

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

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Motivation

- The simultaneous pursuit of economic growth and environmental sustainability is among the major challenges faced today
- International trade functions as a primary driver of economic growth for many developing economies
- Impact on environmental pollution of international trade is mixed (*Bombardini and Li 2020; Cherniwchan 2017; Copeland et al., 2021*)
- Multinationals and their foreign affiliates contribute to two-thirds of international trade (*OECD 2018*)
- Labor standards improved with more responsible sourcing and enforcement by the MNCs, but environmental concerns did not get the same attention (*Boudreau 2023*)

Responsible Sourcing

- RMG and leather are the most polluting manufacturing industries (*UNCTAD, 2020*)
- Enforcing effluent standards on local firms is challenging
- Private enforcement from the foreign buyers can help



"Fashion is still neglecting its impact on water"
- Vogue Business, September, 2020

"Out Of Fashion - The Hidden Cost of Clothing Is A Water Pollution Crisis"
Forbes, September, 2020

"Top clothing brands linked to water pollution scandal in China"
- Dialogue Earth, October, 2012

Photo: Piyas Biswas/ Getty Images

This Paper

- We conduct the first study to investigate whether multinationals responsible sourcing improves the quality of the local environment
 - Does exporting to brand firms compared to non-brand firms impact water pollution differently?
- We analyze the impact of RMG export on environmental pollution in Bangladesh
 - Does trading with multinationals affect the environmental performance of local suppliers?

Context: Bangladesh Apparel Industry

- Second-largest exporter of clothing after China; 8% of global RMG export (*WTO, 2019*)
- Around 90% of total export in 2019
- Around 5 million people employed in the industry



- Washing, dyeing, and finishing sections discharge large amounts of wastewater
- Industrial wastes severely affecting the downstream areas of rivers
- Higher scrutiny from foreign buyers since the tragedy of the Rana Plaza incident in 2013

Data

- Export customs records (National Board of Revenue)
 - bill of entry in 2014-2021 (ASYCUDA)
 - buyers' information (brand vs. non-brand)
 - suppliers' transaction information| shipment dates, value and weights, HS codes, etc.
 - factory addresses converted to latitude and longitude and verified by Google Maps
- Water quality data (Department of Environment)
 - in 2010-2019
 - 127 unique monitoring stations in rivers all over the country
 - monthly data on dissolved oxygen (DO) and biochemical oxygen demand (BOD)

Who are the Brands? Fashion Transparency Index

- Fashion Revolution | world's largest fashion activism movement post Rana Plaza



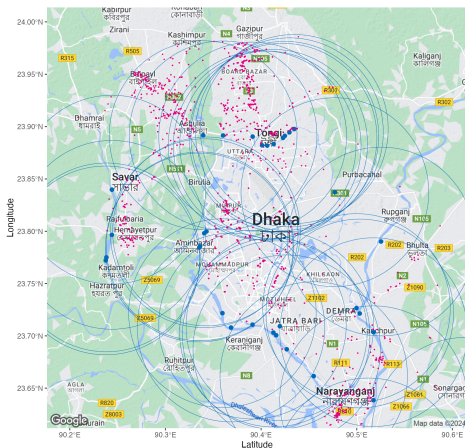
Rank	Brand Name	2021 Final Scores
1	OVS	196
2	H&M	168.75
3	The North Face	164.25
4	Timberland	164.25
5	C&A	162.75

Identification: Water Quality Monitoring Stations



Identification: Water Quality Monitoring Stations and RMG Factories

- Factories assigned to the closest stations within a 10 km buffer
- Only use factories located upstream of monitoring stations



Summary Statistics

	Mean	Std	Median	Min	Max	Observation
<i>WaterQuality</i> _{<i>i,m,y</i>}						
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
<i>Export</i> _{<i>i,m,y</i>}						
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.

FE Approach: Effects on Water Pollution

$$\operatorname{arcsinh}(\text{WaterQuality}_{i,m,y}) = \delta_i + \theta_m + \gamma_y + \beta_{fe} \text{Export}_{i,m,y} + \varepsilon_{i,m,y} \quad (1)$$

where i is monitoring station, m is month-of-year, and y is year

- $\text{Export}_{i,m,y}$: Exporter shares around each monitoring station i in month m in year y
- The inverse hyperbolic sine transformation allowing for zero observations using natural logarithmic approximation
- Station-level fixed effects, δ_i , Month fixed effects, θ_m , and year fixed effects γ_y are used
- Standard errors clustered at the monitoring station level

Results: Effect of Export Shares on Water Quality

	All Exports			Exports to Brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Share	-0.334*** (0.108)	-0.334*** (0.078)	-0.401*** (0.099)	-0.109 (0.089)	-0.109 (0.073)	-0.090 (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.

Staggered DiD Approach: Brand vs. Non-brand

$$\operatorname{arcsinh}(\text{WaterQuality}_{i,m,y}) = \beta_{DiD} \text{ExportBrand}_{i,m,y} + \delta_i + \theta_{my} + \varepsilon_{i,m,y}, \quad (2)$$

where i is monitoring station, m is month-of-year, and y is year

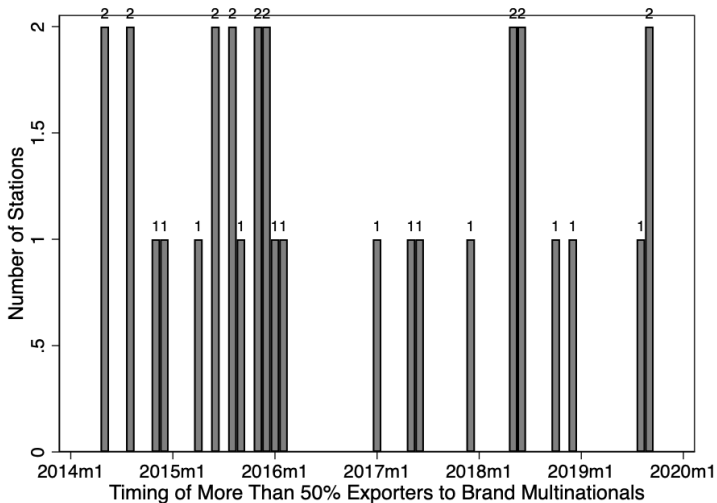
- $\text{ExportBrand}_{i,m,y}$ turns to one and remains one when more than 50% of the firms surrounding station i starts exporting to brand firms.
- year-by-month fixed effects, θ_{my} ; more conservative measure to enhance the validity of parallel trend assumption
- Callaway and SantAnna (2021) estimator that is robust to negative weights in the staggered DiD setting

Event Study Specification

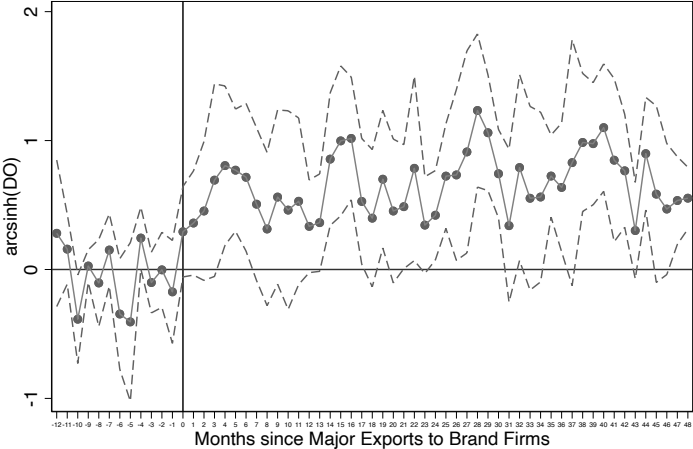
$$\operatorname{arcsinh}(\operatorname{WaterQuality}_{i,m,y}) = \sum_{\tau=-\underline{T}}^{\bar{T}} \beta_{\tau} \operatorname{ExportBrand}_{i,\tau} + \delta_i + \theta_{my} + \varepsilon_{i,m,y}, \quad (3)$$

- To examine pre-trends and the dynamic evolution of the treatment effects
- $\operatorname{ExportBrand}_{i,\tau}$ serves as a treatment indicator for each month relative to the start of major exports to brand multinationals

Differential Treatment Timings



Results: Event Study



Results: Exports to Brand Multinationals on Water Quality

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

- Alternative outcome - BOD decreases by 73.4%

Mechanism and Policy Implications

- Brand multinationals require the local suppliers to obtain environmental certifications from non-governmental international organizations for different standards
- Monitoring effluent treatment plants (ETP) to clean their wastewater
- Developing warning system when pollution level goes up from a threshold and check within a week
- Centralize the environmental certificates that Bangladeshi firms are required to obtain from brand multinationals

Thank You

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