Does Trade with Multinationals Induce Greener Production? Evidence from the Bangladesh Fashion Industry*

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Abstract

Global fashion brands face growing pressure to ensure that suppliers in developing countries comply with environmental standards. This concern is especially salient in the apparel industry, whose production processes generate and discharge large volumes of wastewater. We examine how exporting to global fashion brands influences the environmental performance of apparel exporters in Bangladesh. Using a novel dataset that combines custom data with river water quality data, we find that increased export activity near monitoring stations is associated with worse water quality. However, river water quality improves once the majority of nearby firms export to brand buyers. Our finding highlights the important role multinational buyers can play in mitigating industrial pollution, particularly in developing-country contexts where regulatory enforcement is often weak.

Keywords: Responsible sourcing, Water quality, Apparel industry, Bangladesh

JEL Classification: F18, F64, O13, Q56

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1 Introduction

Seeking economic development and environmental sustainability in tandem is one of the significant challenges modern society has faced. This issue is especially crucial as economies advance up the development ladder, particularly in the context of weak state capacity. In recent years, there has been a growing concern that companies in developed countries profit from products manufactured in factories with weak enforcement of production standards in developing countries. Some severe incidents have attracted global attention, such as the issue of child labor in sweatshops that manufacture Nike products in Pakistan, as well as the Rana Plaza collapse, the deadliest disaster of garment factories for international apparel brands in Bangladesh. These events caused public backlash and media scrutiny, which led firms to take greater responsibility for ensuring their suppliers comply with production standards. As a result, responsible sourcing initiatives have become one of the most challenging issues for global firms (Guo et al., 2016).

Does responsible sourcing induce environmentally sustainable practices in developing countries? We investigate this question by focusing on the ready-made garment (RMG) industry in Bangladesh. The majority of RMG firms in Bangladesh produce for foreign companies, including global fashion brands such as H&M, ZARA, and UNIQLO. This sector has played a key role in the Bangladeshi economy, accounting for around 80% of total exports in 2026. Thus, the potential impact of exports on the local environment is significant and wide-ranging. Further, the RMG sector is recognized as the most polluting manufacturing industry, according to the World Bank (2019).[1] Producing the products requires dyes, bleaching agents, and other chemicals, and these pollutants directly affect water quality and threaten the health of residents near factories through water-borne diseases (Hasan et al., 2019). Given this background, international NGOs and the media have increasingly advocated for foreign buyers, especially well-known fashion brands, to require and

[1] Reference to the article: *How Much Do Our Wardrobes Cost to the Environment?* https://www.worldbank.org/en/news/feature/2019/09/23/costo-moda-medio-ambiente (last access on September 2024).

assist Bangladeshi local firms in adopting environmentally friendly manufacturing processes. Nowadays, responsible sourcing is one of the top priorities for global fashion brands (Berg et al., 2019).

To the best of our knowledge, we conduct the first study to investigate whether multinationals' responsible sourcing improves the quality of the local environment. In the context of water pollution, global fashion brands can ask Bangladeshi suppliers to install effluent treatment plants and reduce the use of hazardous chemicals through monitoring and inspections. We construct a novel dataset by combining customs data with water quality data of Bangladeshi rivers from 2014 to 2021. Specifically, we use customs data to identify which local firms export to apparel companies with established global brands (hereafter referred to as *brand multinationals*) in a given month and analyze the impact of exporting to brand multinationals on river water quality. Water quality is measured at monitoring stations located along Bangladeshi rivers. We use dissolved oxygen (DO), which indicates the amount of oxygen in water, as a measure of the quality of the river water.

First, we study the overall relationship between exports and water quality using a two-way fixed effects approach. In our dataset, we focus on the RMG manufacturers located upstream and within a 10 km radius of water monitoring stations. Among firms in a cluster associated with each monitoring station, some export, while others do not in a given month. Using this monthly variation, we examine the correlation between river water quality and the share of exporters in each firm cluster. We find that the coefficient for the share of all exporters (including those exporting to brand and non-brand multinationals) is negative and statistically significant. However, when we focus exclusively on the share of exporters to brand multinationals, the coefficient becomes insignificant. These results suggest that higher export intensity is more likely to degrade river quality, but this negative impact weakens when exporters are primarily suppliers to brand multinationals.

Our main analysis employs a staggered difference-in-differences (DiD) approach to investigate the causal effects of trading with brand multinationals on local water quality.

Specifically, we analyze the cumulative share of exporters to brand multinationals for each monitoring station (again, we consider firms located upstream and within a 10km radius assigned to each station) and define a monitoring station as treated once this cumulative export share exceeds 50%. In our DiD design, the treatment group consists of monitoring stations with more than 50% of nearby exporters supplying to brand multinationals, while the control groups include monitoring stations with 50% or fewer exporters supplying to such multinationals, as well as monitoring stations without any nearby exporters. We find that when more than 50% of exporters start to supply to brand multinationals, DO levels increase by 50.3%, which suggests significant water quality improvement. We also show that this positive impact on water quality persists over four years, and there is no differential effect during the pre-treatment periods. A variety of robustness checks support our findings on the positive effects of trading with brand multinationals on water quality. For example, our results still hold with an alternative water quality indicator and a different aggregation of water quality data.

To shed light on the mechanisms underlying these effects, we complement our analysis with a brief survey of 60 RMG factories. The survey collects information on buyer practices related to environmental compliance, including inspections, recommendations, and assistance, as well as firm-level outcomes such as certification and the adoption of effluent treatment plants. While the survey is descriptive in nature, the evidence suggests that firms with higher exposure to brand multinationals face more intensive compliance monitoring and are more likely to adopt environmentally friendly practices. These patterns are consistent with the interpretation that private enforcement by multinational buyers plays an important role in shaping firms' environmental behavior.

As for policy implications, our research sheds light on how foreign buyers can promote the private enforcement of environmental regulations for local firms. Developing countries, including the Government of Bangladesh, have already set various environmental standards to address industrial wastewater pollution. However, enforcing these effluent standards on local firms is challenging: firms have little incentive to reduce their pollution levels, while the government has limited resources to ensure compliance, and corruption further weakens the effective implementation of regulations. In this context, our results underscore the role of foreign buyers in incentivizing local firms to comply with environmental standards and mitigate river pollution.

Our study contributes to the growing literature on international trade and the environment by presenting a new channel of responsible sourcing. The relationship between export and pollution is ambiguous in theory. An increase in exports is typically associated with more production and thus leads to higher pollution levels, while exports can improve environmental quality by contributing to the local economic growth (Grossman and Krueger, 1995; Copeland and Taylor, 2004). One notable study examining the causal relationship between export growth and pollution is Bombardini and Li (2020), which finds a negative but insignificant effect of an export boom on pollution and infant mortality using Chinese data from 1990 and 2010. Unlike their study, we introduce responsible sourcing—where multinationals directly demand improved environmental performance from their suppliers—as a new avenue for exploring the linkage between exports and environmental outcomes.

This study also relates to the literature on the impact of responsible sourcing of multinational firms in developing countries. The existing literature focuses on the effects on labor outcomes, including real wages in Indonesia (Harrison and Scorse, 2010), poor working conditions and labor rights in Bangladesh (Boudreau, 2020), and domestic welfare in Costa Rica (Alfaro-Ureña et al., 2022). In contrast to these studies, we investigate whether multinationals' responsible sourcing initiatives encourage local firms to adopt more environmentally friendly production processes.

Lastly, this research is connected to the extensive literature on water pollution in developing countries, such as studies emphasizing the roles of environmental regulations (Greenstone and Hanna, 2014), third-party auditors in regulatory enforcement (Duflo et al., 2013), political boundaries (Kahn et al., 2015; Lipscomb and Mobarak, 2016), and public infrastructure

(Motohashi, 2023). In this paper, we study the role of foreign buyers (not governments alone) in inducing local firms to comply with environmental regulations through the private enforcement mechanism.

The outline of the paper is as follows. We introduce data in Section 2 and present our empirical strategies in Section 3. We report the results regarding the effect of exporting to brand multinationals on water quality in Section 4. Section 5 explains the underlying mechanisms and discusses survey results. Section 6 concludes.

2 Data

Our primary datasets consist of information on Bangladeshi exporters and water quality data from rivers in Bangladesh. We also incorporate a list of global fashion brands (i.e., brand multinationals) in the RMG industry. In addition, we collect primary survey data from a sample of RMG factories to better understand the mechanisms of compliance enforcement. These datasets enable us to identify which local firms export to brand multinationals and analyze the effect of trading with brand multinationals on the water quality of the surrounding rivers.

Administrative Customs Data

The information on Bangladesh exporters is sourced from the National Board of Revenue (NBR)'s Automated System for Customs Data (ASYCUDA++). ASYCUDA++ is a computerized system designed by the United Nations Conference on Trade and Development (UNCTAD). Our dataset, which spans from 2014 to 2021 at a daily level, includes shipment dates, details on Bangladeshi exporters and foreign importers (such as names and addresses), and product details (such as transaction amounts, value, and HS codes). We focus on transactions involving commodities with HS codes related to apparel and textile products.

We prepare the customs data in two steps. First, we identify unique exporters using the firm names and aggregate their transactions at the monthly level. The distribution of the number of transactions is highly right-skewed, indicating that a small number of firms made the majority of transactions during our data period. For instance, firms with more than 500 transactions account for 19% of all firms in the dataset (1,741 firms out of 9,304 firms), yet they represent 96% of total transactions. Given this concentration, we use firms with more than 500 transactions in our two-way fixed effects analysis. For the DiD analysis, we apply a cutoff of 100 transactions to more accurately capture the timing of significant exports to multinational brands. Second, we manually search for and obtain the geographic coordinates (latitudes and longitudes) of each exporter using Google Maps. Accurately determining the location of local firms is essential for assessing the distance between these firms and the nearest water quality monitoring stations in our study.

Water Quality Data

We use surface water quality data provided by the Department of Environment, Government of Bangladesh, covering the period from 2010 to 2019. The data are collected at 127 water quality monitoring stations located along rivers in Bangladesh. Similar to the process for determining the location of Bangladeshi exporters, we manually obtained the geographic coordinates of each monitoring station using Google Maps.

Our primary indicator for river water quality is DO, as it is a widely accepted metric and the most frequently recorded measure in our dataset. DO is the amount of oxygen present in water, and higher DO levels indicate better water quality. For our analysis, we exclude outlier values for water quality indicators that are improbable in real-world conditions: DO levels exceeding 20 mg/L. For a robustness check, we also use Biochemical Oxygen Demand (BOD), another commonly used indicator. BOD measures the amount of oxygen required by aerobic organisms to decompose organic matter. In contrast to DO, higher BOD levels indicate poorer water quality. We restrict the observations to those with BOD levels not exceeding 100 mg/L.

Lists of Brand Apparel Firms

Our hypothesis is that as more local firms start exporting to brand multinationals, the water quality will be improved because these importers typically require local firms to follow more stringent environmental standards. In the customs data, we observe many foreign buyers to which Bangladeshi firms supply their products. To identify brand multinationals among importers, we cross-reference the list of global apparel brands in the Fashion Transparency Index (Fashion Revolution, 2021), determining which of these importers qualify as brand multinationals.

3 Empirical Strategy

We analyze the causal relationship between trading with brand multinationals and the water quality of the rivers surrounding these multinationals' suppliers. First, we define the variables used in our regression analysis and explain the identification strategies. We then present the results in the next section.

3.1 Main Variables

Our dependent variable is $WaterQuality_{i,m,y}$ that represents the water quality measured at monitoring station i, in month m, and year y. The monitoring stations are located along rivers in Bangladesh, where wastewater discharged by RMG firms affects the water quality. Figure 1 shows the location of monitoring stations (blue dots) and local firms (red dots). We consider local firms situated within 10 km of each monitoring station and focus on firms located upstream of monitoring stations. For each monitoring station i, we calculate the share of exporting firms, $Export_{i,m,y}$, which indicates the ratio of local firms that export in month m and year y to the total number of firms surrounding the monitoring station. Our

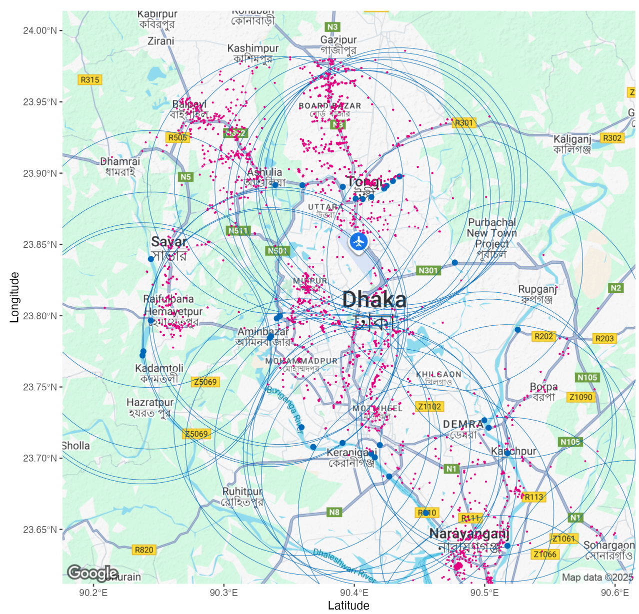

Figure 1: Water Quality Monitoring Stations and RMG Firms

Notes: This figure shows water quality monitoring stations as blue dots, 10 km buffers around the monitoring stations as blue circles, and local firms as red dots.

data for regressions are at the water monitoring station level. Due to the proximity of some monitoring stations, we aggregate the water quality data from the stations located within 1 km along the same river and use them as an alternative specification.

We distinguish between two types of exporting shares: (i) the share considering all exporters, and (ii) the share considering only exporters who supply brand multinationals. Specifically, two types of $Export_{i,m,y}$ are:

For all exporters,

$$\frac{\text{Number of firms that export in a given month and year}}{\text{Total number of firms in the customs data surrounding monitoring stations}}$$

and for all exporters to brand multinationals,

$$\frac{\text{Number of suppliers to brand multinationals that export in a given month and year}}{\text{Total number of firms in the customs data surrounding monitoring stations}}.$$

Firms in our dataset are those identified in the customs data, and some of these firms

Table 1: Summary Statistics

	Mean	SD	Median	Min	Max	Observation
$WaterQuality_{i,m,y}$						
DO (mg/L)	3.18	2.59	3.12	0	17	1,226
BOD (mg/L)	11.99	13.55	7.20	0	86	1,099
$Export_{i,m,y}$						
All exporters	0.86	0.14	0.87	0	1	1,226
Exporters to brand multinationals	0.43	0.24	0.41	0	1	1,226

Notes: The data are at the monitoring station-month-year level.

export in certain months while not in others. For the export share considering all exporters, we calculate the proportion of firms that export in each month and year. Since most garment products are produced for export, a firm's production tends to increase during periods when it has active transactions. Unlike the export share of all exporters, the second export share represents the proportion of exporters that are suppliers to brand multinationals. Before a firm begins supplying to a brand multinational, the brand multinational (i.e., buyer) typically requires the firm (i.e., supplier) to comply with environmental regulations, including the installation of effluent treatment plants. This anecdotal evidence is from interviews with Bangladeshi RMG firms. Once the firm adopts these regulations, environmentally friendly production practices tend to continue within the firm, even in the months when the firm does not export to brand multinationals. We expect that as more firms start supplying to these brand multinationals, the overall effect on river water quality may diminish.

Our sample consists of 127 monitoring stations, 37 of which are located near RMG factories. Table 1 presents the summary statistics for the 37 water monitoring stations with both water quality and export share during our data period. Each station starts monitoring water quality at a different time, and water quality data are missing in some months; thus, our data are an unbalanced panel.

Our primary indicator for water quality, $WaterQuality_{i,m,y}$, is DO. According to the US

Environmental Protection Agency (EPA), DO levels below 5 mg/L are challenging conditions for fish, and fish have difficulty surviving with DO levels below 3 mg/L. The mean value of DO is 3.1 mg/L in our dataset, which indicates that rivers in Bangladesh are generally not ideal environments for aquatic life. We also use BOD as an alternative indicator. Rivers are considered severely polluted when BOD values exceed 8 mg/L. Our data show that the mean BOD level is 13 mg/L, further suggesting that rivers surrounding RMG firms are highly polluted.

We use the share of exporters, $Export_{i,m,y}$, to measure the intensity of exporting activity of firms surrounding monitoring stations. For the shares considering all exporters (exporters both to non-brand and brand multinationals), around 79% of RMG firms export every month during our data period. When focusing only on exporters to brand multinationals, the suppliers to brand multinationals that export account for, on average, 44% of all exporters. The standard deviations of both export shares are similar, which suggests both variables exhibit similar variation.

3.2 Two-way Fixed Effects Specification

We first examine the correlation between river water quality at monitoring stations and the share of exporting firms surrounding the stations. Specifically, we run the following two-way fixed effects regressions:

$$arcsinh(WaterQuality_{i,m,y}) = \beta_{FE} Export_{i,m+1,y'} + \delta_{i,m} + \theta_y + \epsilon_{i,m,y}, \tag{1}$$

where $WaterQuality_{i,m,y}$ is the water quality observed at station i, in month m of year y. To account for potential time lags between production and export, we use the shipment recorded one month after the water-quality measurement, $Export_{i,m+1,y'}$, where y' denotes the corresponding year when $m+1$ falls in the next calendar year.[2] We control for local

[2]Since our customs data only record shipping dates, we need to account for these potential time lags. Here, we assume that the production process, which generates pollution, occurs one month prior to the

seasonal patterns specific to each monitoring station (e.g., lower water levels in dry seasons that vary with the geographical features and industrial compositions around stations) using station-month level fixed effects, $\delta_{i,m}$. We also include year fixed effects, θ_y, to account for secular national trends in water quality (e.g., changes in water quality regulation over the years). Standard errors are clustered at the station level to address potential autocorrelation within stations over time. Our coefficient of interest is β_{FE}, which captures the relationship between water quality and the export share.

Additionally, we apply the inverse hyperbolic sine transformation to $WaterQuality_{i,m,y}$. This transformation approximates the natural logarithm of the variables while allowing for zero observations. The formula for the inverse hyperbolic sine transformation is $arcsinh(x) = \ln(x + \sqrt{x^2+1})$.

3.3 Difference-in-Differences (DiD) Specification

We use a staggered DiD design to estimate the causal effects of trading with brand multinationals on local water quality. This design exploits the variation in the timing of exports to brand multinationals around each monitoring station. We define a station as treated once more than 50% of the firms within 10 km of that station start exporting to brand multinationals. Stations where 50% or fewer nearby firms export to brand multinationals are placed in the control group. Unlike the two-way FE specification, monitoring stations without any surrounding exporters also serve as control groups.[3] The staggered treatment timing varies substantially across different stations, as illustrated in Figure 2.

We run the following DiD regression with two-way fixed effects:

$$arcsinh(WaterQuality_{i,m,y}) = \beta_{DiD} ExportBrand_{i,m,y} + \delta_i + \theta_{my} + \varepsilon_{i,m,y}, \quad (2)$$

shipment or export of the apparel goods.

[3]The two-way fixed effects specification uses 37 stations with surrounding RMG factories, where export shares can be calculated. In contrast, the DiD specification also includes stations without surrounding RMG factories as never-treated stations.

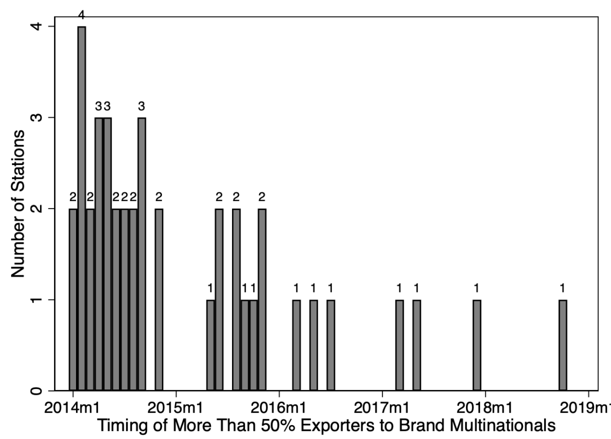

Figure 2: Differential Treatment Timing Across Monitoring Stations

Notes: This figure illustrates the variation of the timing when 50% of the firms located within 10 km of each station begin exporting to brand multinationals.

where the treatment variable is $ExportBrand_{i,m,y}$, which takes a value of one when more than 50% of the firms surrounding station i start exporting to brand multinationals; otherwise, it equals zero. We include station-level fixed effects, δ_i, following the two-way fixed effects specification. Additionally, we include year-by-month fixed effects, θ_{my}, which provides a more conservative approach to control for time trends, thereby enhancing the validity of the parallel trends assumption. Our coefficient of interest is β_{DiD}, which we hypothesize to be positive for the DO values considering the private enforcement of effluent standards by the brand multinationals. Standard errors are clustered at the station level.

We also adopt an event study specification to examine pre-trends and the dynamic evolution of the treatment effects:

$$arcsinh(WaterQuality_{i,m,y}) = \sum_{\tau=-\underline{\tau}}^{\overline{\tau}} \beta_\tau ExportBrand_{i,\tau} + \delta_i + \theta_{my} + \varepsilon_{i,m,y}, \tag{3}$$

where $ExportBrand_{i,\tau}$ serves as a treatment indicator for each month τ relative to the start of major exports to brand multinationals. Although the event time τ can range from -68 ($\underline{\tau}$) up to 67 ($\overline{\tau}$), our main event study plots focus on β_τ within the range of $-12 < \tau < 48$, where sufficient water quality data from monitoring stations are available. Additionally, we present more aggregated dynamic effects at the quarterly level by collapsing the data and including year-by-quarter fixed effects. We examine β_τ from $\tau < 0$ to test for parallel-pre trends and β_τ from $\tau \geq 0$ to investigate the dynamic treatment effects over time.

Given the potential bias in the two-way fixed effects estimator applied to staggered DiD designs, we use an alternative DiD estimator as our baseline specification. Recent literature has highlighted that the two-way fixed effects estimator can produce biased results due to the negative weights caused by bad comparisons between early and late adopters, particularly in the presence of heterogeneous treatment effects across different cohorts and time periods (Goodman-Bacon, 2021). To mitigate this issue and obtain unbiased estimates, we use the alternative estimator proposed by Callaway and Sant'Anna (2021), which is robust to the problems associated with negative weights.[4]

4 Results

We first study the correlation between export shares and river water quality using two-way fixed effects. Our main analysis comes from event studies, where we investigate the impact of exports to brand multinationals on water quality through the DiD specification we introduced in the previous section.

4.1 The Effect of Export Shares on Water Quality

Table 2 shows the results of the two-way fixed effects specification using the share of all exporters surrounding monitoring stations (in Columns 1–3) and the share of exporters supplying to brand multinationals (in Columns 4–6). In Column 1, the negative coefficient for DO suggests that as more firms export, water quality deteriorates. Specifically, a 50 percentage point increase in export shares leads to an approximately 17% decline in DO

[4]The event study results of the Callaway and Sant'Anna (2021) estimator in Section 4.2 include the coefficients for event time -1. This is because a varying base period is used for estimating the pseudo-effects in pre-treatment periods, aligning with the parallel trends assumptions outlined in Callaway and Sant'Anna (2021). Here, the base period is the immediately preceding period.

Table 2: The Effect of Export Shares on Water Quality (Arcsinh of DO)

	All Exports			Exports to Brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Share	-0.336***	-0.336***	-0.381***	-0.069	-0.069	-0.074
	(0.100)	(0.061)	(0.129)	(0.101)	(0.054)	(0.106)
Number of observations	1,226	1,226	1,180	1,226	1,226	1,180
R^2	0.854	0.854	0.854	0.853	0.853	0.853
Level of clustering SE	Station	River	Station	Station	River	Station
Grouping nearby stations	NO	NO	YES	NO	NO	YES
Mean of Dep. Variable	3.182	3.182	3.370	3.182	3.182	3.370

Notes: This table reports the two-way fixed effects regression estimates. We include station-month fixed effects and year-fixed effects in the regressions. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 3 and 6 present the results when averaging the water quality data from stations located within 1 km of each other.

values. In contrast, we observe an insignificant effect in Column 4 when using the share of exporters to brand multinationals. These findings support our hypothesis: when focusing on exports from suppliers to brand multinationals, the negative impact from export (i.e., larger production size) on water quality is mitigated.

We conduct a variety of robustness checks. Our results are robust to clustering standard errors at the river level, accounting for potential spatial correlation of water quality across multiple stations within the same river (Columns 2 and 4 of Table 2). Additionally, the same results are observed when using an alternative dataset, which averages water quality data from stations located within 1 km of each other (Columns 3 and 6 of Table 2). Our results are also robust to alternative lag structures for the treatment indicator (i.e., two or three months instead of one month), which account for potential lags between production and export (Appendix Table B1). Lastly, we find similar detrimental effects on water quality when using the alternative water quality indicator (BOD), although the estimates become imprecise (Columns 1–3 of Appendix Table B2).

Table 3: The Effect of Exports to Brand Multinationals on Water Quality

	arcsinh(DO)			
	(1)	(2)	(3)	(4)
ATT	0.503***	0.503**	0.675***	0.409***
	(0.185)	(0.257)	(0.144)	(0.151)
Level of clustering SE	Station	River	Station	Station
Grouping nearby stations	NO	NO	YES	NO
Time Unit	Monthly	Monthly	Monthly	Quarterly

Notes: This table reports the estimated ATT from the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-month-fixed effects (or year-by-quarter fixed effects) in the regressions. Standard errors, clustered at the station or river level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Column 3 presents the result when averaging the water quality data from stations located within 1 km of each other. Column 4 shows the quarterly result, where the water quality data are averaged at the quarterly level and year-by-quarter fixed effects are included.

4.2 The Effect of Exports to Brand Multinationals on Water Quality

In our main analysis, we focus on the event when firms begin exporting to multinationals and examine its effect on river water quality. Table 3 presents the average treatment effect on the treated (ATT) derived from the Callaway and Sant'Anna (2021) estimator, which corresponds to β_{DiD} in equation 2. In our baseline specification using monthly data, the ATT is 0.503 (Column 1). This result shows that major exports from local firms to brand multinationals increase DO levels in nearby rivers by 50.3%, suggesting substantial water quality improvement.

Our result is robust to a variety of specifications. First, the result holds when clustering standard errors at the river level instead of at the station level (Column 2). Second, a similar magnitude of effect is observed when using a collapsed dataset, which averages

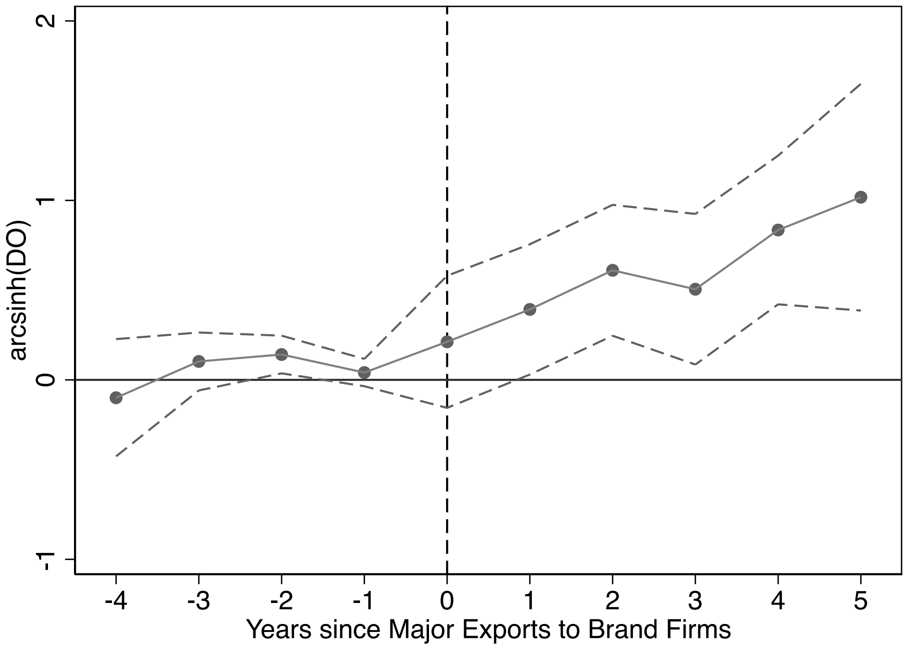

Figure 3: The Effect of Exports to Brand Multinationals on Water Quality

Notes: This figure shows the coefficients of the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-month-fixed effects in the regressions. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the station level.

water quality data from stations located within 1 km of each other (Column 3). Third, the quarterly analysis also supports the same water quality improvement (Column 4). Lastly, when adopting an alternative water quality indicator, we find a similar effect: major exports to multinational brands decrease BOD levels by 65.2% in the monthly analysis (Appendix Table B3).

Event study analysis further reveals that this positive impact on water quality persists over several years, accompanied by parallel pre-trends. Figure 3 shows the dynamic effects both before and after major exports to brand multinationals, using the Callaway and Sant'Anna (2021) estimator. First, we find no differential effects during the pre-treatment periods, supporting the validity of the parallel trends assumption. Second, the positive effects on water quality are sustained for up to 5 years. The monthly and quarterly results show a consistent pattern, as shown in Appendix Figures A1 and A2, respectively. This event study result is also robust when using the alternative water quality indicator (BOD), as demonstrated in Appendix Figure A3.

5 Mechanisms

So far, we have tested the hypothesis that becoming a supplier to brand multinationals incentivizes firms to adopt cleaner production processes, which in turn help reduce pollution in nearby river water. Our empirical analysis based on administrative data supports this hypothesis. However, the administrative data do not allow us to identify how brand buyers, relative to non-brand buyers, induce local exporters to adopt cleaner practices. One potential driver is the stringency of compliance enforcement. Our pre-survey discussions with business associations and compliance managers suggest that brand buyers place strong emphasis on environmental standards and are less willing to compromise on them. To capture this channel, we focus on three dimensions of compliance enforcement: inspections, certifications, and effluent treatment plants.

5.1 Types of Compliance Enforcement

On-site and Off-site Inspections

Our discussions with business leaders suggest that inspections involve both document verification and on-site physical inspections. Document verification includes certificates issued by the Government of Bangladesh, such as the Environmental Clearance Certificate from the Department of Environment (DOE). On-site inspections conducted by auditors cover a wide range of issues, which typically include ETPs, liquid and solid waste management, chemical storage, the use of chemicals, water and energy consumption, and air quality. While third-party audits by internationally recognized firms such as SGS, Bureau Veritas, and TÜV SÜD are standard practice, business leaders noted that brand buyers often prefer a hybrid model that combines inspections by their own auditing teams with those conducted by third parties. In both cases, auditors follow a structured process that combines national legal requirements with global sustainability standards, resulting in benchmark assessments and continuous compliance monitoring. Both compliance requirements and the quality of inspections are likely to differ between brand and non-brand buyers. Reputation-conscious brands are likely to invest more in the inspection of environmental compliance than non-brand buyers.

Certifications

Environmental certificates are often described as "green passports" to international markets, as major global retailers mandate them as a prerequisite for participation in their supply chains. Although the subscription and renewal fees are substantial, local exporters are likely to use these certificates to signal the quality of their environmental compliance to potential buyers. Our discussions with compliance managers reveal that LEED, OEKO-TEX, ISO 14001, GOTS, and Higg FEM are the certificates most commonly obtained by local exporters. While there is some overlap across certificates, each focuses on a different dimension of compliance. For example, OEKO-TEX verifies that every component of a garment, including threads and buttons, is free from harmful substances, whereas GOTS certifies standards for textiles made from organic fibers. Consequently, local exporters are often required to obtain multiple certificates, and this requirement is likely to be more demanding for suppliers to major brands.

Effluent Treatment Plants

An ETP is installed on factory premises to treat wastewater generated during dyeing, washing, and finishing processes before discharge into nearby water bodies. This wastewater contains substantial biodegradable organic matter and is also often toxic, highly colored, and chemically contaminated. There are two major types of ETPs: (i) biological ETPs, which use microorganisms (such as bacteria) to break down biodegradable organic matter in wastewater and are typically better suited for treating large volumes of wastewater cost-effectively; and (ii) chemical ETPs, which rely on chemical reactions to remove pollutants such as heavy metals, color, and other chemical contaminants and are often more costly because they require chemical inputs. Biological ETPs are therefore more directly related to our water quality measures, especially BOD and, indirectly, DO, whereas chemical ETPs are less directly related to these measures. According to business leaders, RMG buyers treat ETPs as a non-negotiable, "zero-tolerance" requirement for any factory involved in wet processing. Our hypothesis is that reputation-conscious brand buyers place pressure on suppliers to have an ETP with sufficient capacity to properly treat wastewater. In addition, factories supplying such buyers may be more likely to adopt biological ETPs, which are better suited to treating large volumes of wastewater cost-effectively.

5.2 Descriptive Evidence from the Survey

We conducted a short survey of 60 RMG factories to gain insights into the potential channels of compliance enforcement discussed above. The sample was randomly drawn from the customs data, restricting to exporters located in Gazipur, Narayanganj, and Savar, and stratifying firms based on their export composition into brand-only, non-brand-only, and mixed exporters.[5]

Table 4 reports differences in means for a set of key variables capturing the extent of compliance enforcement across factories with low and high brand exposure. We define brand exposure as the share of exports to brand buyers in total export value, measured using the 2021 customs data, and classify firms according to whether their brand exposure is above or below the median.[6]

[5]Specifically, the sampling frame was constructed from firms that exported in 2021 and were located in Gazipur, Narayanganj, or Savar. Using export values, firms were then stratified into three groups: those exporting more than 95% to brand buyers, those exporting only to non-brand buyers, and those exporting to both brand and non-brand buyers with a brand-export share between 0.40 and 0.60. Within the non-brand-only group, firms were chosen to span the transaction-value distribution using percentile-based cutoffs.

[6]In our sample of 60 firms, the share of exports to brand buyers ranges from 0 to 100. Half of the sample is classified as having high brand exposure.

Table 4: RMG Factory Practices by Share of Exports to Brand Buyers

	Means			
Variable	Brand Export: Low	Brand Export: High	Difference	Obs.
Panel A. Inspections and Assistance				
Share of buyers conducting inspections	0.769 (0.388)	0.989 (0.061)	0.220*** (0.072)	60
Average frequency of buyer inspections (per year)	2.397 (2.406)	2.808 (3.483)	0.412 (0.798)	55
Share of buyers recommending environmental compliance	0.744 (0.396)	0.933 (0.155)	0.189** (0.078)	60
Share of buyers assisting with environmental compliance	0.249 (0.387)	0.461 (0.467)	0.212* (0.111)	60
Inspection by government environment agency	0.667 (0.479)	0.833 (0.379)	0.167 (0.112)	60
Panel B. Certification				
Number of certificates obtained	6.867 (3.471)	8.933 (3.237)	2.067** (0.867)	60
Panel C. Effluent Treatment Plants				
Has an effluent treatment plant	0.233 (0.430)	0.500 (0.509)	0.267** (0.122)	60
Effluent treatment plant capacity (m^3/day)	1,228.571 (1,548.517)	1,941.467 (2,731.763)	712.895 (913.100)	22
Adopts biological treatment in the effluent treatment plant	0.571 (0.535)	0.600 (0.507)	0.029 (0.237)	22

Notes: This table compares compliance enforcement outcomes across RMG factories with low and high brand exposure, where brand exposure is measured as the share of export value to brand buyers in 2021 using customs data. Factories with brand exposure above the median are classified as high exposure, and those below the median as low exposure. Robust standard errors are reported for tests of differences in means. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. In Panel A, the share of buyers is defined as the share of the six major buyers reported by each respondent factory, consisting of three major brand buyers and three major non-brand buyers, that conduct the relevant practice.

Among firms with high brand exposure, approximately 99% of buyers conduct inspections, compared with 77% among firms with low brand exposure, and this difference is statistically significant at the 1% level. However, the average frequency of buyer inspections does not vary significantly between firms with low and high brand exposure. This suggests that the key difference may lie not in the frequency of inspections, but in their nature and intensity. Brand buyers are also more likely to recommend and support environmental compliance: about 93% of buyers of high-brand-exposure firms recommend environmental compliance, compared with 74% for low brand exposure firms. This difference is statistically significant at the 5% level. Similarly, about 46% of buyers of high-brand-exposure firms provide assistance for environmental compliance, whereas the corresponding figure is 25% for low-brand-exposure firms. We also find no statistically significant difference in whether firms received a visit from the Department of Environment, a government agency responsible for enforcing environmental standards, in the past year. This suggests that public enforcement does not vary across firms and reinforces the role of private enforcement by multinational buyers.

Firms with high brand exposure also obtain a larger number of compliance certificates than low-brand-exposure firms, and the difference is statistically significant. On average, high-brand-exposure firms hold 8.93 certificates, compared with 6.87 among low-brand-exposure firms.

Regarding ETPs, 50% of firms in the sample with high brand exposure have an ETP, whereas only about 23% of firms with low brand exposure do so. This difference is statistically significant at the 5% level. The overall adoption rate remains limited because not all factories in our sample engage in wet processing.[7] Among firms with ETPs, treatment capacity and the share using biological treatment are also higher among firms with high brand exposure, although these differences are not statistically significant, possibly due to the smaller sample size.

[7] Among the 60 firms in our sample, 35 engage in at least one wet-processing activity (washing, dyeing, and finishing).

Overall, the survey evidence is consistent with the view that greater brand exposure is associated with stronger environmental compliance. Firms with high brand exposure are more likely to face buyer inspections, receive recommendations and assistance, obtain more compliance certifications, and adopt proper ETPs.

6 Conclusion

Responsible sourcing initiatives have become increasingly prominent as global firms face growing pressure to ensure that their supply chains meet environmental standards. This study provides, to our knowledge, the first empirical evidence on the environmental consequences of such practices in a developing-country context. Focusing on the RMG sector in Bangladesh, we examine how exporting to multinational buyers—particularly those with strong global brands—affects local river water quality.

Developing a novel dataset that links firm-level customs data with station-level water quality measures, we show that increased export activity is generally associated with deteriorating water quality. However, this negative relationship is substantially mitigated when exporters are suppliers to brand multinationals. Our staggered difference-in-differences analysis further establishes a causal relationship: once the majority of firms surrounding a monitoring station begin exporting to brand multinationals, river water quality improves significantly, with effects that persist over several years.

To better understand the mechanisms underlying these effects, we complement our empirical analysis with primary survey data. The survey evidence indicates that firms with higher exposure to brand buyers are subject to more intensive compliance monitoring, are more likely to receive guidance and assistance on environmental practices, obtain a greater number of environmental certifications, and are more likely to adopt effluent treatment plants. At the same time, we find no statistically significant difference in government inspections across firms, suggesting that public enforcement alone does not explain the observed improvements in environmental outcomes. Together, these findings point to the importance of private enforcement by multinational buyers as a key channel through which responsible sourcing affects environmental performance.

Our results have important policy implications. In settings where regulatory capacity is limited and enforcement is imperfect, multinational buyers can play a complementary role by incentivizing compliance with environmental standards. This highlights the potential for aligning global supply chain governance with domestic environmental policy objectives. At the same time, reliance on private enforcement raises important questions about coordination and efficiency, particularly given the fragmented nature of certification requirements across different buyers. Policymakers may therefore consider facilitating greater standardization of environmental requirements and leveraging monitoring data to better target enforcement efforts.

This study also opens several avenues for future research. First, further work could examine the long-term sustainability of privately enforced environmental compliance and whether these practices persist in the absence of continued engagement with brand buyers. Second, future research could explore downstream impacts on health outcomes, particularly in communities exposed to industrial pollution. Finally, extending this analysis to other sectors and countries would help assess the generalizability of responsible sourcing as a tool for improving environmental performance in global supply chains.

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Online Appendix

Does Trade with Multinationals Induce Greener Production?

Evidence from the Bangladesh Fashion Industry

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Appendix A Additional Figures

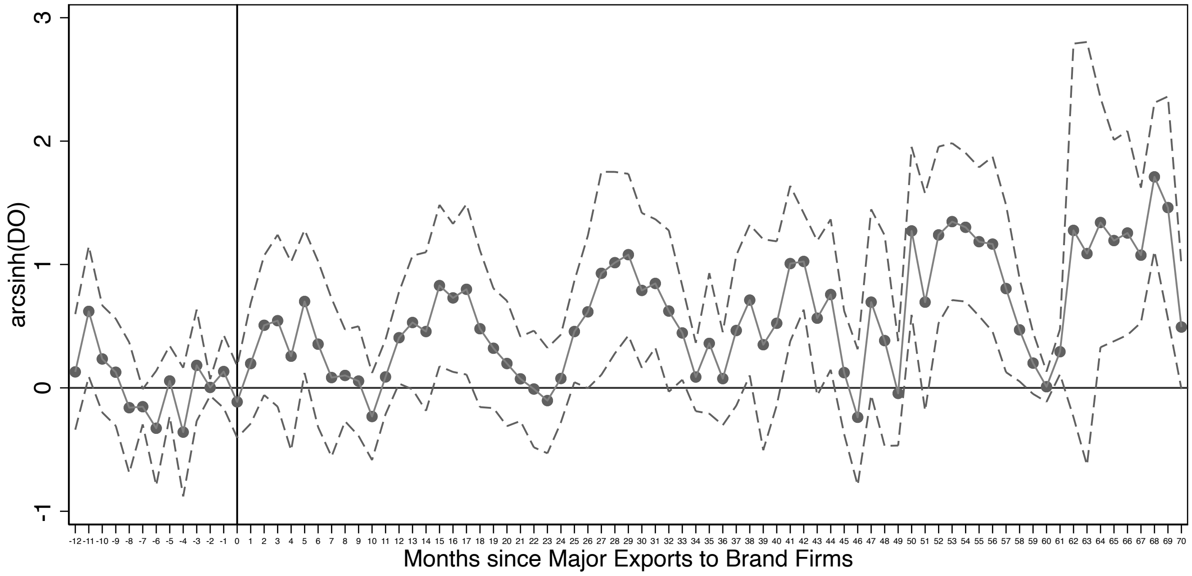

Figure A1: Event Study Results with Full Months

Notes: This figure shows the coefficients of the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-month-fixed effects in the regressions. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the station level.

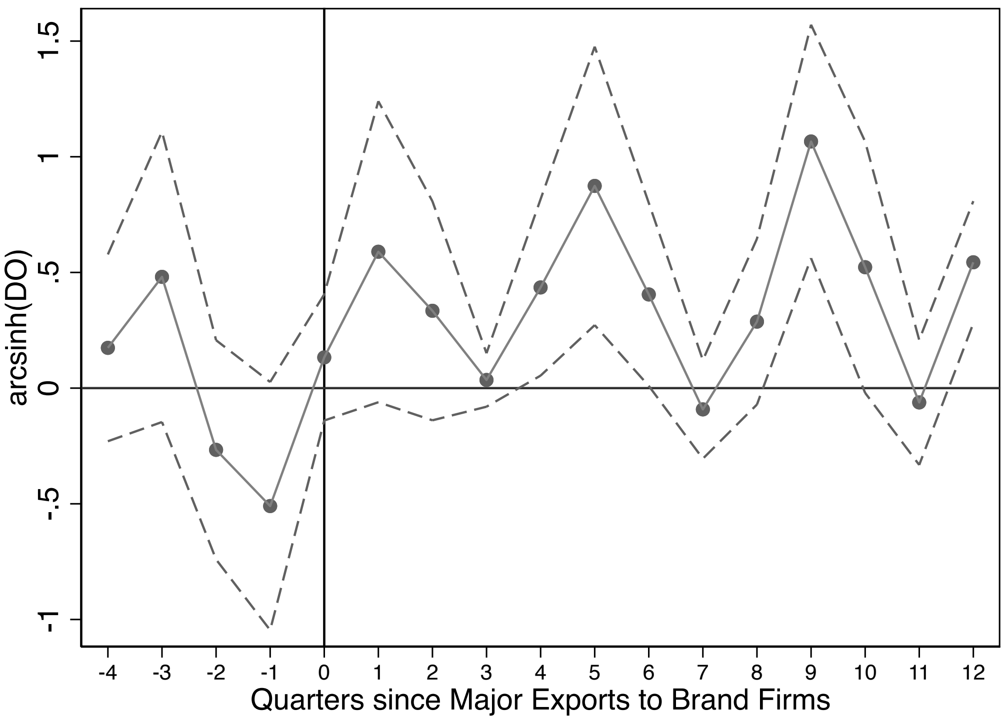

Figure A2: Event Study Results at the Quarterly Level

Notes: This figure shows the coefficients of the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-quarter-fixed effects in the regressions. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the station level.

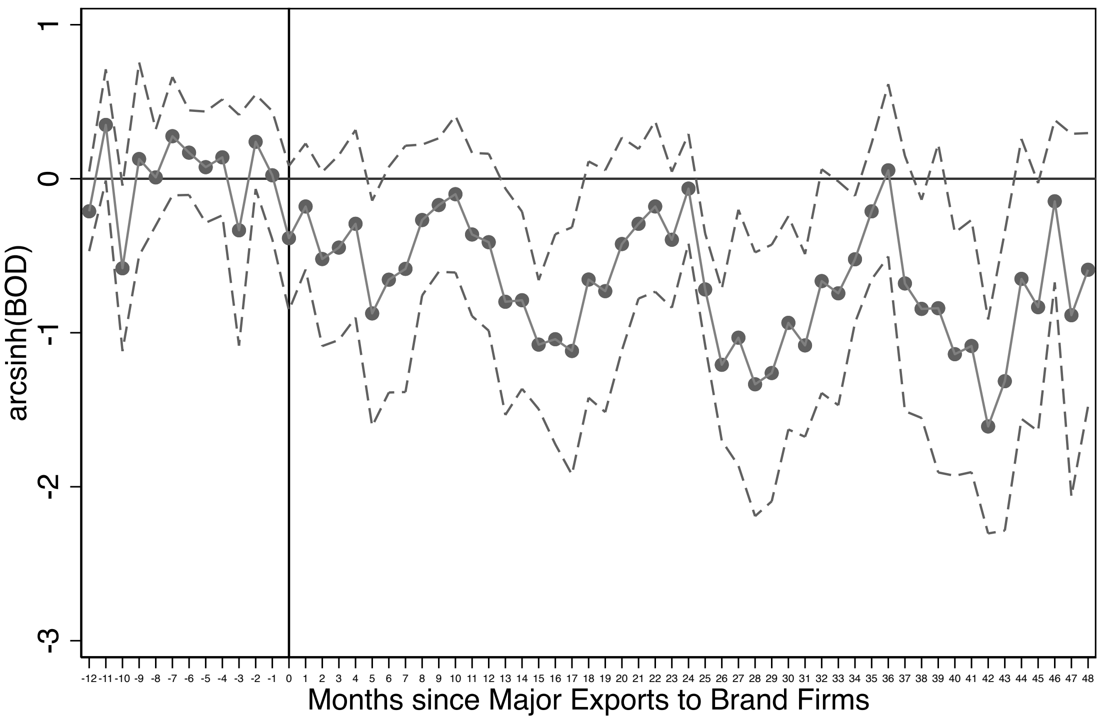

Figure A3: Event Study Results for Alternative Water Quality Indicator (Arcsinh of BOD)

Notes: This figure shows the coefficients of the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-month-fixed effects in the regressions. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the station level.

Appendix B Additional Tables

Table B1: Two-way Fixed Effects Results for Alternative Number of Lagged Months

	All Exports			Exports to Brands		
	(1)	(2)	(3)	(4)	(5)	(6)
	$m+1$	$m+2$	$m+3$	$m+1$	$m+2$	$m+3$
Export Share	-0.336***	-0.310***	-0.413***	-0.069	-0.132	-0.116
	(0.100)	(0.099)	(0.131)	(0.101)	(0.111)	(0.099)
Number of observations	1,226	1,208	1,182	1,226	1,208	1,182
R^2	0.854	0.854	0.855	0.853	0.854	0.855
Level of clustering SE	Station	Station	Station	Station	Station	Station
Grouping nearby stations	NO	NO	NO	NO	NO	NO
Mean of Dep. Variable	3.182	3.162	3.136	3.182	3.162	3.136

Notes: This table reports the two-way fixed effects regression estimates. We include station-fixed effects, year-fixed effects, and month-fixed effects in the regressions. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B2: Two-way Fixed Effects Results for Alternative Water Quality Indicator (Arcsinh of BOD)

	All Exports			Exports to Brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Share	0.403	0.403	0.652	-0.005	-0.005	0.042
	(0.387)	(0.276)	(0.478)	(0.082)	(0.049)	(0.100)
Number of observations	1,110	1,110	1,074	1,110	1,110	1,074
R^2	0.723	0.723	0.698	0.722	0.722	0.696
Level of clustering SE	Station	River	Station	Station	River	Station
Grouping nearby stations	NO	NO	YES	NO	NO	YES
Mean of Dep. Variable	12.596	12.596	11.861	12.596	12.596	11.861

Notes: This table reports the two-way fixed effects regressions estimates. We include station-fixed effects, year-fixed effects, and month-fixed effects in the regressions. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 3 and 6 present the results when averaging the water quality data from stations located within 1 km of each other.

Table B3: DiD Results for Alternative Water Quality Indicator (Arcsinh of BOD)

	arcsinh(BOD)			
	(1)	(2)	(3)	(4)
ATT	-0.652***	-0.652***	-0.817***	-0.043
	(0.221)	(0.245)	(0.212)	(0.344)
Level of clustering SE	Station	River	Station	Station
Grouping nearby stations	NO	NO	YES	NO
Time Unit	Monthly	Monthly	Monthly	Quarterly

Notes: This table reports the estimated ATT from the Callaway and Sant'Anna (2021) estimator. We include station-fixed effects and year-by-month-fixed effects (or year-by-quarter fixed effects) in the regressions. Standard errors, clustered at the station or river level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Column 3 presents the result when averaging the water quality data from stations located within 1 km of each other. Column 4 shows the quarterly result, where the water quality data are averaged at the quarterly level and year-by-quarter fixed effects are included.