015-2017 as an alternative indicator for waste imports.

4 Empirical Strategy

This study aims to assess the environmental impacts of waste imports on water quality. The causal identification of these effects is complicated by the non-random variation in the quantity of imported waste received across regions and over time, likely influenced by local economic activities and other unobserved factors. As we discussed in previous sections, the National Sword policy created a discontinuity in waste import on January 1, 2018, by imposing a total import ban on four types of waste: plastics, textiles, paper, and slag. The import volume of these banned items has dropped to virtually zero after January 1, 2018. To identify the causal effect of waste import on water quality, we, therefore, exploit the discontinuity on January 1, 2018, using the local-linear regression discontinuity design (RDD) approach. Specifically, we estimate the following regression:

$$Y_{it} = \alpha + f(d_t) + \beta NS_t + \varepsilon_{it} \tag{1}$$

where Y_{it} represents the water quality readings in monitoring station i on date t that are filtered by month and day fixed effects (see Section 3.4). Our running variable d_t denotes the distance in day(s) between the date of the water quality readings were recorded and the cut-off date (January 1, 2018). $f(d_t)$ is a first-degree polynomial in our running variable that is allowed to differ on both sides of the cutoff. To avoid overfitting, we use polynomials up to a quadratic in our estimations (Gelman and Imbens, 2018). Our policy variable, NS_t, is an indicator that equals 1 if the date is on or after January 1, 2018 ($d_t \geq 0$, i.e., the post-policy period). Our analysis primarily focuses on prefectures that imported any type of waste in 2017. Hence, the parameter of interest, β, measures the causal effect of the waste import ban policy on water quality in prefectures that imported any waste. In the results section, we will further investigate heterogeneity across different types of waste and compare the results with the prefectures that did not import any waste.

The RDD closely resembles randomized controlled experiments, where the assignment of treatment status is effectively random. As a result, the inclusion of control variables in RDD is generally unnecessary, similar to randomized controlled experiments. However, to ensure robustness, we include prefecture fixed effects as covariates in our robustness checks. Further, in our analysis, we adopt the data-driven optimal bandwidth selection approach as described by Cattaneo et al. (2019). To ensure the robustness and reliability of our findings, we also extend our analysis by applying various bandwidth selection procedures. Our baseline estimations utilize a triangular kernel, which gives more weight to observations that are closer to the cutoff. Additionally, to test the stability of our findings, we conduct estimations using a rectangular kernel.

We observe a clear decline in the volume of imported waste, starting immediately after the policy announcement in August 2017 and reaching zero by the end of the year (see, Figure 1). The reduction in waste imports during the transition period (September-December 2017) is likely influenced by the impending total waste ban policy, while shipments received during this period are also likely to include waste shipments sent out before the policy announcement.[16]

[16] Waste imported to China typically employs surface transportation, known for its time-consuming nature, making it challenging to manage the shipping period.

To provide additional evidence on the transition period, in Figure 3, we present the changes in water oxygen outcomes during this transition period in prefectures that imported any waste in 2017 (subfigure (a)-(c)), as well as for prefectures that did not import any waste (subfigure (d)-(f)). Consistent with Figure 1a, which demonstrates that the waste imports continuously declined during the period, Figure 3 (a)-(c) illustrates that all three water oxygen level indicators gradually improved, leading to a big contrast in water quality between the time the policy was announced and the time it was fully implemented. On the other hand, as expected, no significant changes in water quality indicators were observed during this period in prefectures that did *not* import banned waste, further supporting the validity of our analysis.

We employed two methods to incorporate this four-month transition period into our identification strategy. The first method involves adding a transition-period dummy to our main estimation model, while the second method simply drops the observations during the transition period. This second approach resembles the 'donut hole RD' strategy, which removes observations around the cutoff to address the sorting issue near the cutoff (Barreca et al., 2011). The difference is that the primary reason for applying the donut strategy in this study is driven by the policy design, rather than the necessity to address endogeneity issues. We find that both approaches essentially show the same results. For simplicity, we present the second approach in our main text and present the results of the first approach in the Appendix. Due to the exclusion of the transition period, therefore, August 31, 2017, is the last day before the cutoff date. We formally test the continuity assumption required for the RD design on both January 1, 2018 and August 31, 2017. Additionally, we note that our outcomes have already been adjusted using month-fixed effects and day-fixed effects, reducing the likelihood of bias from general seasonal differences between August and January.

The validity of the RD design relies on the continuity assumption which asserts that any abrupt shifts in water quality indicators at the discontinuity are solely attributable to the implementation of the waste ban policy. One concern is the potential manipulation of the running variable around the cut-offs, which, in our study, is the date. The continuity assumption requires that water quality readings are smoothly observed around the cutoff points and that the automated water monitory system is not intentionally turned on/off around the cutoff for unobserved reasons. We examine this assumption by analyzing the distribution of the observations of dissolved oxygen by day, as illustrated in Appendix Figure A.2. Our analysis reveals no evidence of manipulation around August 31, 2017, and January 1, 2018, as the observations are smoothly distributed around these two days.

We further demonstrate the absence of similar discontinuities in observed water quality by conducting several placebo experiments. In these tests, we arbitrarily assign a cutoff for the policy change to a previous year while mimicking our current setting by either excluding or not excluding a transition period applied in our main analysis. Additionally, we experiment with other hypothetical cutoff points in the months before the actual policy change. These placebo tests consistently fail to detect any discontinuities at the artificial cutoffs, thereby reinforcing the credibility of our RD approach. A detailed description of these robustness checks is provided in the next section.

To further support the continuity assumption, we also explore the possibility of abrupt changes in other prefecture-level factors that could influence environmental outcomes. Although the National Sword policy is part of broader initiatives aimed at reducing pollution in China, there is no evidence suggesting that its timing coincides with sudden shifts in other variables affecting water quality or abrupt changes in prefecture-level macroeconomic or socioeconomic indicators. Specifically, we analyze prefecture-level outcomes such as population, GDP per capita, and the presence of large firms to ensure these factors remain stable around the cutoff. In Appendix Figure A.3, we present the yearly prefecture-level data for these variables, applying a first-order polynomial to each side of the discontinuity point. The absence of significant changes in these macroeconomic indicators near the cutoff point strengthens the validity of our RD estimates. While prefecture-level macroeconomic data is unavailable at the monthly level, preventing a direct test of discontinuity on August 31, 2017, the observed yearly data show a consistent trend across 2017–2018, similar to previous years. This suggests that the likelihood of a sudden change on August 31, 2017, is minimal. Taken together with other continuity tests discussed above, we conclude that the continuity assumption is likely satisfied on both January 1, 2018, and August

31, 2017, reinforcing the credibility of our RD estimates.

5 Estimation Results

In this section, we begin by presenting the baseline estimates using the Regression Discontinuity (RD) design. Next, we investigate potential spillover effects and perform various sensitivity analyses to assess the robustness of our results under alternative specifications. Finally, we examine heterogeneity across different ownership types of waste importers and explore potential mediators, such as landfill use and industrial wastewater discharge, to better understand the mechanisms underlying our results.

5.1 Baseline Estimation

As is customary in RD design, we begin with the graphical illustration of the RD estimates. Panel A of Figure 4 presents RD plots for dissolved oxygen level. Each point represents the sample average of dissolved oxygen within a 10-day bin, while the lines depict a first-degree polynomial fitted separately on each side of the day cutoff. The discontinuity at day zero provides an estimate of the gap in dissolved oxygen caused by the waste ban policy. Subfigure (a) in Panel A indicates that the reduction of waste imports to China increases the dissolved oxygen level in the prefectures importing waste by 2.6 mg/L.

To further explore the diverse environmental impacts of the National Sword policy across different types of banned waste, we present RD graphs centered on prefectures categorized by the type of imported waste. The subfigures (b)-(e) demonstrate a clear impact of the policy, with a significant increase in dissolved oxygen levels, especially in prefectures that imported plastic, textiles, and slag. In contrast, the final subfigure, which restricts the sample to prefectures that did not import any waste in 2017, shows no observable change before or after the policy. The estimates provided in Panels B and C which focus on indicators for suboptimal dissolved oxygen levels ($DO \leq 6.5\,\mathrm{mg/L}$) and extremely low dissolved oxygen level ($DO \leq 3\,\mathrm{mg/L}$) are consistent with the findings in Panel A, further reinforcing the robustness of our results.

Building on the evidence illustrated in the RD plots, we now proceed to formally estimate our sharp RD model. Table 2 presents the bias-corrected and variance-adjusted robust RD estimates (Cattaneo et al., 2019). Consistent with the finding from the RD plot, the first column of Panel A demonstrates that the waste import ban has improved the dissolved oxygen levels in prefectures which imported any of the banned waste categories by 2.65 mg/L. This improvement corresponds to a one-standard-deviation increase in dissolved oxygen levels compared to right before the policy came into effect, and it is about 0.34 (= 2.654/7.7) of the mean dissolved oxygen level in the whole sample. Similarly, the RD analysis in the first column of Panel B indicates a significant decrease of 24 percentage points in the likelihood of reporting suboptimal oxygen levels following the implementation of the policy. This decline represents a reduction of 0.5 standard deviations (= 0.237/0.467) in reports of low oxygen levels at water monitoring stations after the policy took effect. Panel C yields statistically and quantitatively similar results, even when focusing on the rarer instances of extremely low oxygen levels, further demonstrating a consistent pattern of environmental improvement after the policy. Similar to results from RD plots, we find no discernible change in the water quality indicators for the prefectures that had no waste import before the National Sword policy (column 6 of Table 2).

We observe significant heterogeneity in water quality improvements across waste types (columns (2)-(5)). Prefectures that imported slag experienced the largest improvement, with effects nearly double those observed in prefectures importing textiles or plastics. On the other hand, prefectures that previously imported paper waste experienced limited effects. These differences are likely attributable to variations in recycling processes. As discussed in Section 2.3 and Appendix B, extracting vanadium from slag generates substantial volumes of toxic water, which is challenging to reuse and highly detrimental to ecosystems. In comparison, recycling paper to produce low-grade cardboard requires minimal water use, resulting in a limited impact on dissolved oxygen levels.

5.2 Spillover Effects

Our investigation further examines the spillover effects on prefectures that did not import any waste before the National Sword policy, focusing on how river streams influence the effects downstream and upstream, respectively. To classify upstream and downstream prefectures, we adopted the framework outlined in He et al. (2020) and Cai et al. (2016). In China, rivers generally flow from east to west. As illustrated in detail in Figure 5, we categorized non-waste-importing prefectures as upstream or downstream based on their location relative to waste-importing prefectures. Water stations in downstream prefectures capture water flowing from waste-importing prefectures, leading us to hypothesize that only downstream stations would show improvements in water quality as a positive spillover effect of the policy, while upstream prefectures would not exhibit such improvements. To ensure the robustness of our findings, we analyze water quality data from stations at varying distances–from 50 km to 150 km–where rivers cross prefectural boundaries.

Our findings, summarized in Table 3, support this hypothesis. Stations located upstream of the waste-importing prefectures show no significant change in water quality (column (1)). We note that upstream also includes isolated stations that are far away from waste-importing areas. In contrast, downstream prefectures exhibit a notable decline in the presence of suboptimal dissolved oxygen (Panel B, columns (2) and (3)). However, the spillover effects appear to be relatively moderate. We see that the effect on the presence of extremely low oxygen levels and the overall oxygen level is not statistically significant at the conventional levels, though the direction of the coefficient is consistent with our hypothesis. As water flows downstream, pollutants from waste-importing prefectures likely dissipate, reducing their impact on downstream areas. Consequently, before the policy, the negative spillover effect on downstream prefectures was likely to be relatively small compared to the pollution level caused by the prefectures that imported waste. This likely explains the relatively moderate, though significant, improvement in downstream prefectures after the implementation of the waste ban policy.

The absence of the effect on upstream prefectures also validates our identification strategy and strengthens the argument against confounding variables. If there are any confounding factors around the cut-off, that bias our results, these factors must also exhibit a special geographic pattern, systematically affecting only the prefectures importing waste and their immediate downstream prefectures, but not immediate upstream prefectures.

5.3 Alternative Estimation Strategy: DinD

In this subsection, we employ a Difference-in-Differences (DinD) strategy to estimate the impact of the National Sword policy on water quality. The DinD strategy is used in existing studies that examine the impact of waste import ban on air quality in China (Li and Takeuchi, 2023; Shi and Zhang, 2023; Unfried and Wang, 2024).

Since there is a clear spillover effect on downstream prefectures, the control group in our DinD framework comprises 44 upstream prefectures that did not import any waste prior to the policy. This group helps capture the potential influence of confounding factors that may have systematically affected water quality across China before and after the policy.

We implement a standard DinD model, regressing the water quality indicator on an interaction term between the treatment status of prefectures and a post-2018 dummy, while controlling for year and prefecture fixed effects. The treatment status here is defined in two ways. The first specification sets a treatment dummy equal to one if a prefecture imported any waste in 2017, and zero if the prefecture is an upstream prefecture without any waste import in 2017. The second specification of treatment status uses the log of the volume of banned waste imported in 2017 in each prefecture.[17] *Post* dummy equals one if the date is on or after January 1, 2018. The transition period of September- December 2017 is not included in the estimation. Similar to our RDD specification, our DinD results remain consistent when treating the transition period as a dummy variable instead of excluding those observations.[18]

We first implement the DinD strategy using observations within the bandwidth estimated in the RD design. This "RD-DinD" approach allows us to leverage the strengths of both strategies, mitigating potential confounding factors by comparing outcomes immediately before and after the policy within a sufficiently short time frame while also accounting for differences between affected and control prefectures.

Table 4 reports the estimation results. Each cell reports the estimation of a separate regression. To estimate the optimal bandwidth, column (1) first conducts an RD design using the sample including both treated prefectures and upstream control prefectures. The estimated

[17] Prefectures did not import any banned waste is defined as 0.
[18] Estimation results available upon request.

optimal bandwidth of 204 days, which includes 31,800 effective observations, is subsequently utilized in the DinD analysis shown in column (2). The remaining columns examine the results across different sample periods. Column (3) use half of the optimal bandwidth, including only 102 days before and after the cutoff; column (4) double the optimal bandwidth, extending the sample to 408 days before and after the cut-off, while column (5) includes the entire sample period (2015-2019) and estimates the DinD specification reminiscent of earlier studies.

Applying our DinD strategy to different sample periods, we find that the impact of the National Sword policy is stronger in the short run and gradually declines over time. For instance, in Panel A of Table 4, where Dissolved Oxygen is used as the outcome variable, the DinD estimator is 1.854 when only 102 days before and after the cutoff are included. The size of the effect decreases to 0.608 when the sample extends to 408 days before and after the cutoff and further declines to 0.434 when the full sample period is included. All results are statistically significant at the 5% level. Overall, the RDD estimator is larger than the DinD estimator, likely because RDD captures the immediate policy effect (comparing water quality in August 2017 vs. January 2018), while DinD estimates the average differences before and after the policy over the entire sample period applied in the estimation.

A similar pattern emerges when alternative outcome variables (Suboptimal DO and Extremely Low DO) are used in Panel B and Panel C, respectively. The findings are also robust to using the volume of imported waste as a continuous treatment measure rather than a binary indicator. Finally, parallel trends tests, reported in Appendix Table A5, confirm that treated and control groups followed similar pre-policy trends prior to the implementation of the National Sword Policy in 2018.

5.4 Robustness Tests and Validity Checks

To strengthen the reliability of our RD estimates, we perform a series of robustness tests summarized in Table 5. The first column of Table 5 incorporates prefecture-level fixed effects to the baseline RDD specification improving the statistical efficiency of our estimates by accounting for historical variations in water quality across prefectures. Subsequent columns in Table 5 present alternative specifications with a quadratic polynomial of the running variable and where we apply the CER-optimal bandwidth selection procedure outlined by Cattaneo et al. (2019). Additionally, we test the sensitivity of our results to data-driven bandwidths by halving or doubling the MSE-optimal bandwidth. In column (6), we further use a uniform kernel for our RDD specification, while column (7) expands our donut specification by excluding data from August 2017, the month that coincides with the announcement of the National Sword policy to test whether our results are sensitive to the data points close to the cut-off. Further, in our baseline specification, a prefecture is defined as "treated" if it imported any waste during 2017. This definition is based on optimal bandwidth of approximately 200 days, which implies the use of observations only in 2017 before the cut-off. To test the sensitivity of this definition, the last column expands the waste-importing period for defining treatment status to include the years 2015–2017. The extensive analyses presented in Table 5 collectively confirm the robustness of our RD estimates across various specifications, bandwidth selections, polynomial choices, and kernel applications.

The RD design enables us to identify the causal effects of the waste import ban on water quality indicators, provided that improvements around the cutoff date can be attributed to the policy change rather than independent temporal changes. This risk is largely mitigated by the daily frequency of our water readings and the relatively narrow estimated bandwidths, which span only a few months at most. Nevertheless, to further validate this assumption, we conduct placebo experiments to test for potential discontinuities unrelated to the policy. Specifically, we falsely assign alternative policy announcement dates, while ensuring that the falsification tests do not overlap with the observations in our main analysis (Imbens and Lemieux, 2008). The results of these falsification tests are summarized in Table 6. The first column mimics the main RD specification, but shifts the start of the policy to January 2016, while dropping the months of September to December 2015, which corresponds to the time between the announcement of the policy in mid-August and its implementation in the upcoming January. We further present the RD plots for this placebo exercise in Figure 6. In column (2), similarly, we retroactively adjust the policy timeline by 365 days, setting August 31, 2016, as the new end date before the policy starts and September 1, 2016, as the beginning. The last column extends this adjustment by two years, with August 31, 2015, as the end date before the policy's start on September 1, 2015. It is comforting that none of these placebo experiments reveal any discontinuities in our data. Taken together, the evidence from Tables 5 and 6 and Figure 6 and Appendix Figure A.3 on other prefecture indicators collectively bolster our confidence that the estimated effects represent the environmental impact caused by the waste import ban policy, not other confounders around the cut-off.

As discussed in the background section, there was a transition period between the announcement of the policy in August 2017 and its implementation in January 2018; thus, we re-estimate Eq.(1) by adding a transition dummy variable, instead of dropping all observations in the transition period. This dummy variable equals one for days between September 1 and December 31, 2017, and zero otherwise to capture the transition period. This specification compares the average water quality during the transition period to the water quality immediately before the announcement of the policy in August 2017. The results presented in Appendix Table A6 indicate that our point estimate of β remains essentially unchanged in this specification. The coefficient of the transition dummy suggests that, on average, the water DO level improved by 0.94 during the transition period (column 1, Panel A).

We further test the robustness of our results by excluding prefectures that imported less than 10% of the median value of each type of waste (see Appendix Table A7). This specification allows us to focus more precisely on prefectures that experienced a more substantial reduction in imported banned waste. Additionally, we extend our baseline specification by exclusively focusing on prefectures that imported only one type of waste, as some prefectures imported multiple types of banned waste. The result of this analysis are summarized in Appendix Table A8.[19] Collectively, the estimation results presented in Appendix Tables A7 and A8 are consistent with the findings in Table 2, further reinforcing the robustness of our baseline results.

One concern related to our estimation is the potential impact from the production side. The main purpose of China's waste imports has been to extract raw materials to meet the large demand in production. Thus, the sudden decline in waste imports could potentially reduce pro-

[19] Since there is no prefecture imported only slag, we are not able to perform these robustness checks on slag.

duction activities and, consequently, influence environmental outcomes. To address this, we first demonstrate that the volume of waste import is relatively small compared to the total volume of production (see Appendix Table A9). For example, the import of textile waste accounted for less than 1% of the total production of intermediate textiles in 2017. On the other hand, for plastics, the volume of waste import is relatively large, accounting for almost 7% of the volume of production. We, therefore, further investigate the change in production level around our cutoff. We find that the production of goods likely to use the banned waste remained relatively stable in 2017 and 2018 (see Appendix Figure A.4). Additionally, we do not observe any significant changes in water quality in prefectures that produce outputs potentially using the banned waste but did not import any waste (see Appendix Table A10). Based on this evidence, we conclude that our results are unlikely to be influenced by any potential changes in production activities around the cutoff.

5.5 Heterogeneity by Firm Ownership

Having shown that the waste import ban has significantly improved a spectrum of water quality indicators, we now investigate the potential sources of heterogeneity in the estimated effects of the National Sword policy. Previous research has documented significant variations in recycling processes across different firm types. Typically, privately-owned enterprises (POEs) exhibit potentially higher pollution levels due to their small-scale and inefficient recycling methods (Collins and Harris, 2002; Eskeland and Harrison, 2003; Cole et al., 2006). In this subsection, we explore potential sources of heterogeneity based on firm ownership.

Our data reveals that 20% of the total banned waste was imported by foreign-owned or foreign-jointly owned enterprises (FOE), while the remaining portion was imported by domestic importers. Among domestic importers, privately-owned enterprises (POEs) were the main actors, accounting for 88% of the imported waste, with the remainder handled by state-owned or collectively owned firms. To examine whether the estimated effect of the policy varies by the firm characteristics, we group prefectures based on the percentage of imported volumes by each type of firm ownership and re-estimate our main specification. The results are summarized in

Table 7. Column (1) focuses on prefectures that were predominantly foreign-owned, i.e., where at least 50% of the imported waste was brought in by FOEs. Column (2) presents results for prefectures where waste imports were primarily handled by domestically owned firms. Column (3) further narrows our focus to prefectures where POEs specifically imported at least 50% of the banned waste.

Our analysis in Table 7, columns (2) and (3), shows that prefectures with a higher presence of domestically owned firms, particularly POEs, experienced significant improvements in water quality following the import waste ban policy. These improvements are reflected in a substantial increase in dissolved oxygen levels (approximately one standard deviation) and a notable reduction in occurrences of dangerously low oxygen readings (around half a standard deviation). In contrast, in prefectures where FOEs predominated, we observe that the dissolved oxygen level and the presence of extremely low oxygen levels are not statistically significant. There is only a significant reduction in the presence of suboptimal dissolved oxygen levels after the policy. These results suggest that the pollution levels caused by FOE importers were likely to be less harmful compared to domestic firms, especially POEs.[20]

Our findings regarding POEs are consistent with previous literature on air quality.Unfried and Wang (2024) have shown that the importation of plastic waste by POEs led to a significant increase in PM2.5 levels. On the other hand, the estimation results from Table 7, suggesting lower water pollution levels from FOEs are intriguing. Given the evidence presented in Table 7, it is possible that the waste imported by FOEs is less contaminated, or FOEs have used more environmentally friendly technologies to recycle the waste, resulting in a reduced environmental burden. The differential effects across firm ownership could likely be attributed to various factors, including the initial levels of technology adoption, the scale of operations, and the firms' capacity to invest in cleaner technologies (Huang and Chang, 2019).

[20] It is possible that the results regarding FOEs are influenced by the type of waste imported by FOEs, particularly if FOEs primarily import paper waste, a type that does not significantly impact oxygen levels. We explore this potential by excluding all FOEs that import paper waste. The results in column (2) remain virtually unchanged in this specification.

6 Mechanisms

In this section, we provide formal evidence on the potential mediators and channels explaining our results. As described in Section 2, both landfill and industrial wastewater discharge generated from the recycling process can contribute to water pollution. Therefore, we exploit the changes in waste management practices brought by the National Sword policy to investigate whether and to what extent each type of waste—plastics, textiles, paper, and slag—pollutes water through these two channels.

Using annual data on landfill and industrial water discharge reported by each prefecture, we first examine the association between landfill, industrial wastewater and dissolved oxygen. This analysis is conducted through a simple OLS regression, controlling for prefecture-fixed effects. The results summarized in Appendix Table A11 confirm that landfill and industrial water discharge are indeed negatively associated with the dissolved oxygen levels in the water and lead to a higher frequency of suboptimal dissolved oxygen readings.

Next, we formally assess the impact of the import ban policy on landfill volumes and industrial water discharge as potential channels. We employ a difference-in-differences specification in this analysis and explore these channels through each of the four types of banned waste. This allows us to examine the post-policy effects by waste type through the interaction between the logarithm of waste imported in 2017 and a post-policy indicator. The findings are reported in Table 8, with the top panel presenting results for landfill volumes and the bottom panel focusing on industrial wastewater discharge.

Consistent with the objective of the National Sword policy, our analysis shows a significant reduction in landfill volumes in prefectures that previously imported significant amounts of waste, with the largest decreases observed in regions importing textiles and paper. Furthermore, the bottom panel in Table 8 indicates a decline in industrial water discharge, particularly in prefectures that imported textiles and, to a lesser extent, slag. However, the effect on plastic and paper is not statistically significant at the conventional level, suggesting that the recycling process of these two types of waste in China is unlikely to consume a large amount of water.

Both Shi and Zhang (2023) and Unfried and Wang (2024) indicated the possible impact of open fires on air quality during waste processing. Their findings raise concerns about an alternative pollution pathway: from air to water transmission. Pollutants in the air could be deposited into water bodies through rainfall, leading to water pollution. However, our estimation results on upstream and downstream prefectures show that the waste ban policy has spillover effects only on downstream control prefectures, but not upstream prefectures, suggesting this pathway is unlikely. If pollution were initially airborne and then deposited in water bodies, the effects would not be strictly confined to downstream locations but would also correlate with wind patterns. For example, previous studies have identified a pollution source as "upwind" if it is within 45 degrees of the dominant quarterly wind vector that passes through the monitor (Freeman et al., 2019; Axbard and Deng, 2024). The absence of patterns correlating with wind implies that pollution mainly operates directly through water, rather than air. This highlights the efficacy of the policy in addressing water pollution and enhancing environmental health.[21]

7 Discussion and Conclusion

This paper provides one of the first pieces of causal evidence on the impact of a major waste reduction policy on water quality in a developing country often labeled a "pollution haven." We examine the effects of waste management practices on water pollution by analyzing China's National Sword policy, enacted in January 2018, which banned the import of plastics, textiles, vanadium slag, and paper. Leveraging the sharp decline in waste imports following the policy's implementation, our study documents significant short-run improvements in water quality.

The most pronounced improvements were observed in areas that imported slag, with notable gains also seen in regions that imported plastics, textiles, and, to a lesser extent, paper. Furthermore, downstream prefectures experienced positive environmental spillovers, consistent with natural water flow patterns. Our findings offer valuable insights into the policy debate on the environmental consequences of waste management, highlighting the critical role of regulation in

[21] Given the prevalence of illegal dumping of both industry waste and household waste across China (Kang et al., 2020; Jiao et al., 2024), it is possible that some of the imported waste and their recycling residuals may have been illegally dumped. Due to a lack of data on the volume of illegal dumping, we are unable to quantify the effect of each type of waste through this channel. Nonetheless, given the estimated positive effects of the waste ban policy on water quality indicators, our results likely represent lower-bound estimates in the presence of illegal dumping.

improving water quality. While the policy had a substantial initial impact, its effects appear to diminish over time—an area that warrants further investigation in future research.

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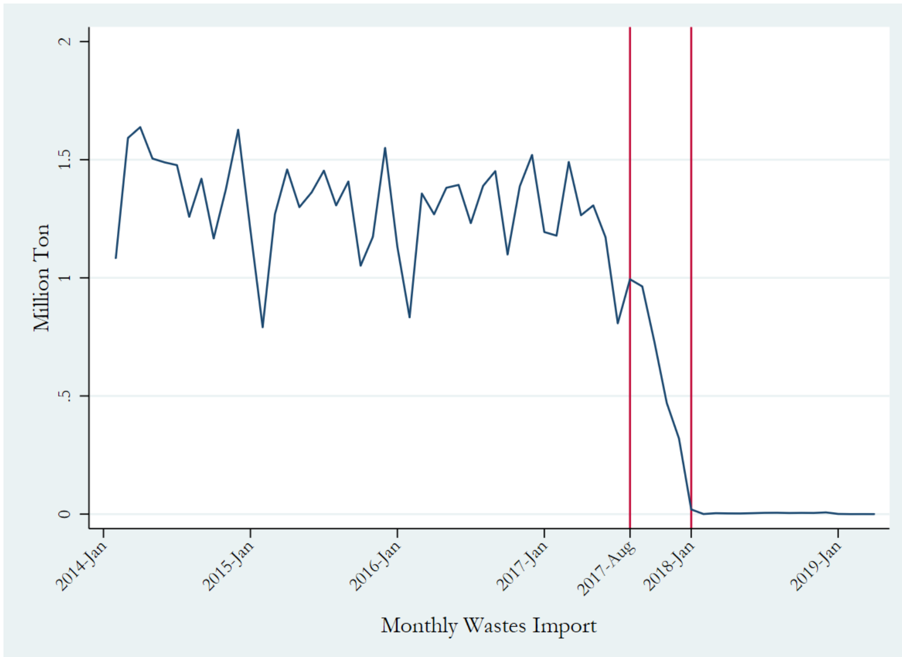
Figure 1: Monthly import of the waste that was banned on January 1, 2018

(a) All four types of banned waste



(b) By type of waste

Data source: China Customs Statistics (CCS) database.

Figure 2: Prefectures have automated water monitoring stations and upload real-time data on CNEMC website during 2015-2019

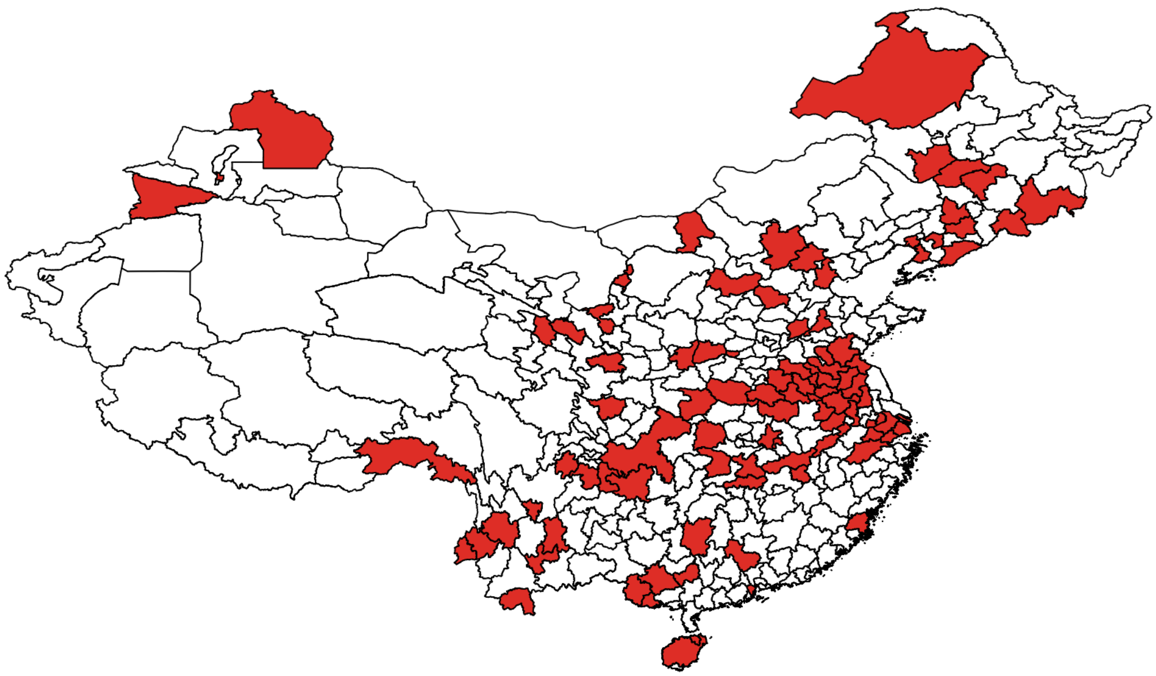
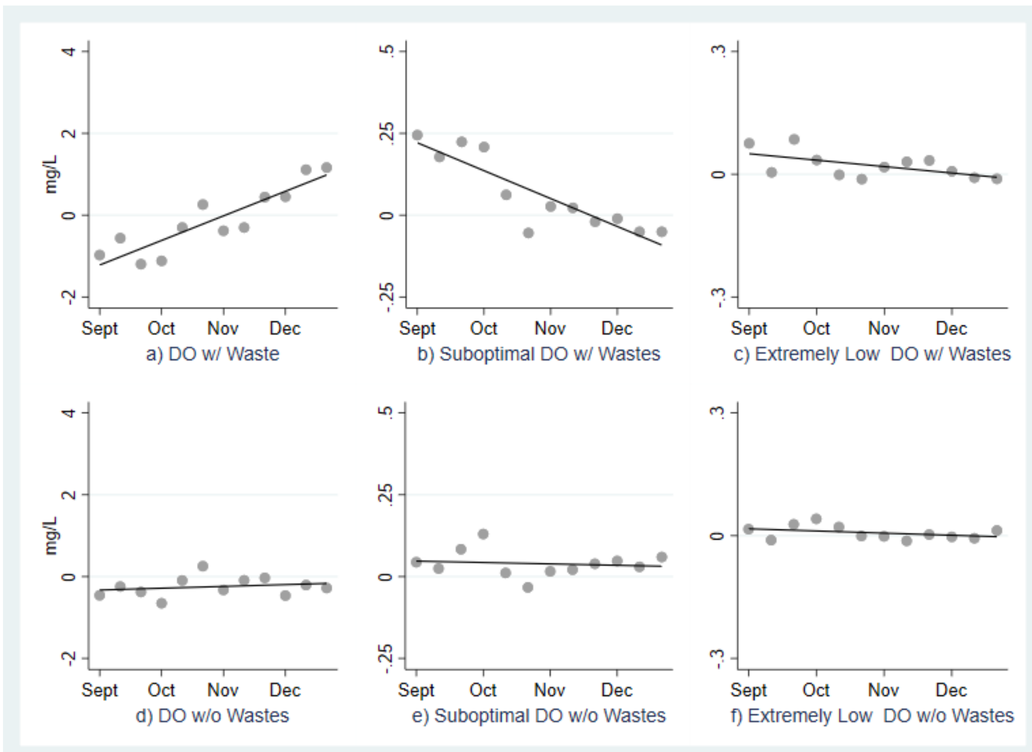
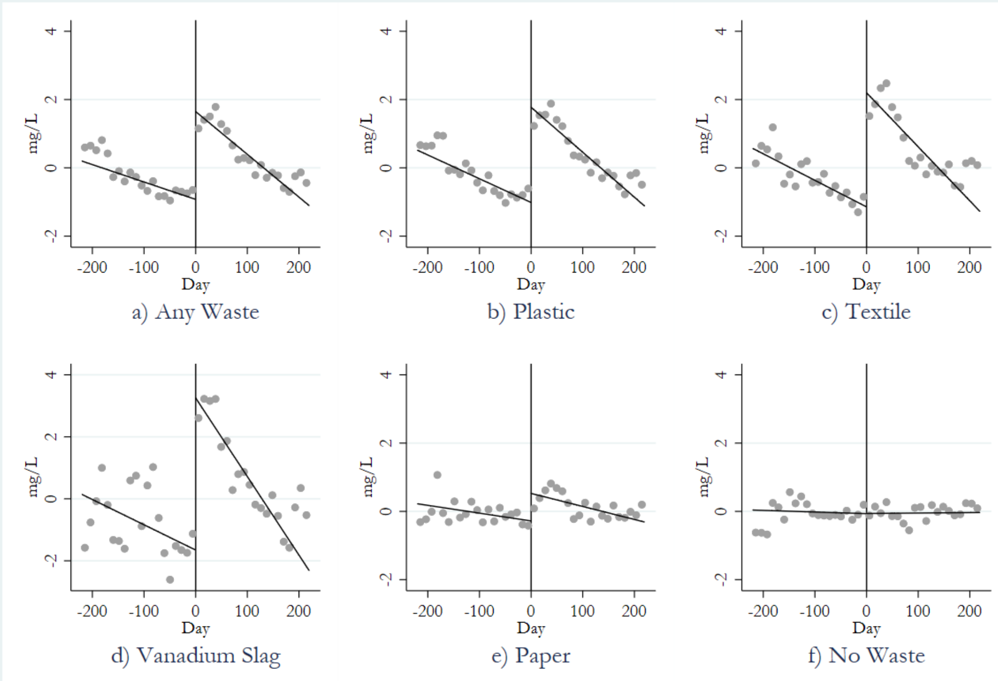


Figure 3: Water quality during the transition period (Sept. 1, 2017 – Dec. 31, 2017) by waste importing status

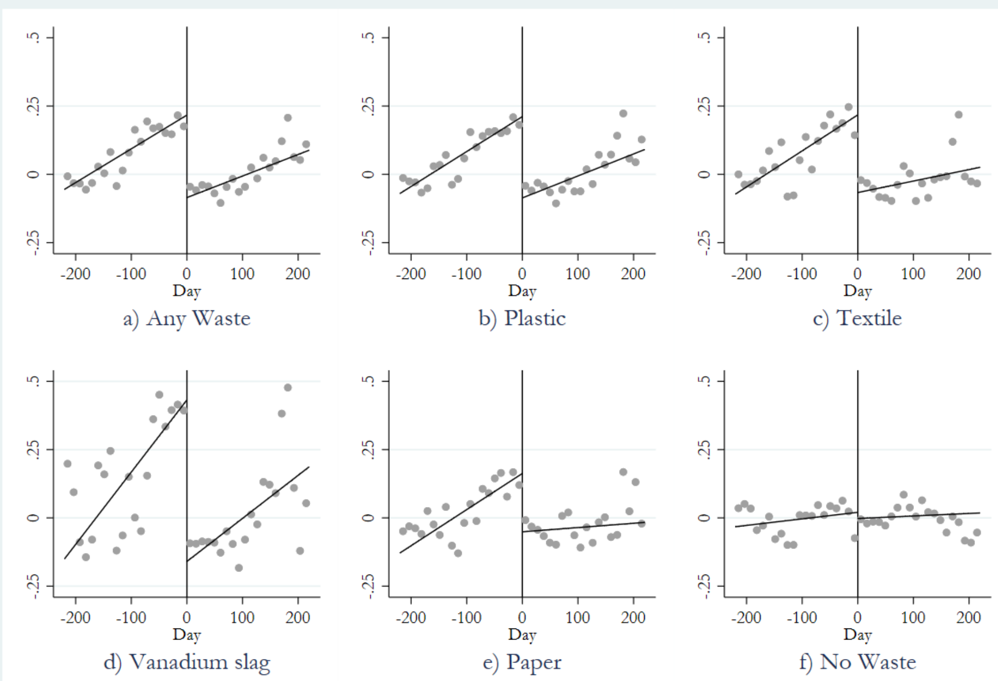


Notes: The graphs show that the water qualities have gradually improved during the transition period in the prefectures imported waste in 2017 (Subfigure a, b and c), while the water qualities remained relatively stable in prefectures did not import any waste and thus not affected by the policy (Subfigure d, e and f). The transition period is the period right after the National Sword Policy was announced in Aug. 2017, but before it fully came into effect in Jan. 2018. Each point in the subfigures denotes the sample average of water dissolved oxygen outcome for a 10-day bin. The lines plot a first-degree polynomial estimated using all the points shown in the graph. Suboptimal dissolved oxygen level indicates DO ≤ 6.5; Extremely low dissolved oxygen level indicates DO≤ 3. All outcome variables are filtered by month and day-fixed effects.

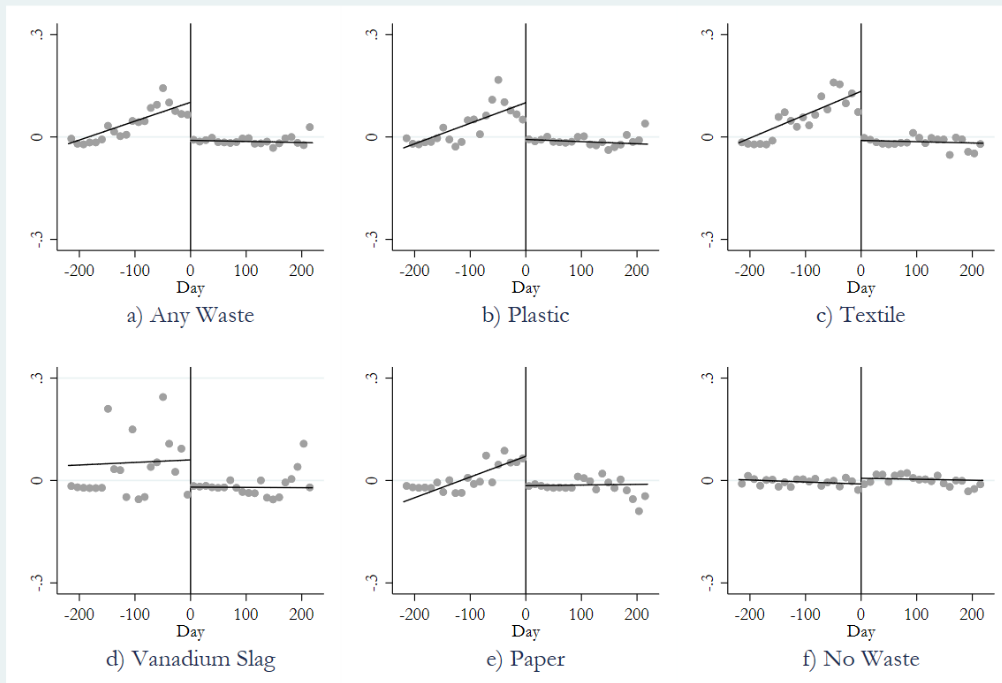
Figure 4: Distribution of water dissolved oxygen around the waste ban cutoff



Panel A. Dissolved Oxygen Level



Panel B. Suboptimal Dissolved Oxygen



Panel C. Extremely Low Dissolved Oxygen

Notes: Each point denotes the sample average of water dissolved oxygen outcome for a 10-day bin. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. The lines plot a first-degree polynomial estimated separately on either side of the day cutoff. Suboptimal dissolved oxygen level indicates DO $\leq$ 6.5; Extremely low dissolved oxygen level indicates DO $\leq$ 3. All outcome variables are filtered by month and day-fixed effects.

Figure 5: Illustration of measured distance from an upstream prefecture with waste import to a water monitoring station located in a downstream prefecture without waste import

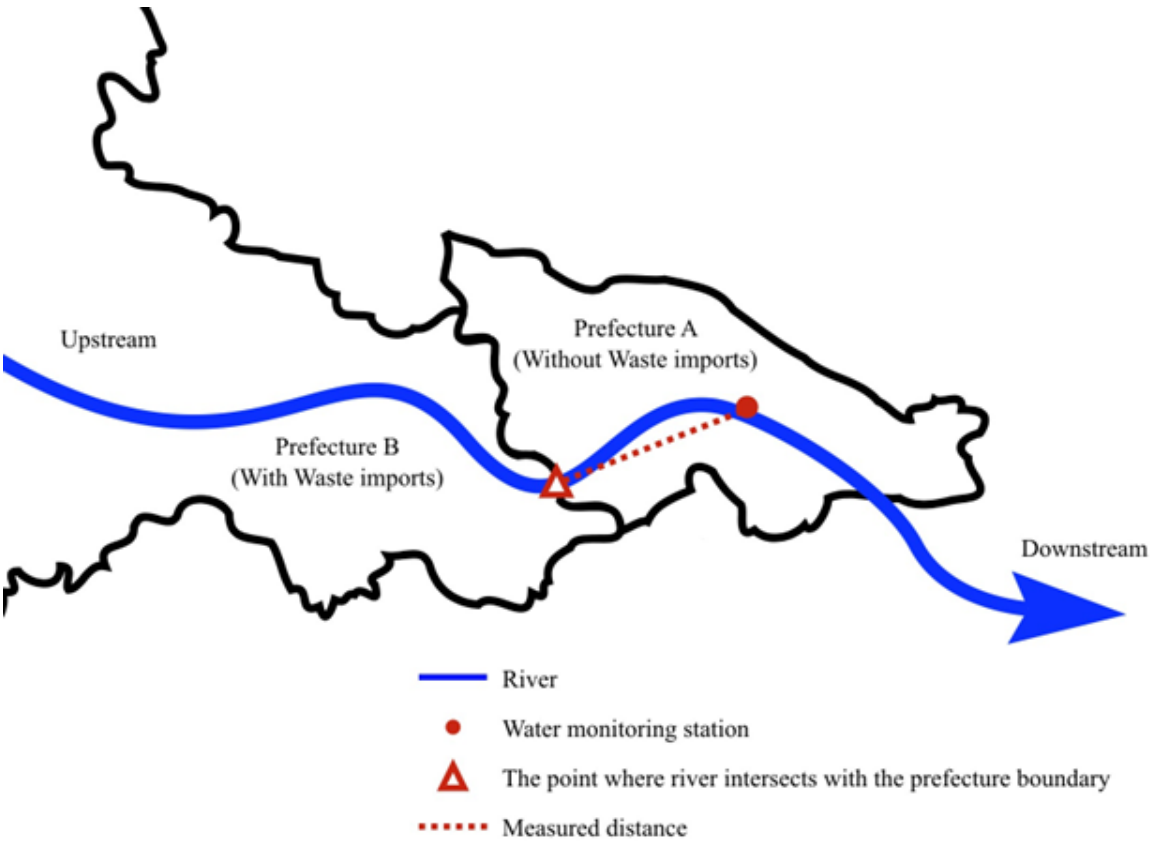
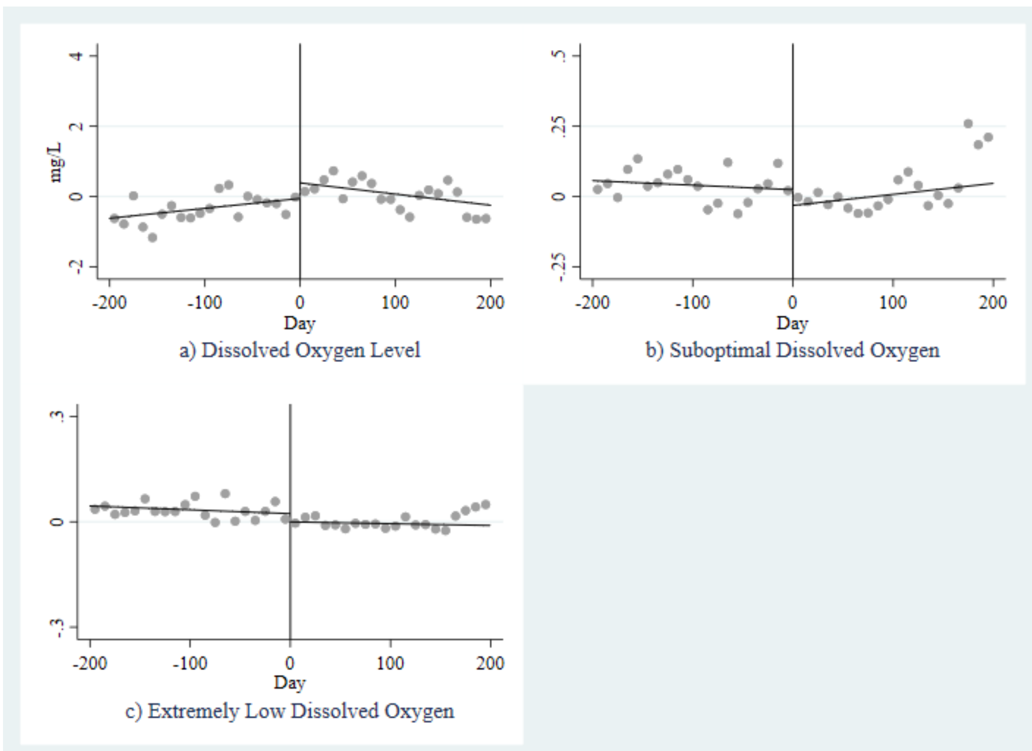


Figure 6: Placebo test: Assign the Waste Ban Policy on January 1, 2016



Note: The figures plot the results of the regression discontinuity design, using the outcome variables reported in the subfigures respectively. The sample is restricted to prefectures that imported any banned waste in 2017 (treated prefectures). The placebo test assumes that Day 0 is January 1, 2016. To be consistent with the estimation used to identify the actual policy, samples between September 1 and December 31, 2015, are dropped. The date right before the cutoff date is August 31, 2015. The lines plot a first-degree polynomial estimated separated on either side of the day cutoff. Suboptimal dissolved oxygen level indicates DO≤6.5; Extremely low dissolved oxygen level indicates DO≤3. All outcome variables are filtered by month and day-fixed effects.

Table 1: Descriptive Statistics

	All	Before the policy (2015-2017)	After the policy (2018-2019)	After-Before (change)
	(1)	(2)	(3)	(4)
DO				
Raw	7.775	7.628	8.098	0.471
	[2.651]	[2.649]	[2.629]	(0.014)***
Filtered	0.000	-0.112	0.246	0.358
	[2.302]	[2.360]	[2.150]	(0.012)***
Suboptimal DO (DO≤6.5)				
Raw	0.289	0.307	0.249	-0.057
	[0.453]	[0.461]	[0.433]	(0.002)***
Filtered	0.000	0.014	-0.030	-0.044
	[0.418]	[0.430]	[0.390]	(0.002)***
Extremely Low DO (DO≤3)				
Raw	0.044	0.049	0.030	-0.019
	[0.205]	[0.219]	[0.170]	(0.001)***
Filtered	0.000	0.006	-0.013	-0.019
	[0.204]	[0.217]	[0.168]	(0.001)***
Obs.	154,532	104,596	49,936	154,532

Notes: Raw variables represent unadjusted data. Filtered variables are generated by regressing each of the raw variables on month-fixed effects and day-fixed effects. The residuals from these regressions denote the filtered variables. Standard deviations are in square parentheses. Standard errors are presented in round parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: RD Estimates of the Waste Import Ban on Water Quality

	Any Waste (1)	Plastics (2)	Textiles (3)	Vanadium Slag (4)	Paper (5)	No Waste (6)
			Panel A			
DO	2.654***	2.505***	3.323***	5.594***	0.729	0.141
	(0.620)	(0.674)	(0.941)	(1.488)	(1.068)	(0.415)
SD. of outcome	2.411	2.389	2.509	2.279	2.314	2.089
Observations	17,353	11,258	7,183	1,376	5,147	19,037
Bandwidth	225.1	168.3	207.1	200.9	217.8	177.9
			Panel B			
Suboptimal DO	-0.237***	-0.263***	-0.259**	-0.636***	-0.200	-0.035
	(0.065)	(0.072)	(0.105)	(0.061)	(0.130)	(0.062)
SD. of outcome	0.467	0.459	0.460	0.416	0.450	0.479
Observations	11,043	11,501	6,040	1,303	4,545	16,228
Bandwidth	139.4	172.2	171.6	187.7	189.6	150.1
			Panel C			
Extremely Low DO	-0.108*	-0.103	-0.162*	-0.076	-0.103	0.013
	(0.056)	(0.065)	(0.090)	(0.079)	(0.078)	(0.029)
SD. of outcome	0.285	0.273	0.290	0.265	0.239	0.220
Observations	18,408	15,987	9,395	2,685	5,937	23,789
Bandwidth	240.5	247	282.6	389.9	256.2	228.1
# of prefectures	32	26	14	2	9	61
Waste (1000 ton/Pref.)	161.5	93.11	9.98	172.9	251.32	0

Notes: Each cell reports the estimate from a separate regression of Equation (1). Prefectures included in each column are determined by their waste-importing status in 2017, as indicated in the top row of the table. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. The outcome variables for each panel are presented in the left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely low DO). All outcome variables are filtered by month and day-fixed effects. All estimations use the optimal bandwidth selected through the procedure outlined by Cattaneo et al. (2019) and employ a local linear specification of the running variable, days. A triangular kernel is applied. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Spillover Effects on Upstream and Downstream Prefectures

	Upstream	Downstream	
		Distance < 150km	Distance < 50km
	(1)	(2)	(3)
Panel A			
DO	-0.030	0.732	0.857
	(0.609)	(0.724)	(0.826)
Observations	11,792	4,838	4,115
Panel B			
Suboptimal DO	0.088	-0.206*	-0.235**
	(0.082)	(0.118)	(0.117)
Observations	11,792	4,838	4,115
Panel C			
Extremely Low DO	0.032	-0.060	-0.083
	(0.025)	(0.079)	(0.091)
Observations	11,792	4,838	4,115
Bandwidth	200	200	200
# of prefectures	44	16	14

Notes: Each cell reports the estimate from a separate regression of Equation (1). Only prefectures that did not import any banned waste in 2017 are included. These prefectures are divided into upstream or downstream based on their location relative to the waste-importing prefectures. Distance from the downstream water monitoring station to the boundary of the waste-importing prefectures is measured as illustrated in Figure 5. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All outcome variables are filtered by month and day-fixed effects. A bandwidth of 200 days is applied to all columns for easy comparison across columns. All other RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: RD Difference-in-Differences Estimates

	RD Estimates	RD-DinD Estimates			DinD Estimates
		Optimal Bandwidth	Half Bandwidth	Double Bandwidth	2015–2019
	(1)	(2)	(3)	(4)	(5)
		Panel A: DO			
RD	1.252***				
	(0.424)				
Treated*Post		0.825**	1.851***	0.608**	0.434**
		(0.332)	(0.568)	(0.250)	(0.179)
Imported Waste Volume in 2017*Post		0.132*	0.250**	0.131***	0.073**
		(0.066)	(0.118)	(0.047)	(0.035)
Observations	31,800	31,800	17,095	60,059	131,619
Bandwidth	204	204	102	408	
		Panel B: Suboptimal DO			
RD	-0.120**				
	(0.051)				
Treated*Post		-0.135***	-0.276***	-0.055*	-0.045
		(0.048)	(0.073)	(0.033)	(0.027)
Imported Waste Volume*Post		-0.028***	-0.045**	-0.020***	-0.011
		(0.011)	(0.017)	(0.007)	(0.007)
Observations	29,221	29,221	15,596	54,787	131,619
Bandwidth	185	185	92	370	
		Panel C: Extremely Low DO			
RD	-0.017				
	(0.030)				
Treated*Post		-0.060**	-0.119***	-0.053***	-0.039***
		(0.026)	(0.045)	(0.019)	(0.014)
Imported Waste Volume*Post		-0.015**	-0.024**	-0.014***	-0.008**
		(0.007)	(0.011)	(0.004)	(0.003)
Observations	34,002	34,002	18,320	64,101	131,619
Bandwidth	219	219	108	438	

Note: 32 Prefectures imported banned waste in 2017 (treated) and 44 upstream prefectures that did not import any waste (control) are included. Column 2-5 reports the DinD estimator of the interaction term indicated in the left side of the table. Each cell reports the estimation of a separate regression. Treated dummy equals one if a prefecture is treated, and zero if the prefecture is an upstream control prefecture. Imported waste in 2017 is measured in logarithmic form and set to zero for upstream control prefectures. Observations during the transition period of Sept-Dec 2017 are dropped. The outcome variables for each panel are: dissolved oxygen level (DO); a dummy indicating DO¡=6.5 (Suboptimal DO); and a dummy indicating DO¡=3 (Extremely Low DO). All outcome variables are filtered by month and day fixed effects. Prefecture fixed effects and a Post dummy (equals one if a date is after January 1, 2018) are included in column 2-4. Column 5 control of Year fixed effects instead of the Post dummy. Effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Alternative Specifications

	Add Covariates (1)	**Quadratic** (2)	**CERRD** (3)	**MSERD/2** (4)	**MSERD*2** (5)	**Uniform Kernel** (6)	**Donut** (7)	**Waste Import 2015-2017** (8)
				Panel A				
DO	2.147***	1.936***	2.571***	1.662***	2.947***	2.420***	2.632***	2.369***
	(0.468)	(0.614)	(0.614)	(0.617)	(0.636)	(0.614)	(0.601)	(0.598)
Observations	10,279	13,908	14,346	9,218	32,304	13,473	14,497	19,356
Bandwidth	128.5	175.9	182.8	112.5	450.1	169.1	190.3	223.7
				Panel B				
Suboptimal DO	-0.219***	-0.188***	-0.220***	-0.239***	-0.285***	-0.238***	-0.254***	-0.219***
	(0.049)	(0.069)	(0.064)	(0.077)	(0.067)	(0.066)	(0.069)	(0.065)
Observations	9,819	12,925	9,509	5,871	21,322	10,717	12,501	13,478
Bandwidth	121.1	162.1	116.3	71.58	286.3	135.9	162.2	151.6
				Panel C				
Extremely Low DO	-0.082**	-0.079	-0.103*	-0.047	-0.125**	-0.106*	-0.142**	-0.127**
	(0.042)	(0.053)	(0.056)	(0.045)	(0.054)	(0.057)	(0.060)	(0.053)
Observations	13,165	18,788	15,218	9,748	33,883	16,322	13,695	20,800
Bandwidth	165.8	245.1	195.3	120.2	480.9	210.4	178.7	241.2

Notes: Each cell reports the estimate from a separate regression of Equation (1). Only treated prefectures (i.e., imported banned waste in 2017) are included. Column 1 includes prefecture fixed effects. Column 2 uses a quadratic polynomial of the running variable. Column 3 applies the CER-optimal bandwidth selection procedure. Columns 4 and 5 use half and double the MSE optimal bandwidth, respectively. Column 6 applies a uniform kernel. Column 7 dropped observations in August 2017. Column 8 defines prefectures as treated if they imported any waste during 2015-2017. The cutoff date is January 1, 2018. The date right before the cutoff is August 31, 2017. Observations during the transition period of Sept-Dec 2017 are dropped. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All outcome variables are filtered by month and day-fixed effects. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Placebo Tests

	Policy come into effect On January 1, 2016 (drop Sept-Dec, 2015)	Cut-off on Sept 1, 2016	Cut-off on Sept 1, 2015
	(1)	(2)	(3)
	Panel A		
DO	0.192	0.025	-0.343
	(0.513)	(0.467)	(0.481)
Observations	5960	10486	7194
Bandwidth	85.84	173.5	100.9
	Panel B		
Suboptimal DO	-0.061	-0.093	0.001
	(0.075)	(0.096)	(0.091)
Observations	7681	10851	8294
Bandwidth	109.1	179.3	115.1
	Panel C		
Extremely Low DO	-0.013	-0.001	0.040
	(0.046)	(0.051)	(0.061)
Observations	9,414	14,001	9,987
Bandwidth	135	226.7	137.7

Notes: The table falsely assigns the waste ban policy at three dates in each of the columns. In column 1, the cutoff date is January 1, 2016; observations during the transition period of Sept-Dec 2015 are dropped. In columns 2 and 3, the cutoff date is September 1, 2016, and September 1, 2015, respectively. Each cell reports the estimate from a separate regression of Equation (1). Only treated prefectures (i.e., imported banned waste in 2017) are included. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All outcome variables are filtered by month and day-fixed effects. All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: RD Estimates of the Waste Import Ban on Water Quality by Firm Ownership

	Foreign≥50%	Domestic>50%	Private≥50%
	(1)	(2)	(3)
	Panel A		
DO	1.773	2.805***	2.761***
	(1.101)	(0.716)	(0.757)
Observations	4422	12852	11888
Bandwidth	249.5	217.7	213.5
	Panel B		
Suboptimal DO	-0.328***	-0.236***	-0.225***
	(0.101)	(0.080)	(0.085)
Observations	2924	11131	10647
Bandwidth	157.2	185.5	189.3
	Panel C		
Extremely Low DO	-0.015	-0.128*	-0.139**
	(0.074)	(0.067)	(0.070)
Observations	4,172	13,478	12,600
Bandwidth	233.1	228.6	227.2
# of Prefectures in all Panels:	8	24	22

Notes: The table divides samples based on importers' ownership. Column 1: Prefectures where Foreign Owned Enterprises (FOEs) imported at least 50% of the banned waste in 2017 are included. Column 2: Prefectures, where domestic importers (i.e., importers that are not FOEs) imported more than 50% of the banned waste in 2017, are included. Column 3: Prefectures where Private Owned Enterprises (POEs) imported at least 50% of the banned waste in 2017 are included. Each cell reports the estimate from a separate regression of Equation (1). The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. All outcome variables are filtered by month and day-fixed effects. All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Potential Mechanisms

	(1)	(2)	(3)	(4)
	Panel A: Landfill			
lnPlastic2017*Post	-16.650*			
	(9.497)			
lnTextile2017*Post		-53.878**		
		(20.854)		
lnSlag2017*Post			-23.524	
			(18.090)	
lnPaper2017*Post				-29.066**
				(12.671)
Observations	1,625	1,625	1,625	1,625
R-squared	0.941	0.941	0.941	0.942
	Panel B: Industry Waste Water Discharge			
lnPlastic2017*Post	1.241			
	(4.990)			
lnTextile2017*Post		-9.446**		
		(4.155)		
lnSlag2017*Post			-3.398*	
			(2.034)	
lnPaper2017*Post				4.292
				(8.508)
Observations	1,326	1,326	1,326	1,326
R-squared	0.843	0.844	0.842	0.843

Notes: The unit of observation is at the prefecture-year level. Outcome variables in Panel A and Panel B are landfill volume (in thousand tons) and industrial wastewater discharge (in million tons), respectively. The post dummy equals one if the year is on or after 2018. All columns control for prefecture fixed effects, and year fixed effects. Standard errors are clustered at the prefecture level.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A Waste Ban Policy and the Ban list

On July 18, 2017, the Chinese government notified WTO regarding its intention to ban four types of waste imported to China, including plastic waste from living sources, vanadium slag, unsorted wastepaper and textile materials. The formal announcement of the waste ban policy was made public on August 10, 2017, through Decree No. 39, 2017, by the Ministry of Ecology and Environment (MEE). Decree No. 39 is published on the MEE website.[22] See Appendix Table A1 for the items banned by this policy. Below is the translation of the decree:

Announcement on the Release of the "Catalogue of Imported Waste Management" (2017)

In accordance with the laws and regulations including the Solid Waste Pollution Prevention and Control Law of the People's Republic of China, the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal, and the Measures for the Administration of the Import of Solid Wastes, the Ministry of Ecology and Environment, the Ministry of Commerce, the National Development and Reform Commission, the General Administration of Customs, and the General Administration of Quality Supervision, Inspection and Quarantine have adjusted and revised the existing "Catalogue of Prohibited Import of Solid Wastes," "Catalogue of Restricted Import of Solid Wastes Used as Raw Materials," and "Catalogue of Unrestricted Import of Solid Wastes Used as Raw Materials": Four categories of 24 types of solid wastes, including waste plastics from domestic sources (8 categories), unsorted wastepaper (1 category), waste textile raw materials (11 categories), and vanadium slag (4 categories), have been adjusted from the "Catalogue of Restricted Import of Solid Wastes Used as Raw Materials" to be included in the "Catalogue of Prohibited Import of Solid Wastes".

This announcement shall be effective from December 31, 2017. Announcement No. 80 of 2014 issued by the Ministry of Ecology and Environment, the Ministry of Commerce, the National Development and Reform Commission, the General Administration of Customs, and the General Administration of Quality Supervision, Inspection and Quarantine, as well as Announcement No. 3 of 2017, are hereby repealed simultaneously.

Hereby announced.

Attachments:

1. Catalogue of Prohibited Import of Solid Wastes
2. Catalogue of Restricted Import of Solid Wastes Used as Raw Materials
3. Catalogue of Unrestricted Import of Solid Wastes Used as Raw Materials

Ministry of Ecology and Environment

Ministry of Commerce

[22]Source: https://www.mee.gov.cn/gkml/hbb/bgg/201708/t20170817_419811.htm

National Development and Reform Commission
General Administration of Customs
General Administration of Quality Supervision, Inspection and Quarantine
August 10, 2017

Appendix B Waste Recycling and Water Pollution

This section documents evidence of how the recycling process could potentially pollute water.

Paper:

Typically, the initial stage of paper recycling involves sorting and removing contaminants (plastic, metal, and non-paper materials) from unsorted paper waste. The paper recycling process has the potential to discharge polluting water. The scale of the recycling facility and what recycled paper would be used to produce largely determine its environmental impact on water (Gavrilescu et al., 2008). A key contributor to water pollution in this process is deinking (bleaching), a procedure that eliminates ink from recycled paper and generates various pollutants in the wastewater system. The deinking process is essential for recycling waste paper into high-grade paper, particularly for products like tissue, printing, and writing paper that require a high level of whiteness. However, when producing paperboard from waste paper, the deinking process is typically unnecessary (Han et al., 2021). There is evidence suggesting that recycled paper mills producing packaging papers, such as corrugated paper or cardboard, often have the lowest freshwater requirements (Jung and Kappen, 2014). The scale of production also matters, with larger facilities more likely to use water efficiently. Due to the natural process of paper recycling which requires more capital and technology compared to recycling plastic, paper recycling facilities are typically larger compared to plastic waste processing facilities in China.

Vanadium slag:

Vanadium-containing slag, a by-product of the metallurgical and steel production industries, is classified as toxic due to its potential environmental and health risks (Shyrokykh et al., 2023; Das et al., 2021). Recycling vanadium slag requires large amounts of water, and the process generates substantial volumes of polluted water. The extraction process of vanadium from slag produces acidic or alkaline wastewater (Yang and Yang, 2023). It is documented that the production of one ton of vanadium product from vanadium slag results in the generation of 30-50 tons of ammonia-contaminated water (Li et al., 2017). Moreover, this wastewater contains high concentrations of sodium and ammonium sulphates, making it difficult to reuse (Shyrokykh et al., 2023).

Plastic:

Plastic waste and its residues may end up in rivers if not properly managed. Chemical leaching and the formation of biofilms resulting from disposal into water bodies can contribute to lower levels of dissolved oxygen in the water. When plastic waste facilities are overwhelmed, illegal dumping of plastic waste into water bodies is often observed. Several studies have indicated that China's rivers carry almost one million metric tonnes (1 Mt, more than half of the world's total) of plastic into the seas each year (Zhang et al., 2018). The decomposition process of organic matter or chemicals dumped in plastic waste could consume water oxygen; waste in the water body could block sunlight and reduce the photosynthesis activities which produce oxygen.

Textile:

Textiles often contain dyes and chemical finishes, and during the recycling process, these substances may be discharged into water, leading to water pollution (Laizer et al., 2022). Moreover, the bleaching and dyeing procedures employed in textile recycling can themselves contribute to water pollution by releasing chemicals. Dyes present in water hinder the penetration of light, eventually diminishing photosynthetic activities and oxygen levels (Bafana et al., 2009; Laizer et al., 2022). Unused textile waste commonly ends up in incineration and landfills. Landfills have the potential to cause water pollution by facilitating the leakage and decomposition of biodegradable waste, leading to soil and groundwater pollution (Dhir, 2021).

Appendix C Alternative Water Outcomes

In Appendix Table A2, our analysis expands to encompass a wider array of water quality indicators, including PI (indicative of carbon dioxide levels), ammonia nitrogen (AN), and pH levels, to comprehensively assess the broader environmental impacts of the National Sword policy. We concentrate on AN and PI readings that are classified as category IV or V according to the Chinese government's official water quality classification system in this analysis. These categories represent the highest levels of pollution: PI readings of 10 and above are categorized as pollution level IV, indicating significant contamination, while readings of 15 or higher are classified as level V, denoting severe pollution. Similarly, AN concentrations of 1.5 and above are categorized as level IV pollution, and readings over 2 are classified as level V, denoting extremely high water pollution levels. Furthermore, our investigation extends to pH levels, particularly those falling below the optimal 6.5 threshold recommended by the U.S. Environmental Protection Agency (EPA).

The findings summarized in Appendix Table A2 indicate a pronounced reduction in category IV and V water pollution readings, indicating a significant decrease in a range of harmful pollutants and a reduction in instances of low pH levels. This sizable reduction in water pollutants demonstrates the comprehensive impact of the National Sword policy on improving water quality and ecosystem health. Moreover, when analyzing results by the type of banned waste, we observe notable differences in the impact on water pollution indicators. Particularly, we find that the prevalence of the PI and AN readings classified as highly polluted has significantly decreased, especially following the ban on paper and textile waste imports. This variation illustrates the distinct environmental footprints associated with the disposal and management processes of different types of waste. Overall, results in Appendix Table A2 offer a more detailed picture of the environmental benefits of the waste ban policy, providing evidence of its efficacy in reducing pollution levels across a spectrum of harmful pollutants and contributing to the overall health of aquatic ecosystems and water quality.

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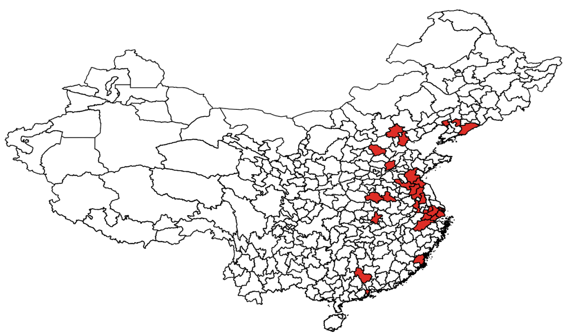
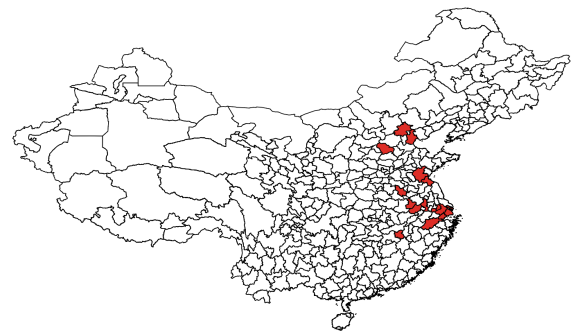
Figure A.1: Prefectures imported the banned waste in 2017 (Conditional on prefectures with a water monitoring station)

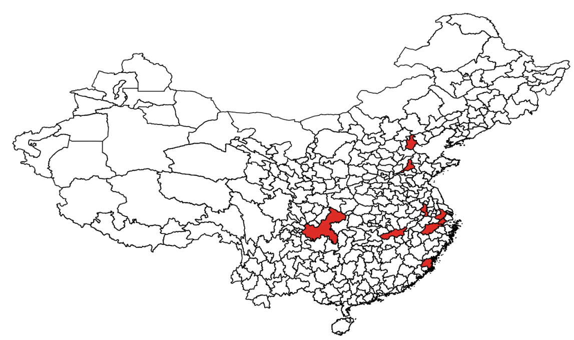


(a) Plastic



(b) Texile

(c) Vanadium Slag



(d) Paper

Figure A.2: Examine of smoothness in observations around cut-off:

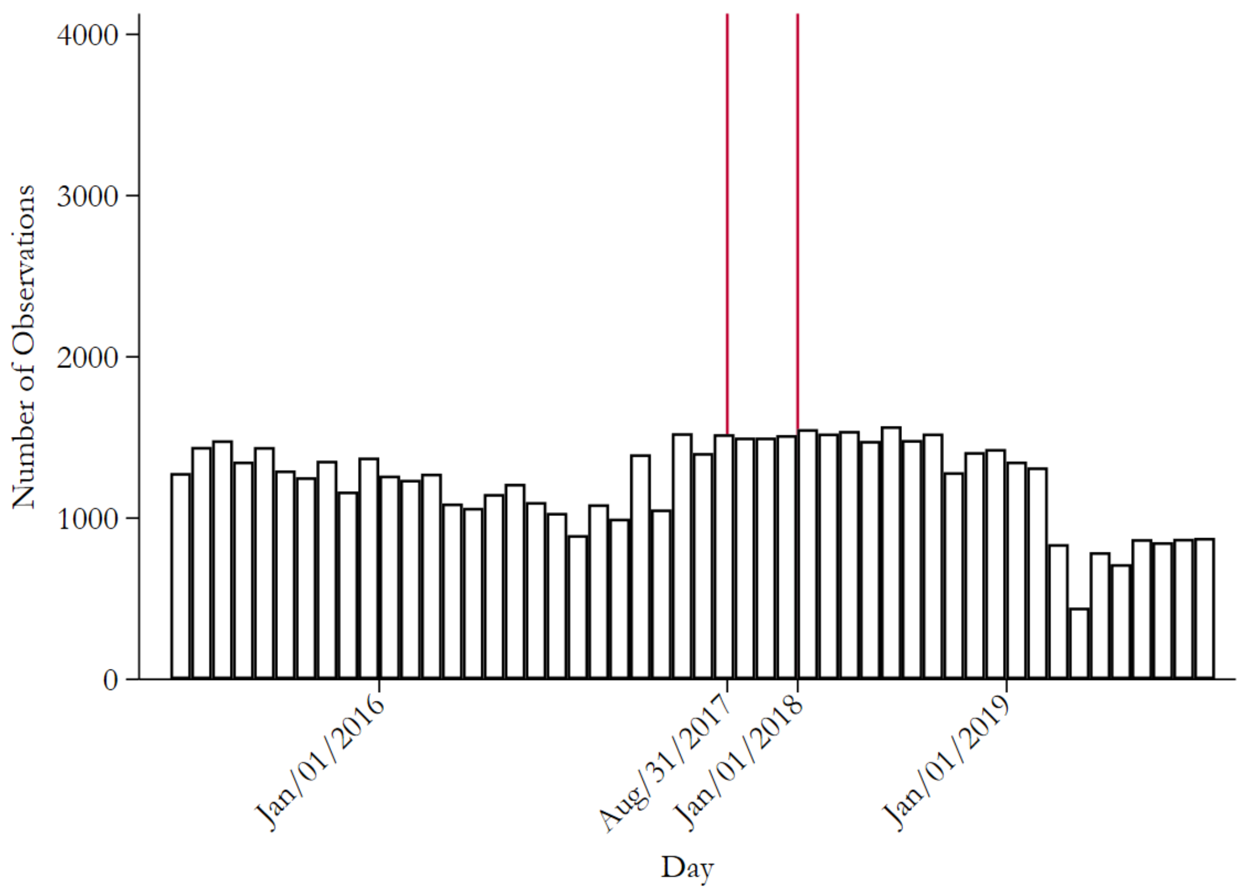
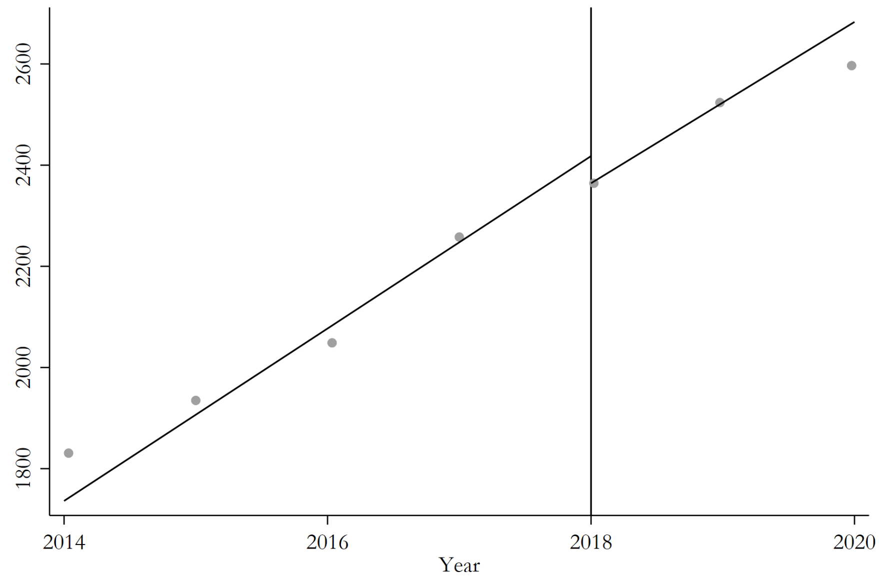
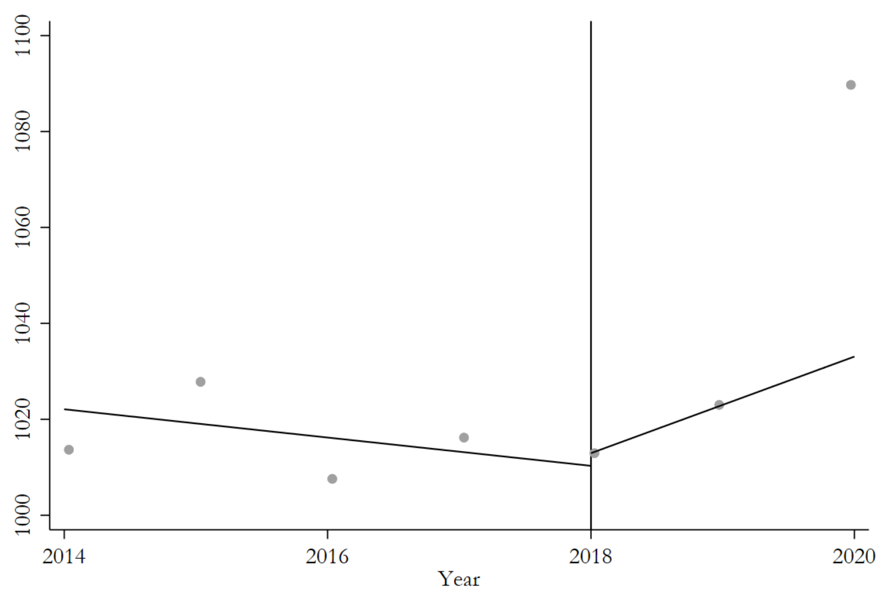


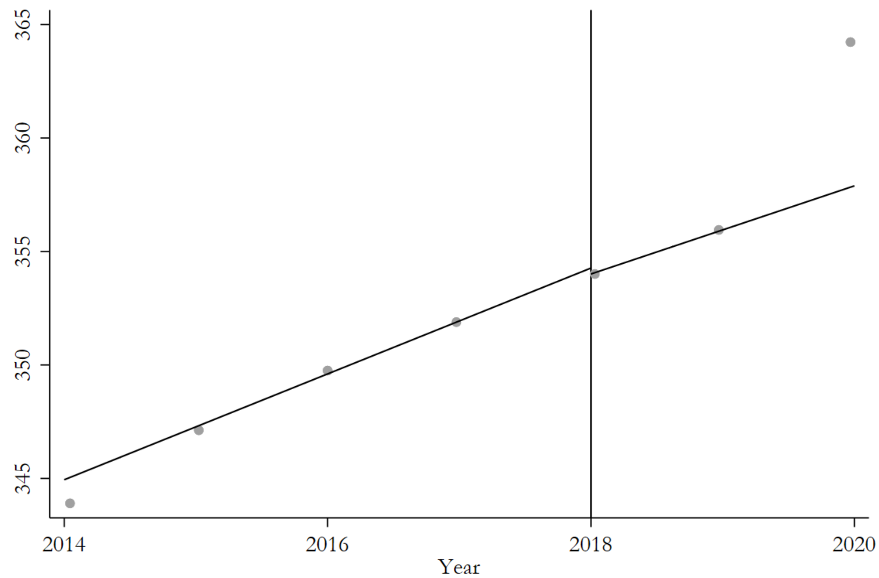
Figure A.3: Discontinuity in prefecture-level variables associated with environmental outcomes



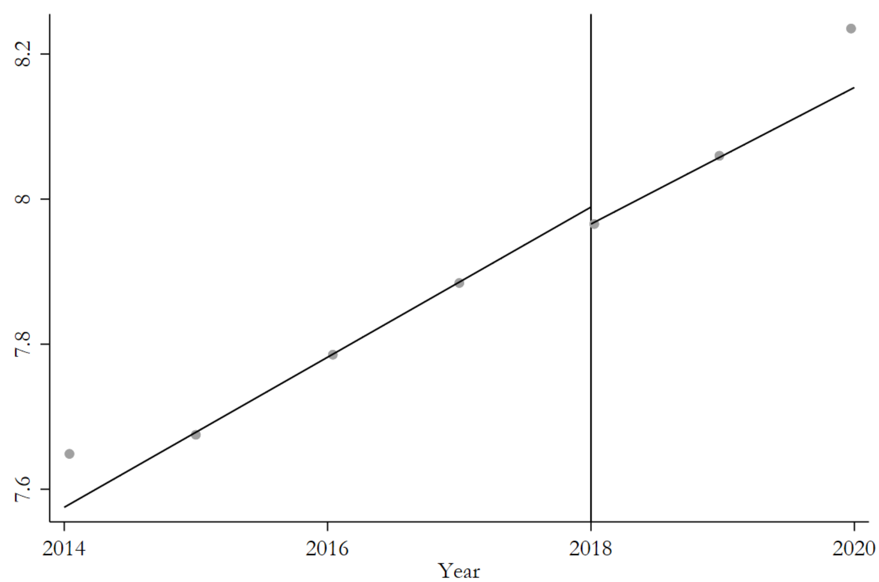
a) GDP



b) Number of Large Firms

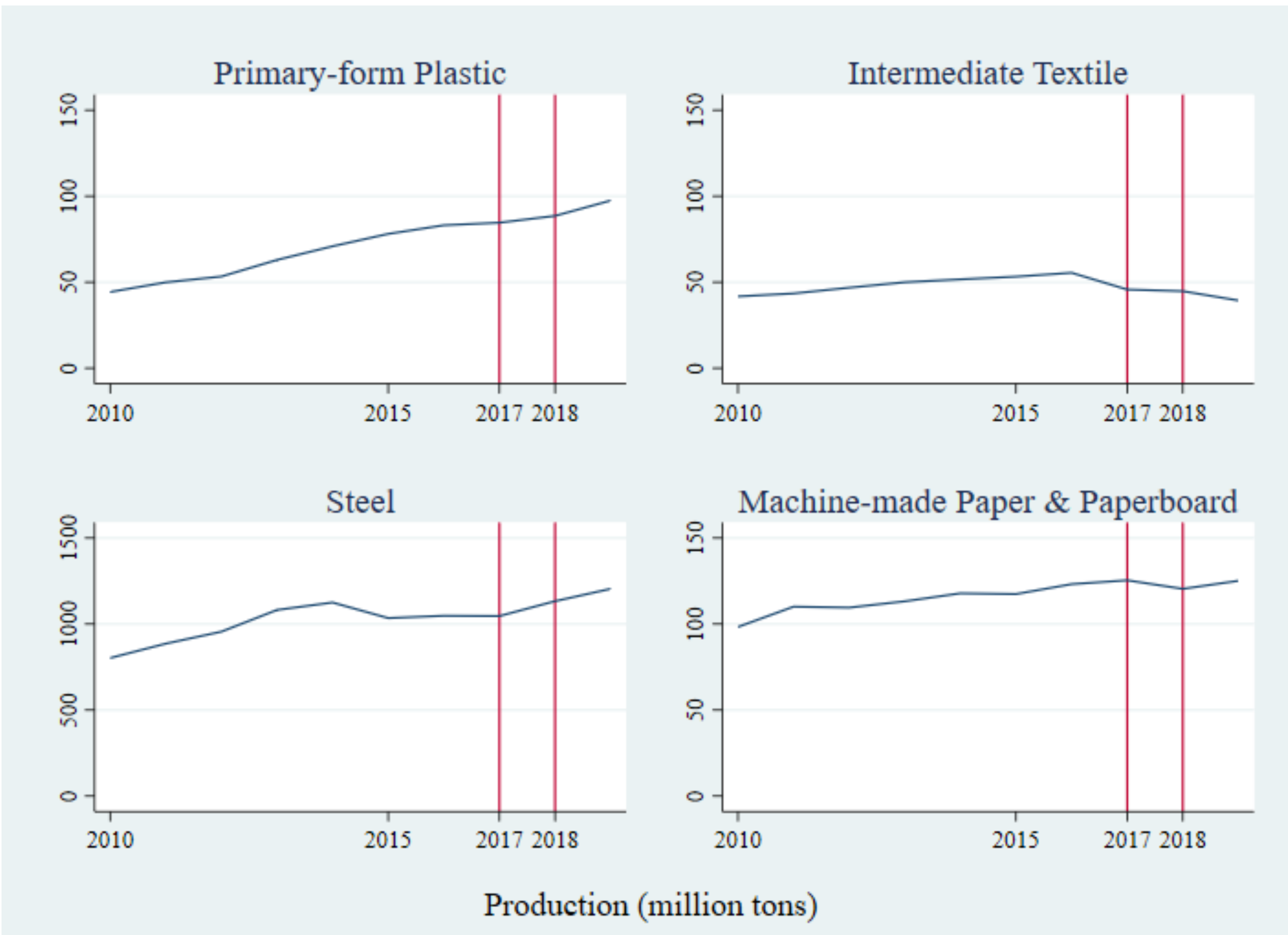


c) Population



d) Number of Colleges or Universities

Figure A.4: Annual production of outputs that likely use imported waste as inputs



Unit: Intermediate textiles account for the annual production of both yarn and cloth. The cloth, as reported by the National Bureau of Statistics of China, is measured in meters. To convert the length of the cloth to its weight, we assume that each meter weighs 0.2 kg. Data source: National Bureau of Statistics of China

Appendix Tables

Table A1: Type and name of the waste banned from importing after January 1, 2018

Waste	Item Number in Document 2017-39	HS Code	Waste name in English	Waste name in Chinese
Slag	18	2619000021	Vanadium-containing slag and smelting slag produced by the smelting of steel, with a vanadium pentoxide (V2O5) content exceeding 20%, excluding granular smelting slag produced by the smelting of steel.	冶炼钢铁所产生的含钒浮渣、熔渣，五氧化二钒含量>20%（冶炼钢铁所产生的粒状熔渣除外）
	19	2619000029	Vanadium-containing slag and smelting slag produced by other smelting of steel (excluding granular smelting slag produced by the smelting of steel)	其他冶炼钢铁所产生的含钒浮渣、熔渣（冶炼钢铁所产生的粒状熔渣除外）
	30	2620999011	Slag, ash, and residues of other metals and their compounds, containing by weight more than 20% of V2O5 (other than those from the manufacture of iron or steel)	含其他金属及其化合物的矿渣、矿灰及残渣，五氧化二钒>20%（冶炼钢铁所产生的除外）
	31	2620999019	Slag, ash, and residues of other metals and their compounds, containing by weight more than 10% but not exceeding 20% of V2O5(other than those from the manufacture of iron or steel)	含其他金属及其化合物的矿渣、矿灰及残渣，10%<五氧化二钒≤20%的（冶炼钢铁所产生的除外）
Plastic	53	3915100000	Waste and scrap of ethylene polymers (waste and scrap of ethylene polymers, excluding aluminum-plastic composite film)	乙烯聚合物的废碎料及下脚料(乙烯聚合物的废碎料及下脚料，不包括铝塑复合膜)
	54	3915100000	Waste and a scrap of ethylene polymers (aluminum-plastic composite film)	乙烯聚合物的废碎料及下脚料(铝塑复合膜)
	55	3915200000	Waste and scrap of styrene polymers	苯乙烯聚合物的废碎料及下脚料
	56	3915300000	Waste and scrap of vinyl chloride polymers	氯乙烯聚合物的废碎料及下脚料
	57	3915901000	Waste and scrap of polyethylene terephthalate (PET waste and scrap, excluding waste PET beverage bottles (bricks))	聚对苯二甲酸乙二酯废碎料及下脚料(PET的废碎料及下脚料，不包括废PET饮料瓶（砖）)
	58	3915901000	Waste and a scrap of polyethylene terephthalate (waste PET beverage bottles (bricks))	聚对苯二甲酸乙二酯废碎料及下脚料(废PET饮料瓶(砖))

Waste	Item Number in Document 2017-39	HS Code	Waste name in English	Waste name in Chinese
	59	3915909000	Waste and scrap of other plastics (waste and scrap of other plastics, excluding waste shattered CDs)	其他塑料的废碎料及下脚料(其他塑料的废碎料及下脚料，不包括废光盘破碎料)
	60	3915909000	Waste and scrap of other plastics (waste shattered CDs)	其他塑料的废碎料及下脚料(废光盘破碎料)
Paper	68	4707900090	Other recovered paper or paperboard, including unsorted waste and scrap (including unsorted waste and scrap)	其他回收纸或纸板(包括未分选的废碎品)
Textile	69	5103109090	Noils of fine hair of other wild animal	其他动物细毛的落毛
	70	5103209090	Waste of fine hair of other animal (including yarn waste but excluding garnetted stock)	其他动物细毛废料(包括废纱线，不包括回收纤维)
	71	5103300090	Waste of coarse hair of other animal (including yarn waste but excluding garnetted stock)	其他动物粗毛废料(包括废纱线，不包括回收纤维)
	72	5104009090	Garnetted stock of fine or coarse hair of other animal	其他动物细毛或粗毛的回收纤维
	73	5202100000	Yarn waste string (including waste cotton yarn)	废棉纱线(包括废棉线)
	74	5202910000	Garnetted stock	棉的回收纤维
	75	5202990000	Other cotton waste	其他废棉
	76	5505100000	Waste of synthetic fibres of man-made fibres (including noils, yarn waste and garnetted stock)	合成纤维废料（包括落绵、废纱及回收纤维）
	77	5505200000	Waste of artificial fibres of man-made fibres (including noils, yarn waste and garnetted stock)	人造纤维废料（包括落绵、废纱及回收纤维）
	79	6310100010	Sorted new or not used rags, including scrap twine, cordage, rope and cables and worn out articles of twine, of textile materials	新的或未使用过的纺织材料制经分拣的碎织物等（新的或未使用过的，包括废线、绳、索、缆及其制品）
	81	6310900010	Other new or not used rags, including scrap twine, cordage, rope and cables and worn out articles of twine, of textile materials	新的或未使用过的纺织材料制其他碎织物等（新的或未使用过的，包括废线、绳、索、缆及其制品）

Notes: The list of banned items was compiled by comparing the Catalogue of Prohibited Import of Solid Wastes published in Decree No. 39, 2017 with the one published in Decree No. 40, 2015. This list has been further verified in accordance with Article 10.6 through a notification to the WTO on July 18, 2017.

Table A2: Alternative Water Quality Indicators

	Any Waste (1)	Plastics (2)	Vanadium Slag (3)	Textiles (4)	Paper (5)
Panel A: PI Pollution Level IV					
Import Waste Ban	-0.016***	-0.018**	-0.018	-0.021***	-0.031***
	(0.006)	(0.007)	(0.019)	(0.006)	(0.010)
Observations	5,614	4,505	1,785	2,755	1,590
Bandwidth	67.25	68.20	230.6	70.12	63.82
Panel B: PI Pollution Level V					
Import Waste Ban	-0.009***	-0.009***	-0.008***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observations	3,043	3,450	219	4,155	2,348
Bandwidth	36.42	52.57	24.65	107.4	94.80
Panel C: AN Pollution Level IV					
Import Waste Ban	-0.014	-0.019	-0.063**	-0.041**	-0.037***
	(0.031)	(0.035)	(0.028)	(0.019)	(0.010)
Observations	19,506	15,877	1,879	6,073	2,505
Bandwidth	258.9	261.2	232.9	164.5	97.51
Panel D: AN Pollution Level V					
Import Waste Ban	-0.021	-0.023	-0.046	-0.053***	-0.037***
	(0.026)	(0.030)	(0.030)	(0.014)	(0.008)
Observations	19,833	13,877	1,780	4,519	2,031
Bandwidth	263.7	224.8	221.1	116.5	78.60
Panel E: pH Level Lower than 6.5					
Import Waste Ban	-0.038***	-0.039***	-0.040***	-0.042***	-0.049***
	(0.003)	(0.004)	(0.000)	(0.006)	(0.011)
Observations	7,969	6,735	281	3,747	2,461
Bandwidth	90.84	95.61	29.55	93.31	96.27

Notes: The sample is restricted to prefectures that imported any type of banned waste before 2017. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. PI Pollution Levels IV or V indicate that permanganate index levels are equal to or higher than 10 mg/L and 15 mg/L, respectively. AN Pollution Levels IV or V denote that ammonia nitrogen levels are equal to or higher than 1.5 mg/L and 2 mg/L, respectively. All outcome variables are filtered by month and day-fixed effects. All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Summary Statistics for Prefecture-level Indicators

Variable	Obs	Mean	Std. dev.
Panel A			
Industry wastewater discharge	1,326	50.91	70.06
Landfill	1,625	353.80	566.73
Panel B			
GDP	2,628	2220.35	3151.06
Number of large firms	2,461	1027.12	1400.26
Population	2,023	352.33	288.50
Number of college	2,227	7.89	13.67

Note: Prefecture-year level data are reported. Data covers the years 2015-2019 in Panel A and 2014-2020 in Panel B, respectively.

Table A4: Prefecture level import of banned waste (Unit: 1000 tons)

	Waste import in 2017		Waste import during 2015-2017	
Type of waste	Total	# of Prefectures	Total	# of Prefectures
Any types	5,168.35	32	15,970.11	38
Plastic	24,20.86	26	7,115.55	32
Textiles	139.74	14	401.41	18
Vanadium Slag	345.86	2	896.68	7
Paper	2,261.89	9	7,556.47	11

Note: The table reports the imports of banned waste in 93 prefectures where automated water monitoring stations are installed.

Table A5: Parallel Trend Test

	DO	Suboptimal DO	Extremely Low DO
	(1)	(2)	(3)
Panel A: Use a dummy to indicate treatment status			
Treated*2016	0.076	0.017	-0.014
	(0.179)	(0.026)	(0.016)
Treated*2017	0.152	0.020	-0.001
	(0.182)	(0.032)	(0.018)
Treated*Post	0.510**	-0.033	-0.043**
	(0.205)	(0.035)	(0.020)
Observations	131,619	131,619	131,619
R-squared	0.207	0.149	0.118
Panel B: Use waste import volumn to indicate treatment statu			
	DO	Suboptimal DO	Extremely Low DO
Imported Waste Volume in 2017*2016	-0.017	0.009	-0.001
	(0.050)	(0.006)	(0.004)
Imported Waste Volume in 2017*2017	0.014	0.008	0.001
	(0.038)	(0.007)	(0.004)
Imported Waste Volume in 2017*Post	0.073*	-0.006	-0.007**
	(0.038)	(0.009)	(0.004)
Observations	131,619	131,619	131,619
R-squared	0.206	0.150	0.117

Note: The base year is 2015 and is omitted in the regression. Prefecture fixed effects and Year fixed effects are controlled. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: RD Estimates of the Waste Import Ban on Water Quality, Adding Transition Period

	Any Waste (1)	Plastics (2)	Textiles (3)	Slag (4)	Paper (5)	No Waste (6)
Panel A: DO						
Waste Import Ban	2.559***	2.823***	3.197***	4.595	0.692	0.077
	(0.591)	(0.690)	(0.737)	(1.304)	(0.770)	(0.389)
Transition	0.942**	0.923*	1.203**	1.947	-0.164	-0.108
	(0.423)	(0.492)	(0.496)	(0.545)	(0.650)	(0.215)
Observation	22,431	15,472	9,451	1,850	6,797	27,307
Panel B: Suboptimal DO						
Waste Import Ban	-0.293***	-0.309***	-0.279**	-0.637*	-0.222	0.022
	(0.067)	(0.077)	(0.100)	(0.076)	(0.136)	(0.059)
Transition	-0.150**	-0.146**	-0.156**	-0.346	-0.107	0.080*
	(0.055)	(0.060)	(0.067)	(0.123)	(0.111)	(0.041)
Observations	16,128	15,714	8,343	1,771	6,199	18,991
Panel C: Extremely Low DO						
Waste Import Ban	-0.122**	-0.115**	-0.144*	-0.077	-0.058	0.021
	(0.051)	(0.055)	(0.076)	(0.050)	(0.066)	(0.028)
Transition	-0.081*	-0.077*	-0.087	-0.083	-0.014	0.017
	(0.040)	(0.044)	(0.060)	(0.060)	(0.036)	(0.016)
Observations	23,566	20,202	11,628	3,160	7,560	32,001

Notes: Each cell reports the estimate from a separate regression of Equation (1), with a Transition dummy added. “Transition” is a dummy variable that represents the period from September 1, 2017, to December 31, 2017. “Waste Import Ban” is a dummy variable that applies to dates on or after January 1, 2018. The date right before the cutoff is August 31, 2017. To compare with the results in Table 2, the optimal bandwidth estimated in Table 2 is added before and after the transition period in all estimations. Prefectures included in each column are determined by their waste-importing status in 2017. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All outcome variables are filtered by month and day-fixed effects. All estimations employ a local linear specification of the running variable, days. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Drop Prefectures Imported Small Amount of Waste

	Plastics	Textiles	Vanadium Slag	Paper
	(1)	(2)	(3)	(4)
	Panel A			
DO	2.495***	2.708***	4.614***	1.431
	(0.704)	(0.956)	(1.512)	(1.128)
Observations	11,529	6,824	1,633	4,110
Bandwidth	187.7	215.6	192.3	222.5
	Panel B			
Suboptimal DO	-0.228***	-0.279***	-0.388*	-0.235*
	(0.078)	(0.094)	(0.216)	(0.134)
Observations	10,458	5,643	2,157	3,568
Bandwidth	168	172.8	256.2	189.2
	Panel C			
Extremely Low DO	-0.099	-0.115	-0.058	-0.162*
	(0.068)	(0.076)	(0.081)	(0.090)
Observations	14,067	6,954	2,928	4,442
Bandwidth	232.3	220.9	348.8	243.1
# of prefectures dropped	3	2	0	4

Notes: For each type of waste, prefectures that imported only a small amount of the waste are dropped. A small amount is defined as less than 10% of the median value of each type of waste. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Drop Prefectures Imported Small Amount of Waste and Using Prefectures Imported Only One Type of Waste

	Plastic Only (1)	Textile Only (2)	Paper Only (3)
	Panel A		
DO	2.190**	4.191***	0.739
	(0.981)	(1.207)	(0.748)
Observations	5,395	880	1,628
Bandwidth	190.9	190.9	285.6
	Panel B		
Suboptimal DO	-0.315***	-0.479***	-0.271
	(0.112)	(0.157)	(0.258)
Observations	5,742	694	1,336
Bandwidth	203.3	150.9	224.1
	Panel C		
Extremely Low DO	-0.090	-0.183	-0.144
	(0.112)	(0.207)	(0.119)
Observations	6,402	2,842	1,415
Bandwidth	228	631.5	242
# of prefectures	11	3	3

Notes: For each type of waste, prefectures that imported only a small amount of waste are dropped. A small amount is defined as less than 10% of the median value of each type of waste. Furthermore, we exclusively focus on prefectures that imported only one type of waste in 2017. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. The date right before the cutoff is August 31, 2017. The outcome variables for each panel are presented in the far left column: dissolved oxygen level (DO); a dummy indicating DO<=6.5 (Suboptimal DO); and a dummy indicating DO<=3 (Extremely Low DO). All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Compare waste import with Production in 2017

Waste Type		**Production**	
Plastic	5.8	Primary-form Plastic	84.6
Textile	0.3	Intermediate Textile	45.7
Vanadium slag	1.5	Steel	1046.4
Paper	4.3	Machine-made Paper and Paper Board	125.4

Notes: Unit is in million tons. Production data is from the National Bureau of Statistics China. Intermediate textiles account for the annual production of both yarn and cloth. The cloth, as reported by the National Bureau of Statistics of China, is measured in meters. To convert the length of the cloth to its weight, we assume that each meter weighs 0.2 kg.

Table A10: RD Estimates of the Waste Import Ban on Water Quality in Provinces with Production but No Waste Imports

	Plastic (1)	Textile (2)	Steel (3)	Paper (4)
	Panel A			
DO	0.124	0.305	0.124	0.147
	(0.415)	(0.410)	(0.415)	(0.417)
Observations	19,037	16,414	19,037	18,959
Bandwidth	177.3	176.7	177.3	178.3
	Panel B			
Suboptimal DO	-0.027	-0.064	-0.027	-0.035
	(0.062)	(0.062)	(0.062)	(0.062)
Observations	16,014	13,266	16,014	15,981
Bandwidth	148.8	142.7	148.8	149.4
	Panel C			
Extremely Low DO	0.015	-0.012	0.015	0.014
	(0.028)	(0.028)	(0.028)	(0.029)
Observations	23,170	24,248	23,170	23,156
Bandwidth	222.1	270	222.1	224.6

Notes: Samples are restricted to provinces that produced plastics, textiles, steel, or paper in 2017 (as listed in the top row of each column) and did not import any banned waste in 2017. The cutoff date is January 1, 2018. Observations during the transition period of Sept-Dec 2017 are dropped. All outcome variables are filtered by month and day-fixed effects. All RDD model specifications are the same as in Table 2. The effective number of observations is reported. Standard errors are clustered at the prefecture level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Association between Waste Disposal and Water Quality Indicators

	Dissolved Oxygen		Suboptimal Dissolved Oxygen		Extremely Low Dissolved Oxygen	
	(1)	(2)	(3)	(4)	(5)	(6)
Landfill	-0.644***		0.012*		0.021***	
	(0.034)		(0.006)		(0.003)	
Industry wastewater discharge		-0.260***		0.039***		0.035***
		(0.018)		(0.003)		(0.002)
Observations	136,250	158,097	136,250	158,097	136,250	158,097
R-squared	0.002	0.000	0.001	0.000	0.001	0.000

Notes: Each column regresses the dissolved oxygen indicator on the landfill or industry water discharge. Prefecture-fixed effects are included. The logarithm value of landfill and industry water discharge is used. The sample is restricted to prefectures that imported any type of banned waste before 2017. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.