Tariffs at the Sourcing Margin:
Supplier Choice in G20 Clean-Technology Goods Markets

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Abstract

Do tariff preferences decide who supplies the clean technologies needed for the energy transition? This paper examines whether relative-tariff treatment shapes sourcing decisions in climate-smart goods markets. Because rival exporters can face different tariffs while selling the same product to the same importing market, access is often unequal. We capture this unequal access through tariff disadvantage, defined as the gap between an exporter's tariff and the lowest tariff available to any rival in the same importer-product-year market. Using HS6 trade and tariff data for 64 climate smart goods, imported by 19 G20 markets from the 30 largest economies over 2010 to 2023, we compare rival suppliers competing in the same sourcing market. The preferred PPML estimate shows that a 1 percentage point higher tariff disadvantage reduces imports from that exporter by about 3.3%. The result survives demanding bilateral year controls, timing tests, placebo checks and major robustness exercises. Market share estimates confirm that tariff disadvantages weaken exporter position within the market. An equal tariff access counterfactual shows that removing these disadvantages reallocates sourcing opportunities, with larger effects in emerging G20 importers. The findings therefore show that relative tariff costs in clean-technology markets shape who wins sourcing opportunities, who loses them, and which countries gain effective access to green supply chains.

JEL Classifications: F13, F14, F18, Q56

Keywords: Climate-smart goods, tariff disadvantage, green trade policy, exporter choice, clean technology supply chains, sourcing reallocation.

1. Introduction

1.1 Clean-technology sourcing and tariff inequality

Clean technologies move through trade before they change production systems. Solar components, wind equipment, grid technologies, pollution-control machinery, efficient lighting, water-treatment equipment and related climate-smart goods are traded products, but they are also inputs into decarbonisation, energy security and industrial upgrading. For this reason, trade policy has become part of the climate policy toolkit. A joint report by the World Trade Organization (WTO) and the United Nations Environment Programme (UNEP) framed trade as one channel through which climate-relevant technologies can diffuse across countries (WTO and UNEP, 2009). The Asia-Pacific Economic Cooperation (APEC) endorsed a list of environmental goods and committed members to reduce applied tariffs on those products to 5% or less (APEC, 2012). WTO members later launched negotiations for an Environmental Goods Agreement with the aim of eliminating tariffs on a wide range of goods linked to climate and environmental protection (WTO, 2014). The United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP, 2011) proposed a wider set of 64 climate-smart goods for climate adaptation and mitigation. More broadly, Shapiro (2021) shows that tariffs and non-tariff barriers are systematically lower in more CO_2-intensive industries than in cleaner industries, creating an environmental bias in trade policy.

These initiatives share a common policy logic that lower trade barriers should improve access to climate-relevant goods. That logic is important, but it does not fully capture how sourcing works in practice. Importing markets often do not face a simple choice between importing and not importing. The most-favoured-nation principle makes non-discriminatory tariff treatment the multilateral benchmark (World Trade Organization, n.d.), but actual applied tariffs can still differ across suppliers because preferential trade agreements, special tariff schemes and country-specific access conditions create preference margins. For a given climate-smart product in a given destination market, one exporter may enter duty-free while another faces a positive tariff. The relevant question is therefore not only whether tariffs are high or low on average. It is also whether an exporter is tariff-disadvantaged relative to its competitors in the same market. The paper therefore asks whether an exporter's tariff disadvantage relative to competing suppliers affects its import value and sourcing share within the same importer-product-year market.

This paper studies that relative margin. Its central argument is that tariff schedules rank rival suppliers through relative tariff costs. An exporter facing a higher tariff than its best-treated rival faces a tariff disadvantage. If that disadvantage is large, the exporter may sell less, lose sourcing share and become less visible in the clean-technology supply chain of that importing market. This point is intuitive, but it has not been measured systematically for climate-smart goods across major G20 markets. The contribution of the paper is therefore not to show that tariffs matter in principle. It is to quantify how unequal tariff access reallocates clean-technology[1] sourcing across rival exporters, and to identify who gains or loses sourcing opportunities when tariff disadvantages are removed.

1.2 Related Literature and Research gaps

The existing literature on environmental goods has mainly developed in three directions. The first studies the policy case and negotiation design for reducing barriers on environmental goods. Balineau and de Melo (2013) show that list-based approaches were central to environmental goods negotiations but also politically difficult because countries disagreed on which goods should be included. De Melo and Vijil (2016) analyse the critical-mass approach and explain why a plurilateral route may be attractive when multilateral agreement is hard. De Melo and Solleder (2020) examine tariffs and non-tariff barriers on environmental goods and ask what developing countries should expect from their removal. At a broader level, Shapiro (2021) shows that trade policy is environmentally non-neutral. In most countries, import tariffs and non-tariff barriers are lower in more carbon intensive industries than in cleaner industries. This creates an implicit policy bias toward emissions-intensive trade. Together, these studies establish that the level and environmental composition of trade protection matter. However, they do not examine how preferential tariff differences rank rival exporters supplying the same climate-smart product within the same destination market.

The second strand estimates trade opportunities and the determinants of environmental-goods trade. Dinda (2014) uses a gravity model to estimate trade opportunities in climate-smart goods across Asian markets. Costantini and Crespi (2008) link environmental regulation to export dynamics in energy technologies, while Cantore and Cheng (2018) examine how environmental regulatory stringency, innovation capacity and conventional gravity determinants shape environmental-goods

[1] Clean technologies refer to the 64 climate-smart goods and technologies identified by UNESCAP (2011).

trade. He et al. (2015) estimate the effects of tariff and non-tariff liberalisation on environmental-goods trade among APEC members. These studies analyse trade potential, bilateral flows and the effects of absolute trade barriers, but they do not compare rival exporters within the same importer-product-year market to isolate the supplier-allocation margin of relative tariff treatment.

The third relevant literature is the preferential-market-access and gravity literature. Fugazza and Nicita (2013) distinguish direct market access from access relative to foreign competitors and show that both affect bilateral trade. Anderson and van Wincoop (2003) show that bilateral trade depends on trade costs relative to multilateral resistance, not only on absolute bilateral barriers. Head and Mayer (2014) describe gravity as the empirical workhorse of international trade. Yotov et al. (2016) provide the applied structural gravity framework for trade-policy analysis, while Santos Silva and Tenreyro (2006) establish the case for PPML when trade data are heteroskedastic and include zero flows. Baier and Bergstrand (2007) show that trade agreements are endogenous and require careful empirical treatment. This literature establishes that relative trade costs matter, but it has not applied that logic to climate goods or environmental goods to examine how tariff rankings affect exporter choice, sourcing shares and the distribution of clean-technology market access.

A related allocation literature also matters. Melitz (2003) shows how trade exposure reallocates activity across heterogeneous firms toward more productive producers. Eaton and Kortum (2002) link trade flows to technology, geography and trade costs across countries. Arkolakis et al. (2012) show that trade shares and trade elasticities are central to welfare implications in many trade models. Caliendo and Parro (2015) quantify the effects of tariff changes in a multi-sector setting with input-output linkages. These studies show that trade policy reallocates activity across producers, sectors and countries. The gap is that they do not ask a specific clean-technology question: when rival exporters face different tariffs within the same climate-smart goods market, does that relative tariff position affect who supplies the market?

The question is now policy-relevant because clean-technology supply chains are concentrated. The International Energy Agency (2023) argues that the clean energy transition depends on scaling secure, resilient and sustainable clean-energy technology supply chains. The International Energy Agency (2024) further shows that clean-technology manufacturing remains geographically concentrated across major technologies. In this context, preferential tariff access may affect not only the cost of importing a good, but also the distribution of sourcing opportunities across countries. That

distribution matters for participation in green supply chains, for supplier diversification and for the ability of emerging economies to compete in climate-smart goods markets.

1.3 Research Contribution

The paper contributes to the literature in three ways. First, it identifies a supplier allocation margin in climate smart goods trade. It compares rival exporters selling the same HS6 product to the same importer in the same year and measures each exporter's tariff position relative to its best treated competitor. This shows whether unequal tariff access is associated with which suppliers gain or lose sourcing opportunities within the same market.

Second, the paper separates aggregate market access from supplier allocation. The market share estimates examine whether tariff disadvantaged exporters lose relative position, while the equal access counterfactual holds total imports fixed and measures how sourcing is redistributed across suppliers.

Third, the paper quantifies who gains and who loses when tariff disadvantages are removed. The counterfactual shows that sourcing reallocation is larger in emerging G20 markets and that tariff equalisation does not necessarily reduce dependence on dominant suppliers. This is directly relevant to current concerns about clean technology supply chain concentration (IEA, 2023; IEA, 2024).

The results show that a one percentage point higher tariff disadvantage is associated with about 3.3% lower imports from that exporter. The result remains robust across demanding fixed effects, timing tests, a future tariff placebo and major robustness checks. Market share estimates also show that tariff disadvantaged exporters occupy a weaker position within the market. The broader implication is that green trade policy[2] shapes not only import costs but also the distribution of effective access to clean technology markets.

[2] Green trade policy refers here to trade policy measures that shape market access for climate-smart and clean-technology goods, including tariffs, tariff preferences, and related liberalization measures.

2. Data

2.1 Data source and unit of observation

The analysis uses product-level bilateral import and tariff data downloaded from the World Integrated Trade Solution (WITS). The merchandise trade values available through WITS are sourced from UN Comtrade (World Bank, n.d.). The dataset contains importer names, exporter names, HS6 product codes, product descriptions, trade years, duty type, simple average tariff rates and import values. The unit of observation is an importer-exporter-HS6-year pair.

The sample covers 64 climate-smart goods at the HS6 level, following the UNESCAP (2011) list of climate-smart goods and technologies. These goods cover clean energy and environmental technologies, including solar-related products, wind-related equipment, energy-efficient equipment, storage-related goods, pollution-control goods and related components. The importer sample consists of 19 individual G20 markets, excluding the European Union (EU) aggregate from the baseline sample. The EU aggregate is retained only for the EU-aggregate robustness check. Exporters are the 30 largest economies by nominal GDP in 2025, based on the World Bank's GDP ranking (World Bank, 2026). They are treated as major potential suppliers of climate-smart goods. The estimation period is 2010 to 2023.

2.2 Main variables

The main dependent variable is import value, measured in thousand US dollars. The tariff variable is the effectively applied tariff and measured as the simple average tariff rate. The key constructed variable is tariff disadvantage. It compares an exporter's applied tariff with the lowest tariff available to any rival exporter selling the same HS6 product to the same importer in the same year.

$$D_{ijpt} = \tau_{ijpt} - \min_{k} \tau_{ikpt} \quad (1)$$

Equation 1 defines tariff disadvantage. The left-hand side, D_{ijpt} , is the tariff disadvantage faced by exporter j when it sells product p to importer i in year t. The right-hand side shows how this disadvantage is calculated. The first term, τ_{ijpt}, is the tariff faced by exporter j in that importer-product-year market. From this, the study subtracts the lowest tariff faced by any competing exporter

k selling the same product to the same importer in the same year. Therefore, the equation measures how much more tariff exporter *j* faces compared with the best-treated rival supplier in that market.

If D_{ijpt} = 0, the exporter is not tariff-disadvantaged because it faces the lowest available tariff in that market. If D_{ijpt} > 0, the exporter faces a higher tariff than at least one rival supplier. A larger value means a larger tariff disadvantage and weaker tariff access. The measure adapts the relative-market-access logic of Fugazza and Nicita (2013) to a narrowly defined sourcing market, using the best-treated rival as the benchmark.

The study also constructs exporter market-share. This is the exporter's import value divided by total imports from the 30 exporters in the same importer-HS6-year market. It is used to test whether tariff disadvantage weakens an exporter's sourcing position. For robustness, we also construct an alternative tariff measure that compares an exporter's tariff with the average tariff in the same market instead of the lowest tariff.

2.3 Additional variables

The timing tests use two variables. The lagged tariff disadvantage is the previous year's tariff disadvantage for the same importer-exporter-HS6 relationship, calculated only when consecutive years are available. The future tariff placebo is the change in tariff disadvantage between the current year and the next year. This checks whether future tariff changes predict current imports.

The robustness checks use several indicators. China exporter and China importer indicators test whether the results are driven by China as a supplier or market. EU indicators are used for the EU-aggregate robustness check. Advanced and emerging G20 importer groups are used in the counterfactual analysis. Following the World Economic Outlook classification of the International Monetary Fund (2026), Australia, Canada, France, Germany, Italy, Japan, Korea, the United Kingdom and the United States are classified as advanced economies. The remaining G20 importers in the sample are grouped as emerging G20 markets. A solar and power-electronics indicator is used to remove selected HS6 products in the product-exclusion robustness check.

Table 1. Estimation sample summary

Sample item	Value
Number of observations used in the study	154013
Number of Importers	19
Number of Exporters	30
Number of HS6 products	64
Estimation Period	2010 to 2023
Importer-product-year markets	9007
Mean tariff disadvantage	4.3233 percentage points
Median tariff disadvantage	2.5 percentage points
Maximum tariff disadvantage	35 percentage points
Mean market share	0.0585

Note: The sample is the importer-exporter-HS6-year panel used in the reported tests. It keeps AHS tariff observations, excludes self-trade and missing key records, and combines repeated rows by averaging tariff rates and retaining the maximum reported import value to avoid double-counting. Markets with no tariff variation are excluded because tariff disadvantage cannot be identified there.

3. Methodology

3.1 Empirical objective and identification

The empirical strategy focuses on the sourcing margin. The paper asks whether relative tariff treatment affects which exporter supplies a given climate-smart good to a given importing market. The core comparison is therefore among exporters selling the same HS6 product to the same importer in the same year.

The main models are estimated using PPML[3]. This is appropriate for trade data because import values are non-negative, heteroskedasticity can make log-linear estimates inconsistent, and zero trade values do not need to be dropped mechanically. This follows Santos Silva and Tenreyro (2006). The use of high-dimensional fixed effects follows the structural gravity literature and computational approaches for PPML with many fixed effects, including Anderson and van Wincoop (2003), Head and Mayer (2014), Yotov et al. (2016), and Correia et al. (2020). Standard errors are two-way clustered by importer and HS6 product. Cameron and Miller (2015) provide the general framework

[3] All regressions are estimated in R using the fixest package (Bergé et al., 2026).

for multiway cluster-robust inference. The fixed-effect structure is designed to absorb the multilateral-resistance, market-level, exporter-side and bilateral sources of confounding while preserving the cross-exporter tariff variation that defines the sourcing margin.

3.2 Main source choice models

The baseline PPML model is:

$$E\left[X_{ijpt} \mid \cdot\right] = \exp\left(\beta D_{ijpt} + \alpha_{ipt} + \gamma_{jp} + \delta_{jt}\right) \tag{2}$$

In this model, X_{ijpt} is import value from exporter j to importer i for HS6 product p in year t. $E\left[X_{ijpt} \mid \cdot\right]$ is the conditional expected import value, where the conditioning set consists of the regressors and fixed effects. D_{ijpt} is tariff disadvantage, and α_{ipt} is an importer-product-year fixed effect that absorbs all shocks common to exporters selling the same product to the same importer in the same year. γ_{jp} is an exporter-product fixed effect that controls for an exporter's product-specific comparative advantage or capacity. δ_{jt} is an exporter-year fixed effect that controls for exporter-wide shocks in a given year. The coefficient β is the parameter of interest. A negative value of β means that exporters facing a higher tariff disadvantage sell less within the same sourcing market.

The preferred strong fixed effect model adds importer exporter fixed effects:

$$E\left[X_{ijpt} \mid \cdot\right] = \exp\left(\beta D_{ijpt} + \alpha_{ipt} + \gamma_{jp} + \delta_{jt} + \mu_{ij}\right) \tag{3}$$

Here, μ_{ij} captures stable bilateral relationships between importer i and exporter j. This includes persistent geography, long-term trade relationships, stable policy ties and other time invariant bilateral factors. This is the preferred model because it removes persistent bilateral differences while preserving the within market tariff variation needed to estimate the sourcing effect.

We also conduct an importer-exporter-year fixed effect model as a stronger stress test:

$$E\left[X_{ijpt} \mid \cdot\right] = \exp\left(\beta D_{ijpt} + \alpha_{ipt} + \gamma_{jp} + \eta_{ijt}\right) \tag{4}$$

Here, η_{ijt} absorbs shocks specific to importer i and exporter j in year t. This controls for time varying bilateral factors such as annual trade policy changes, bilateral disruptions, logistics shocks or diplomatic conditions. If β remains negative in this model, the result is not driven by time varying bilateral shocks. The three main models are reported together because they serve different purposes.

Equation 2 presents the baseline source-choice model. Equation 3 is the preferred specification, as it additionally controls for stable importer-exporter relationships. Equation 4 provides the strongest identification stress test by controlling for importer-exporter-year shocks.

Taken together, these specifications address distinct sources of confounding. Importer-product-year fixed effects hold constant the destination-product market in each year, absorbing importer demand, product-specific market conditions and inward multilateral resistance common to all competing exporters. Exporter-product fixed effects absorb persistent product-specific comparative advantage, production capacity and global specialization of each exporter, while exporter-year fixed effects absorb exporter-wide annual shocks. Importer-exporter fixed effects remove stable bilateral factors, including geography, long-standing commercial relationships and persistent policy ties. The importer-exporter-year stress test goes further by absorbing all annual bilateral conditions common across products, including trade-policy changes, logistics disruptions, exchange-rate exposure and diplomatic shocks. The remaining coefficient therefore compares exporters' relative tariff positions within narrowly defined sourcing markets after accounting for market-level, exporter-side and bilateral confounding.

3.3 Timing and placebo tests

The lagged tariff model replaces current tariff disadvantage with the previous year's tariff disadvantage:

$$E\left[X_{ijpt} \mid \cdot\right] = \exp\left(\beta D_{ijp,t-1} + \alpha_{ipt} + \gamma_{jp} + \delta_{jt} + \mu_{ij}\right) \tag{5}$$

The term $D_{ijp,t-1}$ is tariff disadvantage in the previous year for the same importer exporter product relationship. This test asks whether past tariff disadvantage predicts current sourcing. It is useful because procurement, supplier qualification and delivery relationships may respond with delay.

The future placebo uses the future change in tariff disadvantage:

$$F_{ijpt} = D_{ijp,t+1} - D_{ijpt} \tag{6}$$

The variable F_{ijpt} is then used as the explanatory variable in the same preferred fixed effect structure. This test asks whether future tariff changes predict current import values.

3.4 Robustness tests

The first robustness check replaces tariff disadvantage relative to the lowest tariff with tariff disadvantage relative to the market mean:

$$D_{ijpt}^{mean} = \tau_{ijpt} - \frac{1}{N_{ipt}} \sum_{k} \tau_{ikpt} \tag{7}$$

This check reports relative tariff treatment using the market mean as the reference point instead of the lowest tariff. Because importer-product-year fixed effects absorb market-level tariff constants, the identifying comparison remains the cross-exporter tariff difference within the same market.

Five additional robustness checks are reported. The pre-2018 sample checks whether the result holds before recent trade tensions and pandemic-era disruption. The China-exporter exclusion tests whether the estimate is driven by China as a supplier. The China-importer exclusion tests whether it is driven by China as a market. The solar and power-electronics exclusion removes HS6 850440, 853710, 853720 and 854140, covering static converters, control panels and photovoltaic cells or modules. This checks whether the result is driven by heavily traded solar and power-electronics categories. The EU-aggregate alternative replaces individual EU member importers with the EU aggregate and checks whether the result depends on the treatment of the EU.

The appendix reports a leave-one-product-out exercise. Each HS6 product is removed one at a time and the preferred model is re-estimated. This checks whether the main result is driven by any single climate-smart good.

3.5 Market-share mechanism test

The mechanism test uses exporter market share as the dependent variable:

$$s_{ijpt} = \beta D_{ijpt} + \alpha_{ipt} + \gamma_{jp} + \delta_{jt} + \mu_{ij} + \varepsilon_{ijpt} \tag{8}$$

In this linear fixed effect model, s_{ijpt} is exporter j's market share in the importer product year market, D_{ijpt} is tariff disadvantage and ε_{ijpt} is the error term. The fixed effects have the same interpretation as in the preferred import value model. The coefficient β tests whether tariff disadvantaged exporters lose sourcing position within the market. This test asks whether tariff

disadvantage weakens an exporter's relative sourcing position within the same importer-product-year market. It complements the import-value estimates by showing whether the tariff penalty appears not only as lower sales, but also as a smaller share of sourcing among rival suppliers.

3.6 Equal tariff access counterfactual

The equal tariff access counterfactual uses the preferred coefficient $\hat{\beta}$ and sets tariff disadvantage to zero within each market. The first step predicts raw counterfactual imports:

$$\tilde{X}_{ijpt}^{raw} = X_{ijpt}\exp\left(-\hat{\beta}D_{ijpt}\right) \tag{9}$$

Here, $\tilde{X}_{ijpt}^{raw}$ is the raw counterfactual import prediction before normalisation. X_{ijpt} is observed import value. $\hat{\beta}$ is the estimated coefficient from the preferred strong fixed effect model. D_{ijpt} is observed tariff disadvantage. Because $\hat{\beta}$ is negative, exporters with a positive tariff disadvantage receive a predicted sourcing boost before shares are normalised.

The second step converts raw predictions into counterfactual shares:

$$\tilde{s}_{ijpt} = \frac{\tilde{X}_{ijpt}^{raw}}{\sum_j \tilde{X}_{ijpt}^{raw}} \tag{10}$$

Here, $\tilde{s}_{ijpt}$ is the counterfactual sourcing share of exporter j. The denominator sums raw counterfactual predictions across all exporters in the same importer product year market. This normalisation ensures that counterfactual shares sum to one within each market.

The third step converts counterfactual shares into counterfactual import values while holding market size fixed:

$$\tilde{X}_{ijpt} = M_{ipt}\tilde{s}_{ijpt} \tag{11}$$

Here, $\tilde{X}_{ijpt}$ is the counterfactual import value. M_{ipt} is the original total import value in the importer product year market. Holding M_{ipt} fixed means the exercise does not predict aggregate market expansion. It only measures how sourcing shares would be reallocated across exporters if tariff disadvantages were removed.

The market reallocation index is:

$$R_{ipt} = 50 \sum_{j} \left| \tilde{s}_{ijpt} - s_{ijpt} \right| \tag{12}$$

Here, R_{ipt} measures the total amount of sourcing share that moves across exporters inside market m. The difference inside the absolute value is the change in exporter j's market share. The summation adds the absolute changes across exporters. Multiplying by 50 converts the value into percentage points while avoiding double counting, because one exporter's gain is another exporter's loss.

The counterfactual is reported in four ways. First, exporter redistribution shows which exporters gain or lose sample sourcing share when tariff disadvantages are removed. Second, the advanced versus emerging G20 comparison shows where tariff equalization reallocates sourcing more strongly. Third, the appendix China by reporter table shows how China's sourcing share changes across importing markets. Fourth, the appendix HS6 product reallocation figure shows which climate smart goods experience the largest sourcing reallocation.

4. Results and Discussion

This section reports the empirical evidence on whether tariff disadvantage shapes exporter choice in climate-smart goods markets. We first estimate whether exporters facing worse tariff treatment than their rivals sell less within the same importer-product-year market. We then test the timing of this relationship, examine robustness across alternative definitions and samples, assess whether the effect appears in exporter market shares, and use the preferred estimate to simulate how equal tariff access reallocates sourcing opportunities.

4.1 Tariff disadvantage and source choice

Table 2. Main source choice models

Variable / statistic	Main PPML	Preferred FE Model	Importer-exporter-year FE
Tariff disadvantage	-0.1186*** (0.0250)	-0.0338*** (0.0029)	-0.0556*** (0.0097)
Importer product year FE	Yes	Yes	Yes
Exporter product FE	Yes	Yes	Yes
Exporter year FE	Yes	Yes	No
Importer exporter FE	No	Yes	No
Importer exporter year FE	No	No	Yes
Observations	153,991	153,987	153,745
Pseudo R^2	0.8868	0.9455	0.9515

*Note. The dependent variable is import value in 1000 US dollars. Standard errors are clustered by importer and HS6 product and are reported in parentheses. The preferred specification is Column 2. The importer-exporter-year FE specification in Column 3 is a stress test that absorbs time varying bilateral shocks. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Number of observations are dropped due to fixed effects.*

Table 2 reports the main PPML estimates for the relationship between tariff disadvantage and import value. Across all specifications, the coefficient is negative and statistically significant, showing that exporters facing worse tariff treatment than their best-treated rivals sell less within the same importer-product-year market.

The baseline estimate in Column 1 is −0.1186, implying that a one percentage point higher tariff disadvantage is associated with about 11.2% lower imports. Column 2 is the preferred specification and adds importer-exporter fixed effects. The coefficient is −0.0338, which implies that a one percentage point higher tariff disadvantage reduces imports by about 3.3%. Using the mean tariff disadvantage of 4.32 percentage points (Table 1), the implied import penalty is about 13.6%. The median tariff disadvantage is 2.50 percentage points, which shows that tariff gaps of this size are common in the estimation sample. Column 3 adds importer-exporter-year fixed effects as a stronger

stress test and remains negative at −0.0556. The consistently negative coefficient across increasingly demanding specifications shows that tariff preferences shape exporter choice within climate-smart goods markets.

4.2 Timing and placebo evidence

Table 3. Timing and future tariff placebo

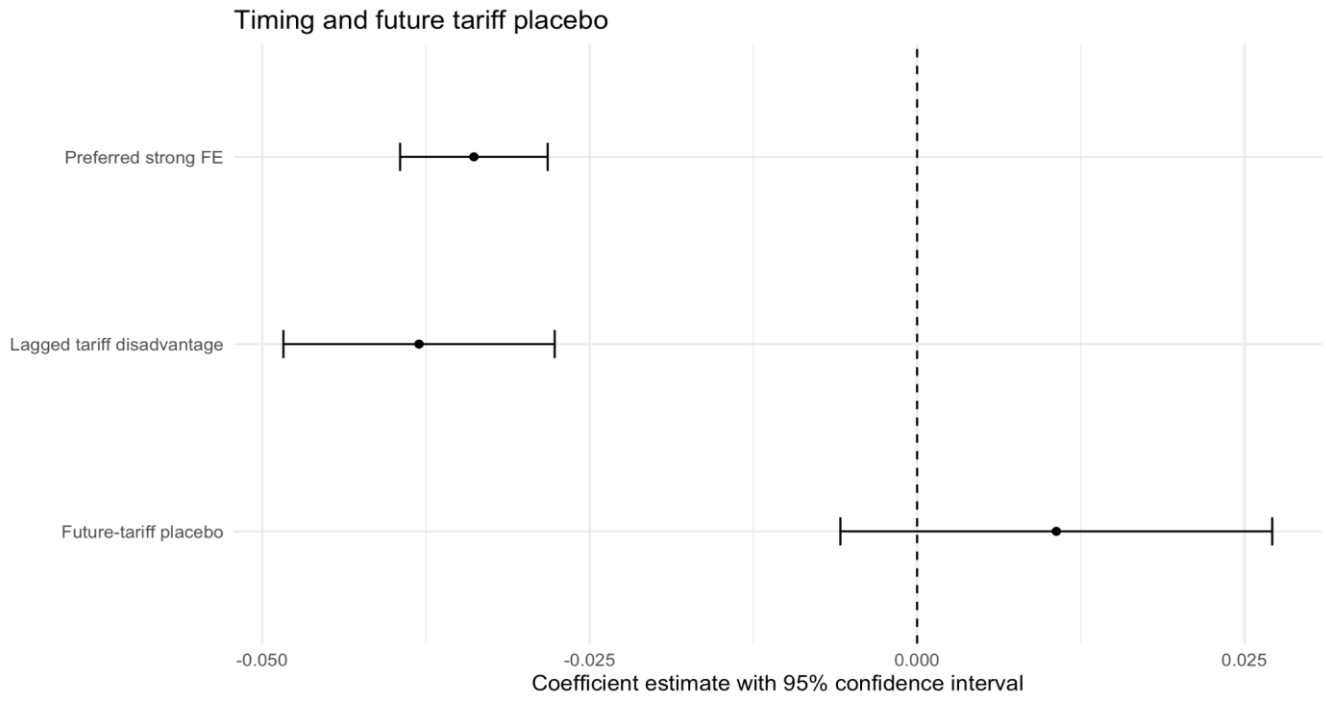
Variable / statistic	Lagged tariff disadvantage	Future tariff placebo
Coefficient	-0.0380*** (0.0053)	0.0106 (0.0084)
Importer product year FE	Yes	Yes
Exporter product FE	Yes	Yes
Exporter year FE	Yes	Yes
Importer exporter FE	Yes	Yes
Observations	118,297	117,366
Pseudo R^2	0.9479	0.9475

*Note. The dependent variable is import value in 1000 US dollars. Column 1 uses lagged tariff disadvantage. Column 2 uses the future tariff change placebo. Standard errors are clustered by importer and HS6 product and are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

Table 3 tests whether the tariff-disadvantage result follows a credible timing pattern. The lagged tariff-disadvantage coefficient is negative and statistically significant at −0.0380, showing that exporters disadvantaged in the previous year also sell less in the current year. This is consistent with delayed sourcing adjustment through procurement cycles, supplier relationships and delivery frictions.

The future-tariff placebo gives a small and statistically insignificant coefficient of 0.0106. Future tariff changes therefore do not predict current imports, which supports the tariff-exposure explanation rather than reverse timing or pre-existing trends.

Figure 1: Timing and future tariff placebo



Source: Author's Calculation

Note. The figure reports coefficient estimates and 95% confidence intervals for the preferred model, the lagged tariff disadvantage model and the future tariff placebo. The future placebo crosses zero, while the current and lagged estimates are negative.

Figure 1 reinforces the same pattern. The current and lagged estimates are negative, while the future placebo confidence interval crosses zero. Overall, the timing evidence supports the source-choice result because tariff disadvantage predicts weaker subsequent exporter performance, but future tariff changes do not explain current sourcing outcomes.

4.3 Robustness and product-level stability

Table 4. Robustness checks

Robustness exercise	Coefficient	Observations
Tariff relative to market mean	-0.0338*** (0.0029)	153,987
Pre-2018 sample	-0.0497*** (0.0079)	83,680
Exclude China exporter	-0.0267*** (0.0062)	145,740
Exclude China importer	-0.0355*** (0.0043)	142,941
Exclude solar and power electronics	-0.0296*** (0.0073)	144,795
EU aggregate alternative	-0.0324*** (0.0040)	141,537

*Note. Each row reports a separate PPML model. The dependent variable is import value in 1000 US dollars. All specifications include importer-product-year, exporter-product, exporter-year and importer-exporter fixed effects except where the sample definition changes. Standard errors are clustered by importer and HS6 product and are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

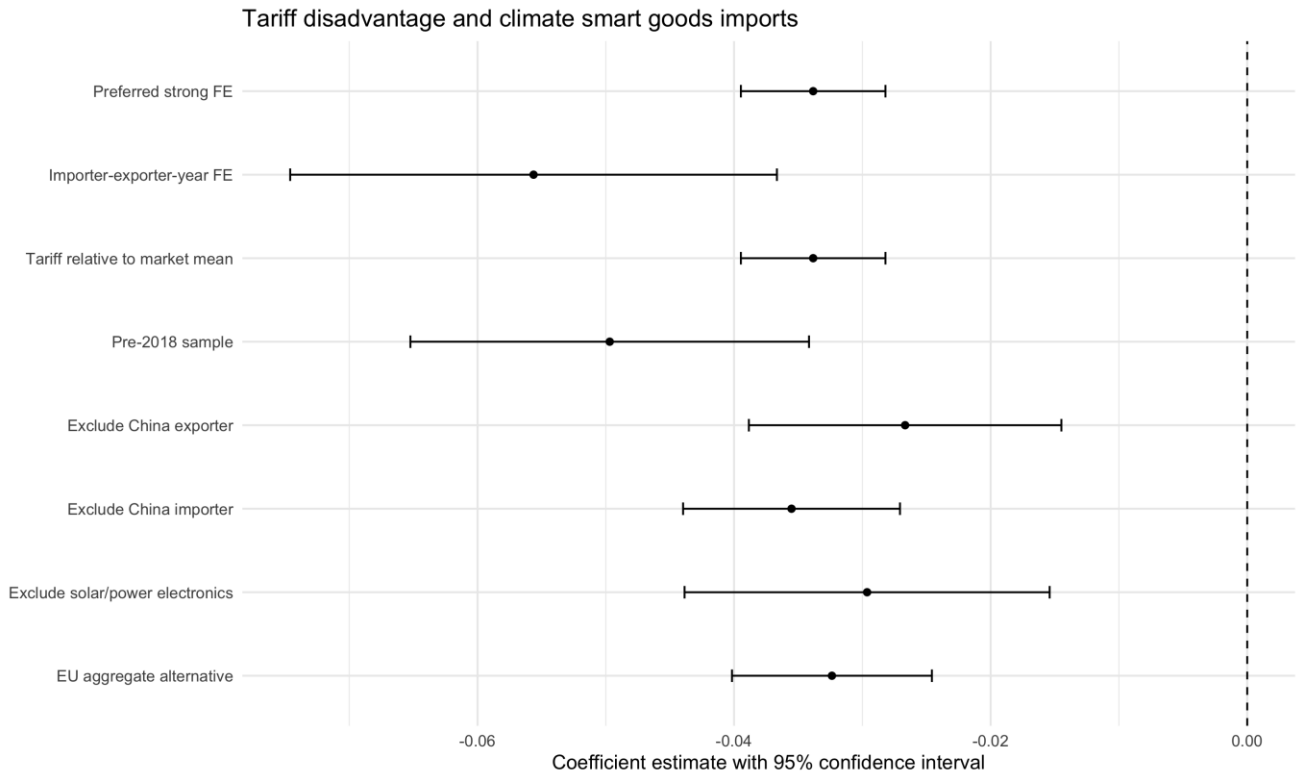
Table 4 shows that the main result is stable across alternative tariff measures and sample restrictions. When the tariff variable is centred on the market mean rather than the lowest tariff, the coefficient remains negative and statistically significant at −0.0338. This confirms that the result reflects within-market relative tariff differences among rival exporters.

The estimate also remains negative in the pre-2018 sample, with a coefficient of −0.0497. This indicates that the relationship was already present before recent trade tensions, supply-chain disruptions and pandemic-era shocks. The result is therefore not specific to the post-2018 period.

The China exclusions address whether the finding is driven by China's central role in clean-technology trade. Excluding China as an exporter gives a coefficient of −0.0267, while excluding China as an importer gives a coefficient of −0.0355. Both estimates remain statistically significant, showing that the tariff-disadvantage effect is not driven by China alone.

The remaining checks give the same conclusion. Excluding solar and power-electronics products produces a negative and significant coefficient of −0.0296, and using the EU aggregate alternative gives a coefficient of −0.0324, close to the preferred estimate. Overall, the robustness evidence shows that tariff disadvantage consistently weakens exporter performance across alternative benchmarks, periods, country exclusions, product exclusions and EU market definitions.

Figure 2: Core and robustness coefficient plot



Source: Author's Calculation

Note. The figure shows the preferred estimate and the main robustness estimates with 95% confidence intervals. All estimates are negative and statistically different from zero.

Figure 2 summarises the robustness evidence. All plotted estimates are negative, and their confidence intervals remain below zero. The coefficient size changes across specifications because the tariff benchmark and sample definitions change, but the direction of the result is stable.

The leave-one-product-out results in Table A1 reinforce this pattern. The preferred model is re-estimated 64 times, each time excluding one HS6 product. The tariff-disadvantage coefficient remains negative and statistically significant in every case, with estimates close to the preferred coefficient. This rules out a single-product explanation and shows that the result is not carried by one HS6 category, China, solar and power-electronics products, the post-2018 period, or the treatment of EU markets. Overall, tariff disadvantage consistently weakens exporter performance across alternative definitions and sample restrictions.

4.4 Market-share mechanism

Table 5. Exporter market share mechanism

Variable / statistic	Exporter market share mechanism
Tariff disadvantage	-0.0010** (0.0004)
Importer product year FE	Yes
Exporter product FE	Yes
Exporter year FE	Yes
Importer exporter FE	Yes
Observations	153,987
R^2	0.6178
Within R^2	0.0003

*Note. The dependent variable is exporter market share within the importer-product-year market. Standard errors are clustered by importer and HS6 product and are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

Table 5 examines whether tariff disadvantage weakens an exporter's position within the sourcing market. The coefficient is −0.0010 and statistically significant. Since market share is measured as a fraction, a one percentage point higher tariff disadvantage reduces the exporter's market share by about 0.10 percentage points. Using the mean tariff disadvantage of 4.32 percentage points (Table 1),

the estimate implies a market-share loss of about 0.43 percentage points. Relative to the mean exporter share of 5.85% (Table 1), this equals about 7.4% of the average exporter share. This supports the sourcing mechanism by showing that tariff-disadvantaged exporters do not only sell less in value terms, but also lose relative position among rival suppliers in the same importer-product-year market. Together, the import-value and market-share results show that tariff disadvantage reduces both exporter sales and sourcing position within climate-smart goods markets.

4.5 Equal tariff access counterfactual

Table 6. Equal tariff access counterfactual summary

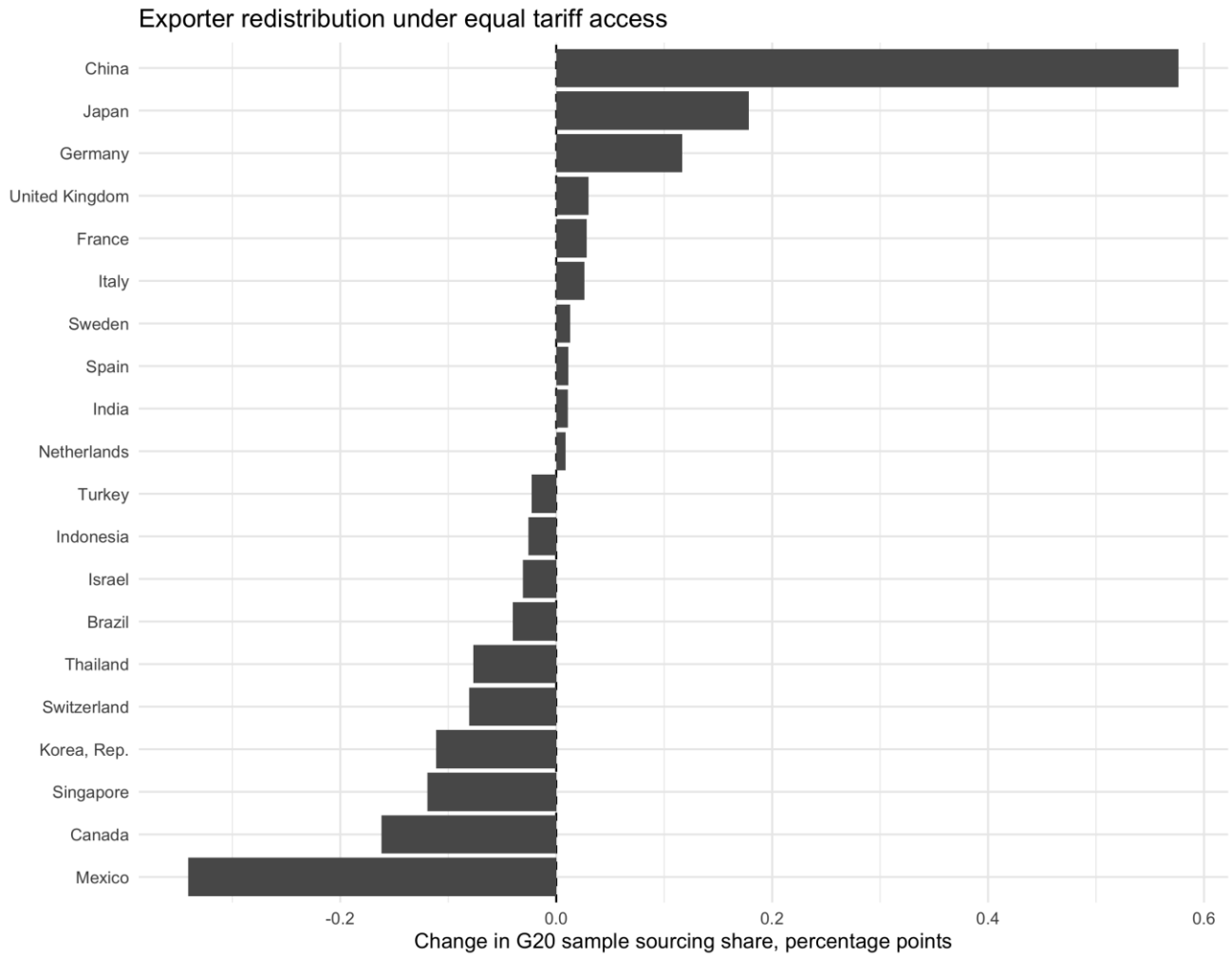
Counterfactual measure	Value
Preferred beta used in simulation	-0.0338
Baseline total imports, 1000 USD	1,743,053,574.7
Counterfactual total imports, 1000 USD	1,743,053,574.7
Markets	9,007
Reporters	19
Exporters	30
HS6 products	64
Mean reallocation index, pp	2.2071
Import weighted reallocation index, pp	1.9146
Median reallocation index, pp	1.4504
Import weighted change in China share, pp	0.5765
Emerging G20 import weighted reallocation index, pp	2.3073
Advanced G20 import weighted reallocation index, pp	1.7084

Note. The counterfactual uses the preferred strong fixed effect coefficient. Total market size is held fixed within each importer-product-year market, so the exercise measures sourcing reallocation, not total import growth. Values in percentage points are reported as pp.

Table 6 reports the equal-access counterfactual. The exercise uses the preferred coefficient and sets tariff disadvantage to zero within each importer-product-year market, holding total imports fixed to measure sourcing reallocation across exporters. The counterfactual covers 9,007 importer-product-year markets, 19 importers, 30 exporters and 64 HS6 products. Baseline and counterfactual total

imports are identical at 1,743,053,574.7 thousand US dollars because the exercise holds market size fixed. The mean reallocation index is 2.2071 percentage points, the import-weighted reallocation index is 1.9146 percentage points and the median is 1.4504 percentage points. These values show that equal tariff access reallocates sourcing opportunities within existing markets, but does not fundamentally reorder climate-smart goods trade.

Figure 3: Exporter redistribution under equal tariff access

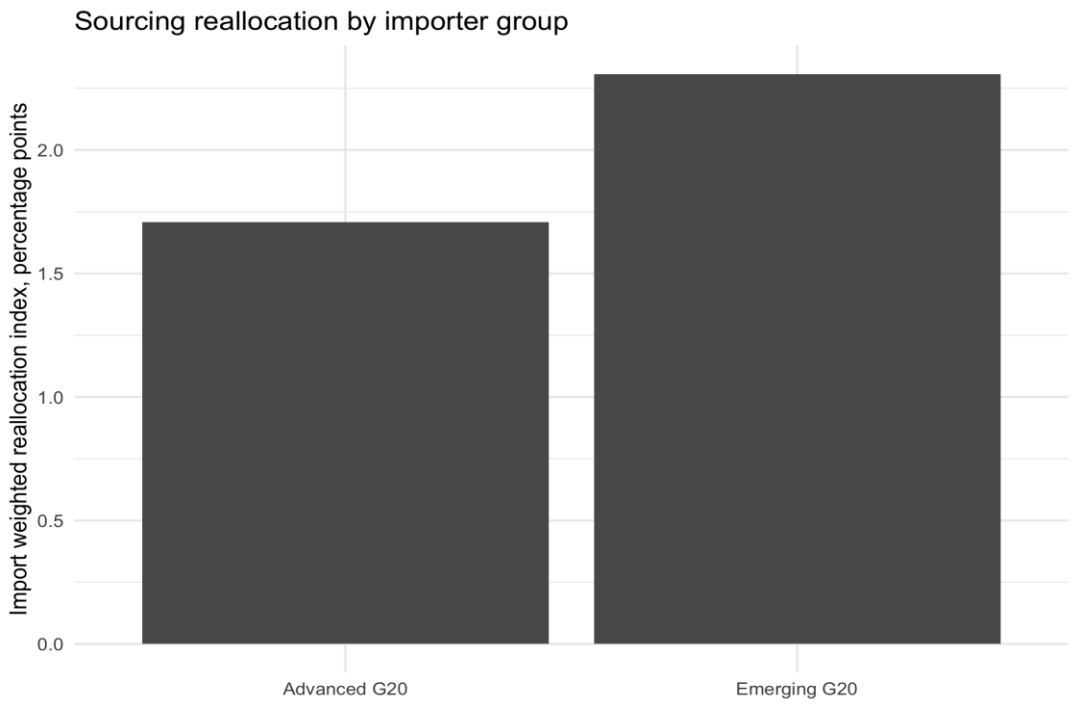


Source: Author's Calculation

Note. The figure reports the largest exporter gains and losses in G20 sample sourcing share after removing tariff disadvantages. The changes are measured in percentage points of sample sourcing share.

Figure 3 shows the exporter-level changes under equal tariff access. China, Japan and Germany gain the most sample sourcing share, while Mexico, Canada, Singapore, Korea and Switzerland lose the most. China's import-weighted sourcing share rises by 0.5765 percentage points. However, Table A2 shows that China's share does not rise in every market. It increases for some importers and falls for others, depending on China's initial market position and tariff treatment relative to competing suppliers.

Figure 4. Advanced versus emerging G20 reallocation



Source: Author's Calculation

Note. The figure compares import weighted reallocation indices for advanced and emerging G20 importers. The larger value for emerging G20 importers indicates stronger sourcing reallocation under equal tariff access.

Figure 4 compares advanced and emerging G20 importers. The import-weighted reallocation index is 2.3073 percentage points for emerging G20 importers and 1.7084 percentage points for advanced G20 importers. Equal tariff access therefore reallocates sourcing more strongly in emerging G20 markets, where clean-technology sourcing patterns may be less settled and supplier relationships may still be developing.

Figure A1 adds the product-level counterfactual by identifying HS6 categories with the largest import-weighted reallocation. The product evidence shows that equal access does not affect every climate-smart good equally, but the main result is not driven by any single product.

Overall, the results show that tariff preferences matter at the supplier-allocation margin. Tariff-disadvantaged exporters sell less and lose sourcing share, while the equal-access counterfactual shows that removing relative tariff disadvantages reallocates sourcing opportunities within existing markets. The timing evidence, placebo test, robustness checks and counterfactual results point to the same conclusion. Green trade policy should be evaluated not only through aggregate tariff levels or total import values, but also through relative tariff gaps that determine which suppliers receive effective access to climate-smart goods markets.

5. Conclusion and policy implications

The results show that tariff preferences shape who supplies climate-smart goods within G20 markets. Exporters facing a higher tariff disadvantage sell less than rival exporters supplying the same product to the same importer in the same year. In the preferred specification, a one percentage point higher tariff disadvantage is associated with about 3.3% lower imports from that exporter. The result survives demanding fixed effects, timing checks, a future-tariff placebo and major robustness tests. The market-share estimate confirms that tariff-disadvantaged exporters lose position within the sourcing market, while the equal tariff access counterfactual shows that removing these disadvantages reallocates sourcing opportunities, especially in emerging G20 importers. The central conclusion is therefore clear: tariff preferences do not only affect the level of market access; they also shape the distribution of clean-technology sourcing opportunities across countries.

The main policy implication is that governments should evaluate green trade policy at the supplier-allocation margin, not only at the aggregate tariff or import margin. A low average tariff on climate-smart goods can still coexist with unequal access if some exporters receive preferential treatment while others face higher applied tariffs. For governments seeking reliable access to solar components, wind equipment, energy-efficient goods, grid technologies and related clean technologies, this matters because tariff schedules can tilt sourcing toward some suppliers and away from others even within the same product market.

Policy design should therefore begin with a mapping of relative tariff gaps. Governments should identify importer-product markets where tariff disadvantages are large, where sourcing is strategically important, and where supplier access is strongly shaped by preference margins. This would allow tariff reform to be targeted at markets where unequal access is most likely to distort source choice. Such monitoring is especially important for emerging G20 importers, where the counterfactual shows stronger sourcing reallocation under equal tariff access.

The results also caution against treating tariff equalisation as a complete supply-chain strategy. Removing tariff disadvantages reallocates sourcing opportunities, but it does not automatically raise total imports or reduce dependence on dominant suppliers. Equal access can benefit large existing suppliers if they are currently tariff-disadvantaged in high-value markets. Governments that want both wider access and supplier diversification should therefore assess tariff reform alongside its expected effects on exporter shares, not only its effect on import costs.

Going forward, governments should assess climate-smart goods policy through three linked indicators: average tariff levels, relative tariff disadvantages across suppliers, and sourcing-share changes. This would shift green trade policy from a narrow focus on tariff liberalisation to a more practical assessment of effective market access. The key policy question is not only whether clean technologies become cheaper to import, but also which suppliers gain or lose access to those markets.

Declarations

Conflict of Interest: The authors declare no competing interests.

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Appendix

Table A1. Leave one product out robustness

Omitted HS6	Coefficient (SE)	Observations
380210	-0.0337*** (0.0033)	151,387
392010	-0.0328*** (0.0035)	149,588
392690	-0.0254*** (0.0095)	148,359
560314	-0.0339*** (0.0031)	150,846
700800	-0.0339*** (0.0028)	152,219
701931	-0.0338*** (0.0029)	152,455
730431	-0.0338*** (0.0028)	152,041
730441	-0.0338*** (0.0029)	152,578
730451	-0.0339*** (0.0029)	152,474
730820	-0.0342*** (0.0030)	153,202
730900	-0.0341*** (0.0029)	151,063
732111	-0.0349*** (0.0031)	150,933
732190	-0.0340*** (0.0028)	150,971
732490	-0.0340*** (0.0029)	150,806
761100	-0.0339*** (0.0029)	152,715
761290	-0.0330*** (0.0034)	149,834
840219	-0.0336*** (0.0032)	152,556
840290	-0.0338*** (0.0030)	151,641
840410	-0.0336*** (0.0029)	152,783
840490	-0.0341*** (0.0029)	152,216
840510	-0.0338*** (0.0029)	152,569
840681	-0.0332*** (0.0031)	153,735
840682	-0.0339*** (0.0029)	153,350
841011	-0.0338*** (0.0029)	153,441
841012	-0.0338*** (0.0029)	153,831
841013	-0.0338*** (0.0029)	153,861

841090	-0.0338*** (0.0029)	152,215
841181	-0.0336*** (0.0030)	153,021
841182	-0.0333*** (0.0031)	153,227
841581	-0.0341*** (0.0028)	151,795
841861	-0.0337*** (0.0032)	152,231
841869	-0.0299*** (0.0043)	150,147
841919	-0.0340*** (0.0026)	151,734
841940	-0.0341*** (0.0027)	152,300
841950	-0.0353*** (0.0025)	149,969
841989	-0.0337*** (0.0029)	150,566
841990	-0.0331*** (0.0033)	149,918
842129	-0.0327*** (0.0027)	150,292
842139	-0.0391*** (0.0000)	149,835
847989	-0.0330*** (0.0054)	149,469
848340	-0.0338*** (0.0036)	150,092
848360	-0.0341*** (0.0027)	150,014
850161	-0.0338*** (0.0028)	151,326
850162	-0.0341*** (0.0027)	152,293
850163	-0.0339*** (0.0028)	153,006
850164	-0.0341*** (0.0025)	152,439
850231	-0.0335*** (0.0028)	153,071
850239	-0.0325*** (0.0030)	152,150
850300	-0.0346*** (0.0016)	149,597
850440	-0.0305*** (0.0042)	150,372
850680	-0.0343*** (0.0030)	150,791
850720	-0.0340*** (0.0034)	150,145
853710	-0.0373*** (0.0026)	149,293
853931	-0.0337*** (0.0029)	150,595
854140	-0.0325*** (0.0031)	153,104
890790	-0.0336*** (0.0031)	152,139

900190	-0.0335*** (0.0034)	151,056
900290	-0.0358*** (0.0000)	151,155
902830	-0.0341*** (0.0030)	151,859
903020	-0.0340*** (0.0029)	152,678
903031	-0.0338*** (0.0029)	151,954
903039	-0.0339*** (0.0028)	152,282
903210	-0.0346*** (0.0027)	150,071
903220	-0.0340*** (0.0028)	151,524

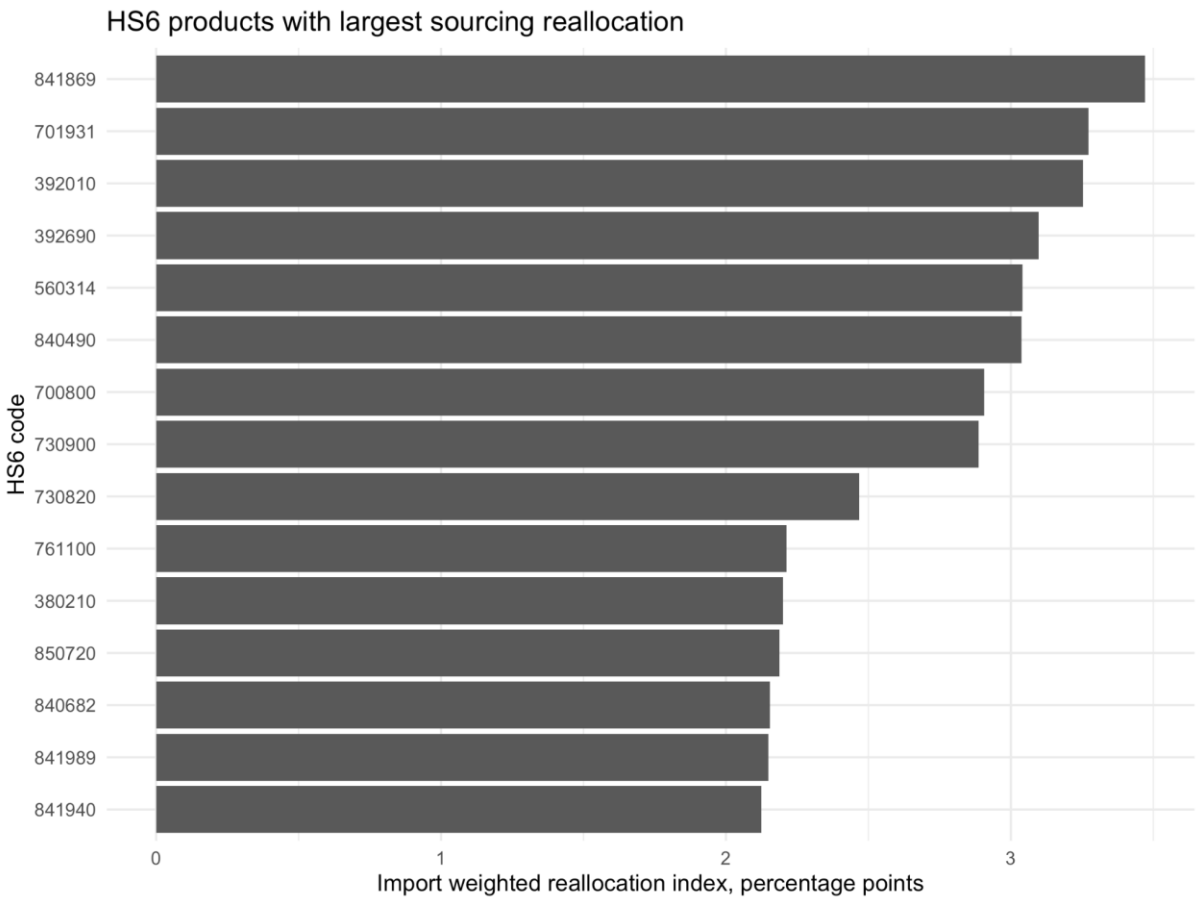
*Note. Each row omits one HS6 product and re estimates the preferred strong fixed effect model. The dependent variable is import value in 1000 US dollars. Standard errors are clustered by importer and HS6 product and are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

Table A2. China's share by reporter under equal tariff access

Reporter	Group	Markets	Baseline China share, %	Counterfactual China share, %	Change, pp	Reallocation index, pp
Indonesia	Emerging G20	796	47.70	45.99	-1.71	3.56
Australia	Advanced G20	650	31.86	31.38	-0.48	2.46
Saudi Arabia	Emerging G20	109	21.40	21.50	0.10	0.56
Brazil	Emerging G20	590	43.60	43.83	0.23	0.92
Korea, Rep.	Advanced G20	411	36.58	36.86	0.28	2.47
France	Advanced G20	691	36.14	36.54	0.40	1.42
United Kingdom	Advanced G20	576	28.03	28.47	0.43	1.54
Italy	Advanced G20	681	51.61	52.17	0.56	1.28
Germany	Advanced G20	689	34.74	35.35	0.61	1.69
United States	Advanced G20	592	29.41	30.20	0.79	1.62
Turkey	Emerging G20	675	26.07	26.96	0.89	1.81
Canada	Advanced G20	250	17.97	18.88	0.91	1.45
Argentina	Emerging G20	597	30.39	31.61	1.22	3.79
India	Emerging G20	515	41.00	42.39	1.39	3.24
South Africa	Emerging G20	311	23.48	25.86	2.38	5.69
Mexico	Emerging G20	218	22.19	24.72	2.53	3.43

Note. The table reports the change in China sourcing share by importing market under equal tariff access. China as reporter is excluded and countries with fewer than 100 markets are not shown.

Figure A1: HS6 product reallocation under equal tariff access



Source: Author's Calculation

Note. The figure shows the HS6 products with the largest import weighted sourcing reallocation under equal tariff access.