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Does trade with multinationals induce greener production? Evidence from the Bangladesh fashion industry

Kazi Iqbal
Moogdho Mahzab
Kazuki Motohashi
Haruka Takayama

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Kazi Iqbal†
Moogdho Mahzab‡
Kazuki Motohashi§
Haruka Takayama¶

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Abstract

There is growing attention to the need for firms to ensure that their suppliers meet production standards (i.e., responsible sourcing). This practice is particularly prevalent in the apparel industry, as buyers—especially multinationals with well-known brands—often require their suppliers to comply with stringent environmental standards. We study how trading with global fashion brands affects the environmental performance of their suppliers in Bangladesh. Using a novel dataset that combines custom data with river water quality data, we find that an increase in the number of exporters to brand multinationals improves the river water quality surrounding these exporters. Our finding highlights the crucial role multinational buyers play in mitigating industrial pollution, particularly in developing countries with weaker regulatory enforcement.

Keywords: Responsible sourcing, Water quality, Apparel industry, Bangladesh
JEL Classification: F18, F64, O13, Q56

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†Bangladesh Institute of Development Studies, kiqbal@bids.org.bd
‡International Food Policy Research Institute, m.mahzab@cgiar.org
§Hitotsubashi University, kazuki.motohashi@r.hit-u.ac.jp
¶University at Albany, State University of New York, htakayama@albany.edu

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 90% of total exports in 2019. Thus, the potential impact of exports on the local environment is massive. 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 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).

[1] Refernce 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).

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. This implies that trade with brand multinationals may help mitigate the adverse environmental effects of exports.

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 64%, 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-trend 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 different aggregation of water quality data.

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. 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 Section 6 discusses the policy implications of our results. Section 7 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., brands multinationals) in the RMG industry. 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 clean 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 Government of Bangladesh, Department of Environment, 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 importers with 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 importers with brand multinationals, we cross-reference the list of global apparel brands in the Fashion Transparency Index, 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 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.

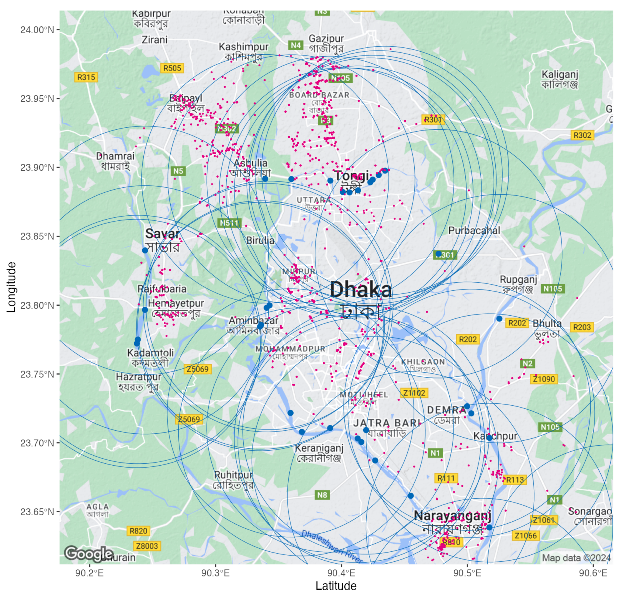

Figure 1: Water Quality Monitoring Stations and RMG Firms

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.

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 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

Table 1: Summary Statistics

	Mean	Std	Median	Min	Max	Observation
$WaterQuality_{i,m,y}$						
DO (mg/L)	3.159	2.579	3.1	0	17	1,339
BOD (mg/L)	13.023	14.613	8	0	98	1,223
$Export_{i,m,y}$						
All exporters	0.785	0.277	0.875	0	1	2,952
Exporters to brand multinationals	0.439	0.286	0.453	0	1	2,952

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

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 are 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 shows 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 exhibits 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:

$$arcsinh(WaterQuality_{i,m,y}) = \beta_{FE} Export_{i,m,y} + \delta_i + \theta_m + \gamma_y + \epsilon_{i,m,y}, \tag{1}$$

where $WaterQuality_{i,m,y}$ is the water quality monitored at station i, in month m and year y, and $Export_{i,m,y}$ is the export share that indicates the proportion of firms exporting at station i, in month m and year y. We control for time-invariant characteristics specific to each monitoring station (e.g., geographical features and industry compositions around stations) using station-level fixed effects, δ_i. Month fixed effects, θ_m, and year fixed effects, γ_y, are also included in the regression to account for seasonality (e.g., lower water levels in dry seasons) and secular trends (e.g., changes in water quality regulation over the years) in water quality. 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 $arcsinh(x) = \ln(x + \sqrt{x^2+1})$.

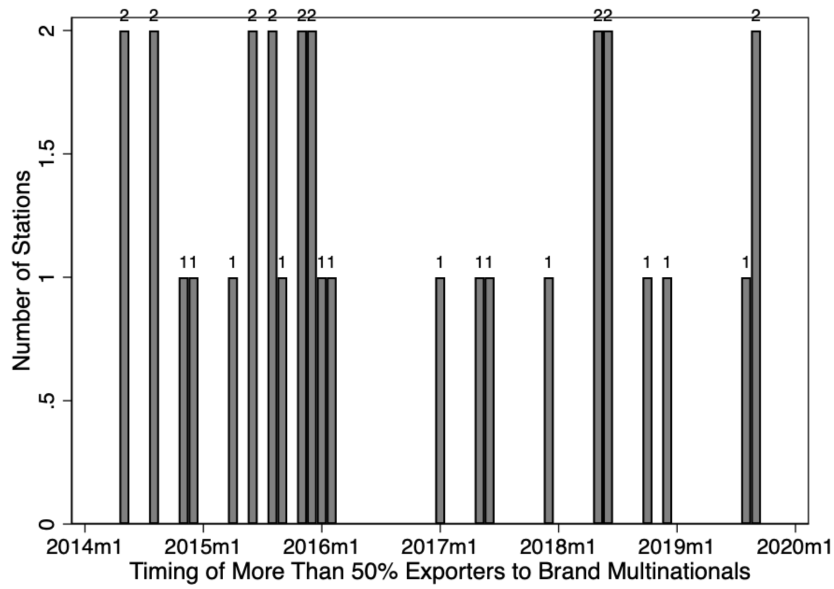

Figure 2: Differential Treatment Timing Across Monitoring Stations

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.

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.[2] 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:

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

[2]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.

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 is expected 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 primary analysis focuses 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 the 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.[3]

[3]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

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	-0.334***	-0.334***	-0.401***	-0.109	-0.109	-0.090
	(0.108)	(0.078)	(0.099)	(0.089)	(0.073)	(0.095)
Number of observations	1,339	1,339	1,267	1,339	1,339	1,267
R^2	0.711	0.711	0.706	0.708	0.708	0.703
Level of clustering SE	Station	River	Station	Station	River	Station
Grouping nearby stations	NO	NO	YES	NO	NO	YES
Mean of Dep. Variable	3.159	3.159	3.370	3.159	3.159	3.370

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.

4 Results

We first study the correlation between export shares and river water quality using two-way fixed effects. Our main analysis 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 values.

(2021). Here, the base period is the immediately preceding period.

In contrast, we observe an insignificant coefficient 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). 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). To account for potential time lags between production and shipment, we also run regressions using the export share from one month ahead, since our customs data only record shipping dates.[4] The results when using this lagged export share are in line with our baseline results (Appendix Table B1). Lastly, we find similar effects for the alternative water quality indicator (BOD), as shown in Appendix Table B2.

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 0.640 (column 1). This result shows that major exports from local firms to brand multinationals increase DO levels in nearby rivers by 64%, 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 water quality data from stations located within 1 km of each other (column 3). Third, the quarterly analy-

[4] This robustness check assumes that the production process, which generates pollution, occurs one month prior to the shipment or export of the apparel goods.

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

	arcsinh(DO)			
	(1)	(2)	(3)	(4)
ATT	0.640***	0.640***	0.554***	0.536***
	(0.139)	(0.128)	(0.168)	(0.203)
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.

sis 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 73.4% 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 48 months (four years).[5] The quarterly results display a consistent pattern, as shown in Appendix Figure A2. This event study result is also robust when using the alternative water quality indicator (BOD), as demonstrated in Appendix Figure A3.

[5]When we extend our examination to the full period, as shown in Appendix Figure A1, the effects persist up to approximately 60 months (five years), although the later effects may be influenced by a subset of stations.

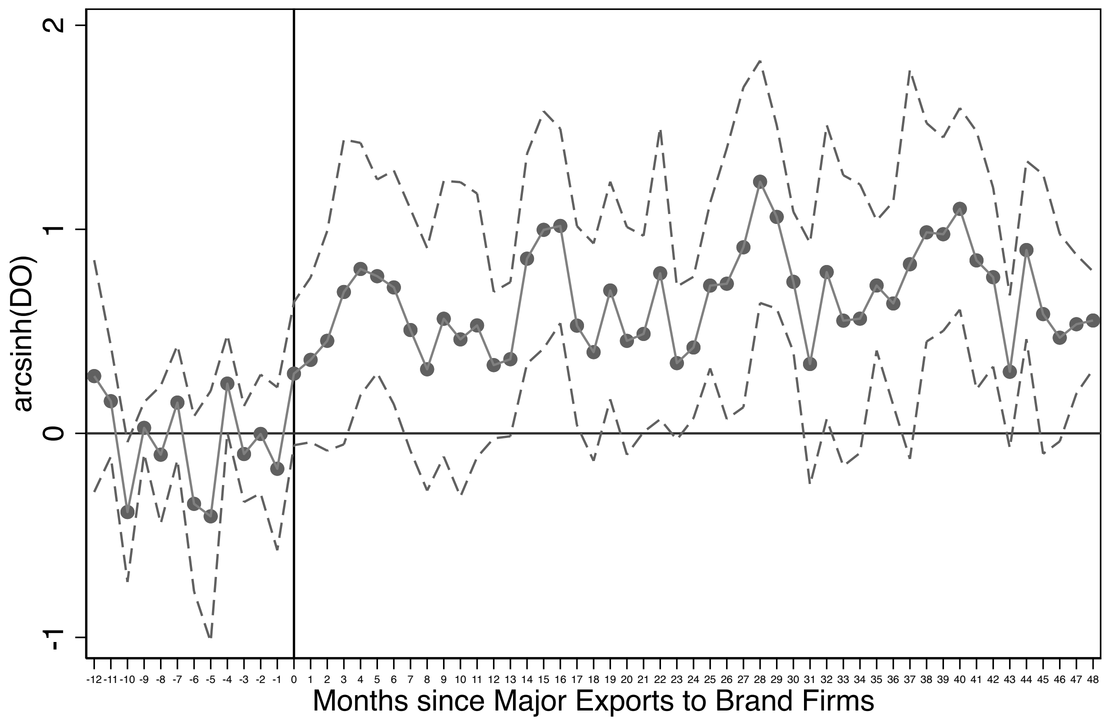

Figure 3: The Effect of Exports to Brand Multinationals on Water Quality

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.

5 Mechanisms

We hypothesize that becoming a supplier to brand multinationals incentivizes firms to adopt cleaner production processes, which, in turn, help reduce the pollution in the river water. Our empirical analysis supports this hypothesis. Additionally, interviews with several RMG firms in Bangladesh provide anecdotal evidence that reinforces our findings.

We conducted interviews with RMG firms, an organization for environmental certifications, and the Department of Environment. All RMG firms are required to adopt basic production standards mandated by the government in terms of labor and environmental practices. Beyond these, brand multinationals require their suppliers (i.e., local firms in Bangladesh) to obtain environmental certifications from non-governmental international organizations, including ISO 9001, Leadership in Energy and Environmental Design (LEED), and OEKO-TEX standards. Each certification focuses on different areas, such as organic textiles and the use of harmful chemicals, with different stringent levels. Among the production stages, dying and washing emit chemically contaminated wastewater that affects river water quality. It is essential for the firms involved in those processes to install effluent treatment plants (ETP) to clean their wastewater.

Obtaining additional environmental certifications helps local firms attract more buyers and sometimes get offered better prices. However, these certifications come at a cost. Different buyers often require different environmental certifications. Firms must pay fees to obtain each certification, which can be very costly to maintain multiple certifications. For example, one of the firms we interviewed spent $4,000 per year to maintain all certifications. In addition to the fees, firms need to prepare for audits conducted by certification bodies and buyers. An audit takes around two months, and firms often have to hire several staff members, especially to manage the audit process.

Overall, our interviews suggest that trading with brand multinationals encourages local firms to follow more stringent production standards, which can mitigate the negative effect of wastewater discharged by RMG firms.

6 Policy Implications and Recommendations

Bangladesh, the world's second-largest RMG exporter, needs to develop policies that integrate environmental considerations related to RMG production. During the past three decades, as the RMG industry has experienced substantial growth, environmental issues have not received the same level of policy focus as labor and trade policies. Our analysis reveals that exports typically elevate river pollution levels. Pollution decreases if exports are made to a multinational company with strong brand values. The probable mechanism for this is that brand companies exert additional pressure on local producers to comply with various environmental regulations. When a firm exports to brand buyers, the firm is typically required to obtain more environmental certifications than companies exporting to non-brand buyers. Brand buyers also send inspectors to monitor the production process of their suppliers and verify the suppliers' compliance with environmental standards.

The Bangladesh government must formulate policies to reduce the industrial pollution that affects rivers in collaboration with manufacturers and exporters associations, such as BGMEA and BKMEA. The government has limited resources, making it sometimes challenging to verify whether each firm is using an effluent treatment plant or not. As we have shown, most of the exporting firms are clustered in specific areas. By using pollution data collected from the Department of Environment's monitoring stations, a warning system could be created to notify firms in those clusters if pollution levels exceed a specific threshold. The Department of Inspection of Fabrication and Establishment, the Deputy Commissioner's office, and the Department of Environment can work together to address this challenge. One potential structure for the warning system is as follows: first, when the pollution level at a monitoring station surpasses the threshold, all upstream firms located within 10 km of the monitoring stations will be alerted. Within a week, a team of officials from three different departments will conduct unannounced visits to randomly selected firms. A firm should receive a warning if it is found not complying with proper environmental production practices. If violations occur twice, the firm's export license could be canceled due to poor practices.

Another potential policy implication is to centralize the environmental certificates that Bangladeshi firms are required to obtain from brand multinationals. Our interviews reveal that firms bear significant costs to acquire and maintain these environmental certificates, partly because each multinational requires different certificates from its suppliers. This creates a considerable burden on Bangladeshi firms. The government could alleviate this by establishing guidelines for multinationals, encouraging them to align their environmental requirements under a unified certificate.

7 Conclusion

Responsible sourcing initiatives have been a growing trend in recent years. This study is the first empirical investigation into the effect of multinationals' responsible sourcing practices on the local environment. We focus on the RMG sector in Bangladesh, where pollution from this industry is a severe issue. Our results indicate that while exports to foreign countries generally increase river pollution levels around local firms, trade with multinational buyers known for their strong brands mitigates these pollution levels. Additionally, we conduct a

DiD analysis to examine the impact of trading with brand multinationals on river water quality. We find that the water quality improves as the majority of Bangladeshi firms export to these brand multinationals. Our study highlights the role of buyers' private enforcement of environmental standards.

This study opens avenues for further exploration. Future studies could examine the health impacts of trade with multinationals, focusing particularly on child mortality. By leveraging geocoded health data, researchers could investigate whether trade with multinational buyers that privately enforce environmental standards contributes to reducing child mortality rates through decreased river pollution.

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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

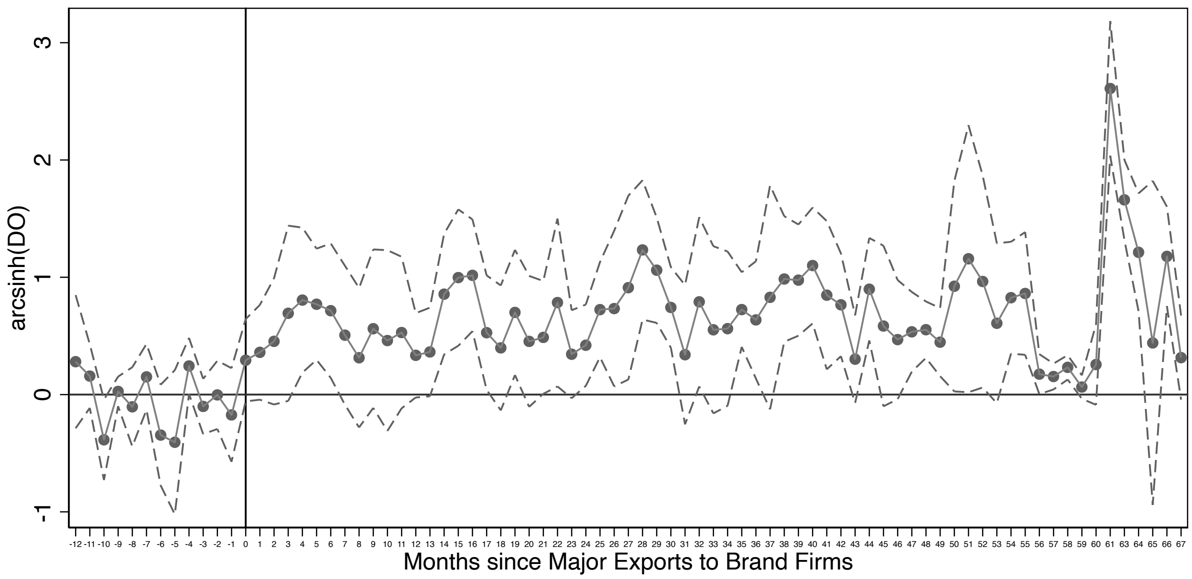

Figure A1: Event Study Results with Full Months

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.

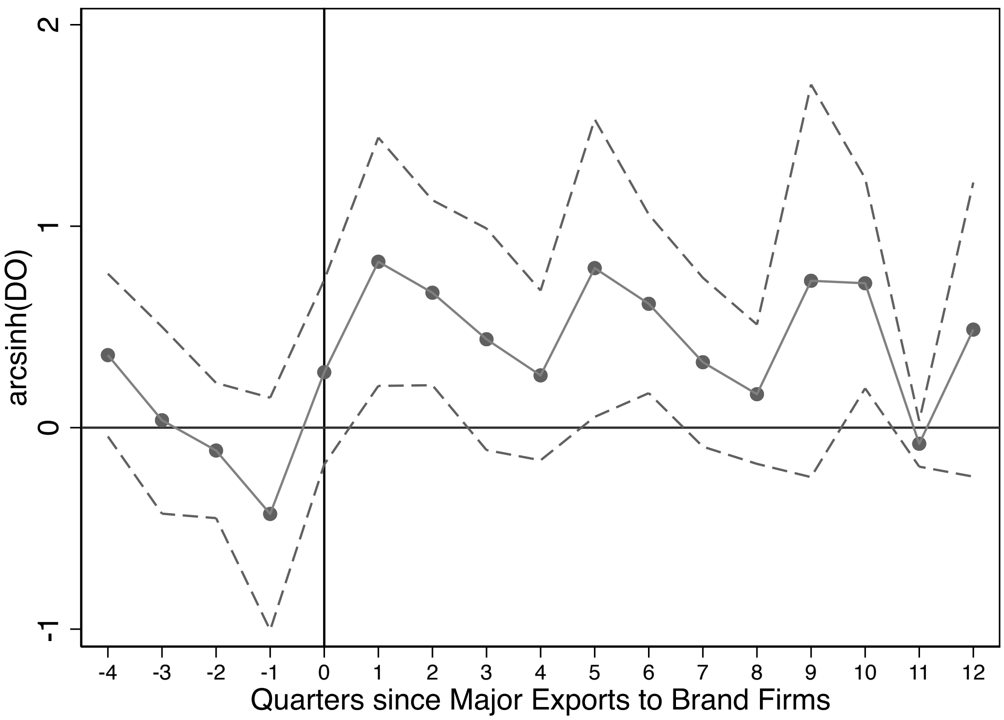

Figure A2: Event Study Results at the Quarterly Level

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.

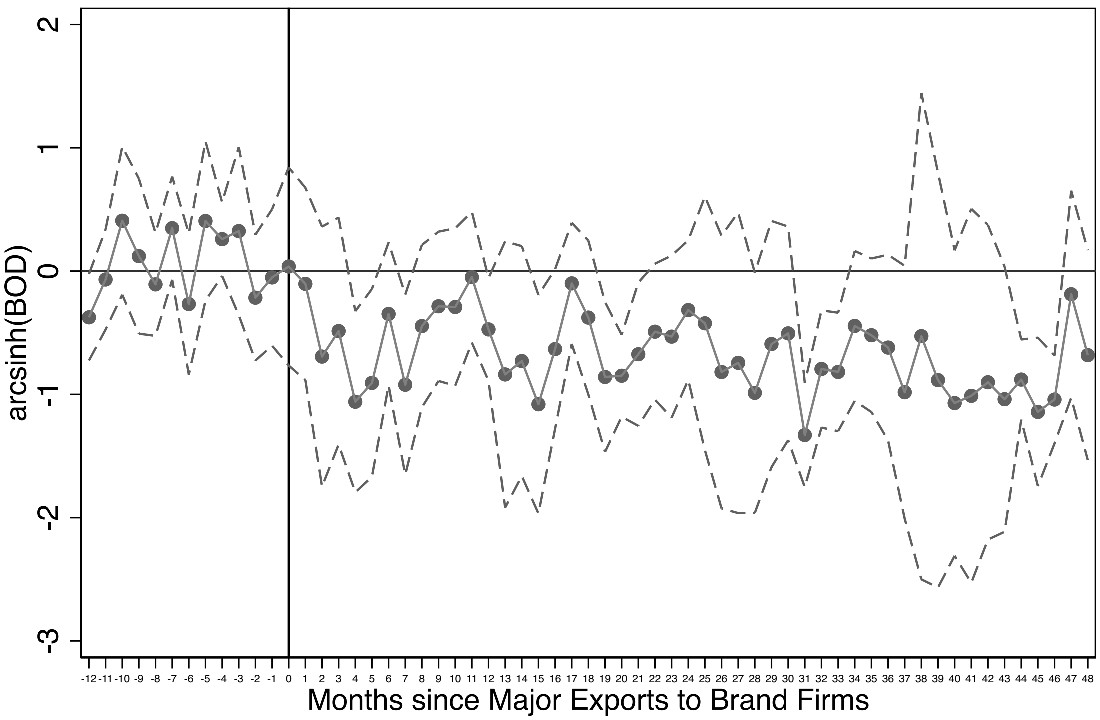

Figure A3: Event Study Results for Alternative Water Quality Indicator (BOD)

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 Using Lagged Export Shares

	All Exports			Exports to Brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Share (1 month ahead)	-0.199**	-0.199	-0.221*	-0.105	-0.105	-0.139
	(0.097)	(0.119)	(0.117)	(0.096)	(0.101)	(0.099)
Number of observations	1,314	1,314	1,244	1,314	1,314	1,244
R^2	0.710	0.710	0.705	0.709	0.709	0.704
Level of clustering SE	Station	River	Station	Station	River	Station
Grouping nearby stations	NO	NO	YES	NO	NO	YES
Mean of Dep. Variable	3.164	3.164	3.375	3.164	3.164	3.375

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 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	0.429*	0.429*	0.617**	0.059	0.059	0.253
	(0.252)	(0.202)	(0.272)	(0.140)	(0.149)	(0.277)
Number of observations	1,233	1,233	1,164	1,233	1,233	1,164
R^2	0.584	0.584	0.568	0.580	0.580	0.563
Level of clustering SE	Station	River	Station	Station	River	Station
Grouping nearby stations	NO	NO	YES	NO	NO	YES
Mean of Dep. Variable	13.023	13.023	12.203	13.023	13.023	12.203

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 (BOD)

	arcsinh(BOD)			
	(1)	(2)	(3)	(4)
ATT	-0.734***	-0.734***	-0.436	-0.548**
	(0.273)	(0.087)	(0.354)	(0.224)
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.

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