Tariff Policy Space as an Uncertainty Multiplier: Evidence from Clean Technology Sourcing

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Abstract

Reliable access to imported clean technology inputs is critical for energy-system decarbonization and infrastructure upgrading. Yet procurement in these sectors involves long lead times, certification, and rigid financing schedules, making cross-border sourcing sensitive to policy risk. This paper examines whether unused tariff policy space, measured as the gap between WTO bound tariffs and applied MFN rates, acts as an uncertainty multiplier for clean technology trade. Combining tariff-line trade data for clean technology goods with the World Trade Uncertainty Index over 2005-2023, I estimate Poisson Pseudo-Maximum Likelihood gravity models within a predetermined matched-control triple-difference framework. Results show wider tariff gaps deepen trade disruptions. During uncertainty spikes, a 1 percentage point increase in the bound-applied tariff gap reduces clean-tech imports by 6.3%. Matched-control evidence shows that, after 2018, clean technology imports remained more exposed to uncertainty than similar manufacturing imports. Sourcing decomposition shows that this fragility works through supplier exit and rising concentration. Counterfactuals indicate eliminating tariff water would have increased clean technology imports by 7% to 15% in peak uncertainty years. Findings show that tariff flexibility can function as a hidden risk premium and that targeted WTO bindings on clean capital goods can strengthen supply-chain resilience.

JEL Classifications: F13, F14, D81, Q56

Keywords: Trade policy uncertainty, tariff policy space, tariff overhang, clean technology imports

1. Introduction

1.1 Policy Space and the Credibility Problem

A central problem in economic policy is the trade-off between discretion and commitment. Discretion gives governments room to respond to future shocks, but it can weaken policy credibility when private agents make forward-looking decisions (Kydland and Prescott, 1977). In trade, this problem is especially relevant because firms respond not only to current tariffs, but also to the risk of future policy changes under uncertainty (Handley, 2014; Handley and Limão, 2017). Trade agreements partly address this problem by converting market access into a more credible commitment and by disciplining unilateral tariff incentives (Bagwell and Staiger, 1999; Limão and Tovar, 2011). Yet WTO commitments also preserve flexibility through tariff bindings that may remain above applied tariff rates, leaving governments with legal room to raise applied tariffs within bound ceilings (Beshkar et al., 2015; Jakubik and Piermartini, 2023).

This flexibility is usually viewed as policy space. It allows governments to keep tariffs low in normal times while retaining room to respond to shocks, but the same flexibility may create uncertainty for firms that must plan sourcing, investment, and supplier relationships before future policy is known (Beshkar et al., 2015; Handley and Limão, 2017). A large gap between bound and applied tariffs means that current market access may be less secure than current tariff rates suggest. When uncertainty rises, firms may care less about the tariff they face today and more about the tariff they could face tomorrow, especially when market entry, contracting, and sourcing decisions involve sunk or adjustment costs (Bloom, 2009; Handley, 2014; Novy and Taylor, 2020).

This issue is especially important for clean technology trade. Clean technology goods such as solar components, static converters, electrical controllers, and specialized machinery are key inputs into renewable energy systems, grid modernization, energy-efficient production, and infrastructure upgrading (UNESCAP, 2011; IEA, 2023; WTO, 2022). Reliable access to these imports supports clean capital formation and technology diffusion, especially in developing and emerging economies (WTO, 2022; Bacchetta et al., 2025). Yet these goods are often embedded in fragmented production networks and supplier-specific relationships, where trade frictions can affect sourcing organization and disruption risk rather than only current prices (Antràs and Chor,

2013; Bonadio et al., 2021). This makes clean technology sourcing sensitive to uncertainty in future trade costs.

This paper asks whether unused tariff policy space makes clean technology imports more fragile when global trade uncertainty rises. The question matters because tariff overhang may not be only a legal reserve of policy autonomy. It may also operate as a hidden source of risk for firms, utilities, and public projects that depend on imported clean technology inputs. If wider bound-applied gaps amplify the import response to uncertainty, then the credibility of tariff commitments becomes part of the policy infrastructure needed for energy-system upgrading, cleaner production, and resilient clean technology supply chains.

1.2 The Missing Link Between Uncertainty and Tariff Commitments

A large literature shows why uncertainty affects economic decisions before policy actually changes. Kydland and Prescott (1977) explain that discretion can weaken credibility when private agents make decisions based on expected future policy. Bloom (2009) shows that uncertainty can reduce investment because firms delay decisions that are costly to reverse. Baker et al. (2016) develop a news-based measure of economic policy uncertainty and show that policy uncertainty is associated with weaker economic activity. Jurado et al. (2015) construct broader uncertainty measures from forecast errors and show that uncertainty has real macroeconomic effects. Pástor and Veronesi (2013) show that political uncertainty affects prices and risk premia because it changes expected future policy states. Hassan et al. (2019) extend this logic to firms and show that firm-level exposure to political risk affects real outcomes. These studies establish the general mechanism that uncertainty matters because firms respond to future risk, not only to current policy. However, they do not identify which concrete features of trade policy make some import markets more exposed to uncertainty than others.

Trade-policy uncertainty studies examine this issue more directly. Handley (2014) shows that trade policy uncertainty can deter exporting when firms must incur sunk entry costs and face the possibility of future tariff increases. Handley and Limão (2017) show that reducing trade policy uncertainty can raise trade and welfare even when applied tariffs are unchanged, because more credible market access changes firm entry and pricing decisions. Caldara et al. (2020) show that trade policy uncertainty is a major aggregate shock that reduces investment and real activity. Novy

and Taylor (2020) show that trade reacts strongly to uncertainty because firms face entry costs, adjustment costs, and inventory decisions. This literature explains why uncertainty can depress trade through market participation and wait-and-see channels but does not explain how an observable importer-product tariff institution, such as the gap between WTO bound and applied tariffs, conditions the trade response to a common uncertainty shock.

A related literature studies trade agreements, WTO commitments, and tariff bindings. Bagwell and Staiger (1999) show that trade agreements discipline unilateral tariff incentives and help governments commit to more credible market access. Limão and Tovar (2011) show that tariff commitments can have political value because they constrain future policy choices. Beshkar et al. (2015) examine tariff bindings and tariff overhang as central features of the WTO system, showing that the gap between bound and applied tariffs is not a minor technical detail but a meaningful part of trade-policy commitment. Jakubik and Piermartini (2023) show that tighter WTO bindings reduce the probability that governments respond to import shocks by raising tariffs. Kuenzel (2020) shows that tariff commitments may also affect the use of temporary protection instruments. Lorz and Thede (2024) further treat tariff overhang as an economically meaningful policy margin, especially in developing-country settings. These studies show that WTO bindings matter for policy behaviour and credibility. Yet they mainly focus on tariff policy choices, trade-agreement commitment, or government responses to shocks, ignoring whether tariff overhang itself transmits uncertainty into import outcomes.

1.3 When Clean Technology Access Depends on Credibility

A separate literature studies environmental goods and clean technology trade. UNESCAP (2011) identifies climate-smart goods and technologies that can support lower-carbon development. WTO (2022) argues that trade can support climate action by improving access to environmental goods and clean technologies. IEA (2023) emphasizes that clean-energy transitions depend on secure and diversified supply chains for technologies and equipment. Bacchetta et al. (2025) show that environmental goods trade liberalization can affect trade and emissions through cheaper access to energy-efficient goods and renewable-energy inputs. This literature shows why clean technology trade matters for climate policy and development. However, it usually focuses on liberalization, tariffs, product lists, and environmental benefits and does not examine whether the credibility of

tariff commitments matters for clean technology sourcing, especially when firms face uncertainty about future trade costs.

This gap is important because clean technology imports are not ordinary traded goods. Many are capital and intermediate inputs used in renewable-energy systems, grid infrastructure, power conversion, industrial upgrading, and energy-efficient production. Their procurement often involves long delivery periods, project-finance deadlines, technical certification, and supplier-specific compatibility. Antràs and Chor (2013) show that global value-chain organization depends on supplier relationships and production sequencing, while Bonadio et al. (2021) show that shocks can spread through global supply chains. These insights imply that trade frictions may affect not only current prices, but also supplier participation, sourcing concentration, and the reliability of project execution. Existing environmental-goods studies often recognize the importance of access to clean technologies, but they rarely connect that access to WTO tariff overhang as a source of uncertainty risk.

Studies of recent tariff conflicts mainly examine realized tariff increases and their effects on prices, trade flows, welfare, and economic activity (Fajgelbaum et al., 2020). Studies of WTO commitments examine how tariff bindings constrain future policy choices and reduce the probability of tariff increases after import shocks (Beshkar et al., 2015; Jakubik and Piermartini, 2023). These studies show that both actual tariff changes and formal commitments matter for trade. What remains less examined is the middle channel between them: firms may respond to the legal possibility of future tariff increases even when applied tariffs do not change. This paper fills this gap by treating the bound-applied tariff gap as a latent policy-risk margin and testing whether unused tariff discretion amplifies the import response to global uncertainty.

Existing trade-policy uncertainty research mostly studies entry, participation, prices, and aggregate trade responses, while supply-chain research shows that shocks can affect trade through supplier relationships and production networks (Handley and Limão, 2017; Antràs and Chor, 2013). What remains less clear is whether tariff-policy uncertainty changes the internal structure of import markets. In particular, existing studies do not show whether uncertainty in high-policy-space markets operates through total import contraction, foreign supplier exit, or rising dependence on dominant exporters. This paper fills this gap by moving beyond aggregate import values and

examining whether high-water markets become thinner and more concentrated when uncertainty rises.

1.4 Conceptual Framework: Tariff Water as an Uncertainty-Transmission Channel

Under WTO rules, an importer's tariff schedule has a bound ceiling and an applied MFN rate. Tariff policy space, or tariff water, is usually viewed as flexibility to absorb shocks without breaching WTO commitments. However, it also creates downside risk because applied tariffs can rise within bound ceilings. When global trade uncertainty spikes, wider tariff water increases the option value of waiting, especially for clean technology goods with long procurement periods, financing milestones, technical certification, and supplier-specific compatibility. Tariff water can therefore delay sourcing, reduce supplier participation, and concentrate imports among dominant exporters.

This framework leads to three empirical questions:

- **Uncertainty Amplification:** Does higher tariff policy space amplify bilateral import contractions during global trade uncertainty spikes?
- **Clean-Tech Specificity:** Do clean technology imports remain more vulnerable to tariff water risk than closely related non-clean manufacturing goods because of high capital intensity and supplier-specific compatibility?
- **Supply-Chain Fragility:** Do import contractions in high-water markets operate through foreign supplier exit and rising market concentration?

These questions connect trade policy uncertainty, WTO commitment, and clean technology trade. The study uses the bound-applied tariff gap not simply as unused policy flexibility, but as measurable exposure to future tariff discretion that shapes firms' expectations about future trade costs. It reinterprets tariff overhang as an **uncertainty-transmission mechanism**: when uncertainty rises, wider bound-applied gaps increase the perceived risk of tariff escalation even if applied tariffs remain unchanged, encouraging firms to delay sourcing, narrow supplier relationships, or avoid market participation. This brings the WTO commitment framework into

fragmented clean-technology supply chains, where tariff overhang can become a hidden source of supply-chain fragility.

The results show that tariff policy space amplifies the import response to uncertainty, that clean technology imports remain more exposed than similar manufacturing imports in the high-uncertainty period, and that the adjustment works partly through supplier exit and rising concentration. This shows that tariff overhang is not only an unused policy flexibility, for green capital goods, it can become a hidden source of import fragility when uncertainty rises.

The remainder of the paper is organised as follows: Section 2 describes the data and variables, Section 3 outlines the methodology, Section 4 presents the empirical results, Section 5 reports robustness tests and additional diagnostics, and Section 6 concludes with policy implications.

2. Data and Variables

2.1 Data sources and sample scope

The empirical analysis combines product-level tariff and trade-flow data with a global uncertainty index to construct a bilateral importer–exporter–product–year panel for clean technology goods over 2005-2023. Bilateral import values and tariff measures are obtained through the World Integrated Trade Solution (WITS), which provides access to merchandise trade and tariff data, including UNCTAD TRAINS tariff profiles and WTO tariff databases (UNCTAD, n.d.; World Bank, n.d.). Products are observed at the HS6 level under the Harmonized System classification (United Nations Statistics Division, n.d.). The dataset extract contains bilateral import values, tariff measures by duty type (including applied MFN and bound tariffs), products (HS6 level), importer and exporter country, and separate time variables for trade flows and tariff schedules.

The time-varying uncertainty shock is measured using the quarterly global GDP-weighted World Trade Uncertainty Index (WTUI) from the World Uncertainty Index database (Ahir et al., 2022; World Uncertainty Index, n.d.). To align the uncertainty measure with the annual trade panel, I convert the quarterly global GDP-weighted WTUI into an annual series by taking the simple average of the four quarterly observations within each year.

2.2 Product sample: focal clean-technology goods

The empirical analysis focuses on five clean technology goods[1] at HS6 product level (Table 1). These goods are drawn from the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP, 2011) 64 climate-smart goods and technologies list. These products form a targeted set of climate-relevant enabling goods used in renewable-energy systems, power conversion, electrical control, photovoltaic applications, and related clean-technology supply chains.

Table 1. HS6 clean technology goods used in the analysis

HS6 code	Product description	Clean tech relevance
392690	Plastic Articles and other materials	Clean-tech plastic components and mounting parts
847989	Machines with Individual Functions NES	Specialized clean-tech machinery and components
850440	Static converters	Power conversion equipment
853710	Photovoltaic System Controllers	Electrical control systems and PV controllers
854140	Photosensitive semiconductor devices, including PV cells and LED	Solar and PV semiconductor devices

Note: These products represent climate-relevant enabling technologies and components used in renewable-energy and power-management systems, including specialized plastic articles and machinery components, static converters (power conversion equipment), electrical control panels, and photovoltaic and semiconductor related devices.

[1] In this study, climate-smart goods (CSG) refers to the five clean technology goods in Table 1. Therefore, CSG is used as shorthand term for these five goods.

The 5 core clean technology goods (Table 1) are also the largest goods in UNESCAP list, accounting for 56.2% of imports, 55.5% of exports, and 55.8% of total trade across all 64 climate-smart goods and technologies during 2005-2023. They are also the top five individual HS6 codes by cumulative import, export, and total trade value within that universe[2]. Their selection also permits consistent HS6-level mapping of applied and bound tariffs, which is necessary for constructing tariff policy space. Focusing on this targeted core set reduces aggregation across highly heterogeneous environmental goods while preserving sufficient bilateral variation for PPML gravity estimation. Broader environmental-goods classifications often face HS6 measurement and dual-use problems, because many six-digit subheadings are not exclusively environmental and some goods may have environmentally beneficial or harmful uses depending on final use (Bacchetta et al., 2025). Against this background, the UNESCAP's list provides a narrower ex ante product universe for the present tariff-line exercise.

2.1.4 Sample size

The estimation panel covers 26 reporting economies as importers and 242 reported partners[3] over 2005-2023. The dataset contains 328,971 importer-partner-product-year observations. The panel is unbalanced across reporting economies because the final estimation sample depends on the availability of same-year trade and tariff observations with non-missing applied MFN and bound tariffs. The initial extraction targeted a broader set of reporting economies, but the final sample[4]

[2] Calculations are based on all UNESCAP's (2011) 64 climate-smart goods and technologies list over 2005-2023. The reported shares are the cumulative shares of five HS6 codes (Table 1) in total imports, exports, and trade of 64 climate-smart goods and technologies.

[3] The partner dimension includes all exporters reported in WITS for the matched HS6 bilateral trade-tariff panel and therefore comprises sovereign countries, territories, and other source-defined partner categories. This avoids arbitrary exporter-side truncation and preserves the full set of valid bilateral trade observations available in the source data.

[4] The final sample of 26 importers reflects two data requirements: same-year trade and tariff observations, and non-missing MFN and bound tariffs in the UNCTAD TRAINS extracts accessed through WITS.

reflects the availability of trade-year observations with usable importer-product tariff information, including non-missing applied MFN and bound tariffs.

The relevant sample condition arises on the importer-product-year dimension because water is an importer-side tariff policy variable. Once usable tariff information is observed for an importer-product-year, the corresponding tariff-space measure is attached to bilateral imports from all reported partner origins serving that market. The sample therefore combines focused reporter coverage with broad partner-origin coverage, which is appropriate for tariff-line bilateral import analysis. The list of reporting economies retained in the final estimation sample is reported in Table B1.

2.2 Data Construction

The empirical analysis is based on a bilateral HS6 tariff-line extract containing import values and tariff information. Because the dependent variable is bilateral imports, the panel is indexed by trade year, defined as the year in which the import flow is observed. I retain observations for which the tariff schedule year matches the trade year, so that tariff measures correspond to the observed annual trade flow.

The raw extract reports tariff information separately by duty type on bilateral importer-partner-product-year records. I retain the applied MFN and bound tariff fields reported for each matched trade record and construct tariff policy space, or water, as the bound tariff minus the applied MFN tariff. Since water is the key policy variable, the sample is restricted to observations with non-missing values for both tariff measures. Import values are reported in thousands of U.S. dollars in the raw extract and are converted to U.S. dollar levels by multiplying by 1,000. The resulting bilateral panel covers 2005 to 2023, the period over which bilateral trade flows and same-year tariff information are sufficiently available for consistent construction of the tariff-policy space measure.

2.3 Variable construction

2.3.1 Tariff policy space ("water")

For each importer-product-year observation, tariff policy space (water) is defined as bound tariff minus applied MFN tariff:

$$Water_{ipt} = Bound_{ipt} - MFN_{ipt} \tag{1}$$

This variable is merged onto each bilateral row (i, j, p, t) for a given importer-product-year. I also construct the transformed MFN tariff term used in the PPML specification. Let the MFN tariff rate in ad valorem units be $mfn_{rate_{ipt}} = \frac{MFN_{ipt}}{100}$. Then:

$$\ln(1 + MFN)_{ipt} = \ln\left(1 + mfn_{rate_{ipt}}\right) \tag{2}$$

2.3.2 Global uncertainty shock (WTUI)

The World Trade Uncertainty Index is available at quarterly frequency. I convert it to an annual series by averaging across the four quarters of each year:

$$WTUI_t = \frac{1}{4}\sum_{q=1}^{4} WTUI_{tq} \tag{3}$$

I use the log transformation:

$$\ln(1 + WTUI_t) \tag{4}$$

and define the baseline exposure interaction:

$$WU_{ipt} = Water_{ipt} \times \ln(1 + WTUI_t) \tag{5}$$

This interaction captures the uncertainty-policy-space slope. Since WTUI varies over time while tariff policy space varies across importer-product markets, the coefficient identifies whether imports fall more steeply during uncertainty increases where tariff policy space is larger.

2.3.3 Exposure measures: contemporaneous and predetermined policy space

The baseline gravity specifications use the contemporaneous exposure WU_{ipt}, the matched-control DDD uses the predetermined exposure WU_{ipt}^{pre} as the preferred quasi-experimental design.

To strengthen the quasi-experimental interpretation in the matched-control design, I additionally construct a predetermined (pre-regime) policy-space measure for each importer–product cell as the pre-2018 mean water:

$$\overline{Water}_{ip}^{pre} = \frac{1}{T_{pre}} \sum_{t \leq 2017} Water_{ipt} \tag{6}$$

where T_{pre} is the number of pre-period years used in the average (2005–2017) and define the predetermined exposure:

$$WU_{ipt}^{pre} = \overline{Water}_{ip}^{pre} \times \ln(1 + WTUI_t) \tag{7}$$

Because the pre-2018 mean policy-space component is fixed prior to the post-2018 regime, this exposure reduces concerns that time-varying MFN adjustments mechanically move water contemporaneously with uncertainty.

3. Methodology

3.1 Empirical setting and unit of observation

The empirical analysis is conducted at the bilateral importer-exporter-product-year level (i, j, p, t). The dependent variable is annual bilateral imports (in USD levels) for a set of clean technology goods. The analysis window is 2005-2023, which aligns with the availability of the tariff-line data and the annualized World Trade Uncertainty Index (WTUI).

3.2 Baseline gravity specification (PPML with high-dimensional fixed effects)

3.2.1 Estimator and motivation

I estimate gravity models using Poisson Pseudo-Maximum Likelihood (PPML) with high-dimensional fixed effects, implemented using ppmlhdfe (Santos Silva and Tenreyro, 2006; Correia et al., 2020). PPML is appropriate for trade data because it handles zero trade flows and is robust to heteroskedasticity under standard gravity model conditions.

3.2.2 Baseline specification with post-2018 slope change

The main specification allows the slope on the uncertainty-policy space interaction to change after 2018:

$$\mathbb{E}\left[Imports_{ijpt}\right] = \exp\left(\begin{matrix}\beta_1 ln(1+MFN)_{ipt} + \beta_2\left[WU_{ipt}\right] + \beta_3\left[WU_{ipt} \times Post2018_t\right] \\ +\alpha_{ij} + \delta_{it} + \gamma_{jt} + \eta_p\end{matrix}\right) \quad (8)$$

where $Post2018_t = 1[t \geq 2018]$

α_{ij} denotes importer-exporter (pair) fixed effects, δ_{it} denotes importer-year fixed effects, γ_{jt} denotes exporter-year fixed effects and η_p denotes HS6 product fixed effects.

This specification absorbs bilateral pair fixed effects together with importer-year and exporter-year fixed effects, which control for multilateral resistance and time-varying country-level shocks (Anderson and van Wincoop, 2003; Yotov et al., 2016). Identification therefore comes from within-year cross-sectional differences in importer-product tariff policy space, interacted with a common global uncertainty shock.

Water is defined at the importer-product-year level. The preferred specification therefore estimates an importer-product policy-space exposure effect, not a conventional bilateral tariff elasticity. Importer-product-year fixed effects are not included because they would absorb water and the exposure term that the paper is designed to estimate. Identification is instead supported by pair fixed effects, importer-year fixed effects, exporter-year fixed effects and product fixed effects.

3.2.3 Post-Period net slope

The post-2018 slope of the uncertainty-policy-space channel is the linear combination:

$$\beta_{post} = \beta_2 + \beta_3 \tag{9}$$

I estimate and report this quantity using linear combination tests (lincom). Economically, the post-2018 linear combination gives the uncertainty-policy-space slope after 2018. A negative value means that larger bound-applied tariff gaps continue to make import declines steeper when uncertainty rises; a smaller absolute value means that the slope has attenuated relative to the pre-2018 period.

3.2.4 Inference

The baseline specification reports standard errors clustered at the bilateral pair level. Additional inference robustness checks use alternative clustering structures, including importer-product clustering and multiway clustering, to assess sensitivity to correlation in policy-panel settings (Bertrand et al., 2004; Cameron et al., 2011).

3.3 Timing discipline: external break diagnostics, break-year sensitivity and event-study dynamics

I define 2018 as the onset of the higher-uncertainty regime, motivated by the rise in WTUI over 2018–2019 (Ahir et al., 2022; Fajgelbaum et al., 2020) and by the possibility that trade responses to uncertainty begin through sourcing, contracting, procurement, and inventory decisions before the full annual import response is observed.

3.3.1 Segmented-trend WTUI break diagnostics

As an external timing diagnostic, I estimate segmented-trend regressions on annual WTUI of the form:

$$WTUI_t = a_0 + a_1 t + a_2 PostB_t + a_3[(t - B) \times PostB_t] + u_t \tag{10}$$

where $B \in \{2017,2018,2019\}$ and $PostB_t = 1[t \geq B]$. This specification allows both a level shift and a slope change at candidate break years. I treat 2018 as the baseline onset of the higher trade-policy-uncertainty regime, motivated by the rise in global trade-policy uncertainty during 2018–2019 and by the fact that trade responses can begin through sourcing, contracting, procurement, and inventory decisions before the full annual import response is observed. The segmented-trend exercise is therefore used as an external timing diagnostic rather than as a mechanical rule for selecting a single break year. To ensure that the results do not depend on the baseline cut-off, the empirical analysis also reports sensitivity checks using alternative 2017 and 2019 post-period definitions. This interpretation is consistent with evidence on the macroeconomic effects of trade policy uncertainty, uncertainty-induced delays in trade-related firm adjustment, and inventory channels in trade dynamics (Caldara et al., 2020; Handley, 2014; Novy and Taylor, 2020).

3.3.2 Break-year sensitivity in the baseline gravity model

To ensure that the estimated regime-dependent slope change is not driven by a single breakpoint choice, I re-estimate the baseline gravity specification using alternative post indicators $1[t \geq 2017]$, $1[t \geq 2018]$, and $1[t \geq 2019]$.

3.3.3 Event-study style dynamic interactions

To examine anticipatory behaviour and post-period dynamics, the single post-break interaction is replaced with year-specific interactions around 2017. I focus on near-leads immediately preceding the onset, 2015 and 2016, and post years, 2018 to 2021. To make 2017 the omitted reference year, the specification includes tail-bin interactions for years ≤ 2014 and ≥ 2022, which are included in estimation but not reported in the main table. Joint tests of near-lead interactions assess anticipatory differential responses, while joint tests of post-period interactions assess post-regime dynamics. The event study uses predetermined exposure, defined as importer×HS6 mean water over 2005–2017 multiplied by ln(1+WTUI).

3.4 Economic magnitude: model-implied counterfactual predictions

To quantify the economic magnitude of the estimated uncertainty-policy-space channel, I compute model-implied predictions from the baseline PPML regression while holding MFN and estimated fixed effects constant.

Let the fitted linear predictor from the baseline model be:

$$xb_{ijpt} = \hat{\beta}_1 \ln(1 + MFN)_{ipt} + \hat{\beta}_2 \left[WU_{ipt}\right] + \hat{\beta}_3 \left[WU_{ipt} \times Post2018_t\right] + \hat{\alpha}_{ij} + \hat{\delta}_{it} + \hat{\gamma}_{jt} + \hat{\eta}_p \quad (11)$$

with baseline predicted imports:

$$\mu_{ijpt} = \exp\left(xb_{ijpt}\right) \quad (12)$$

These exercises are interpreted as economic-magnitude diagnostics implied by the fitted model**,** not literal policy reform estimates.

3.4.1 Counterfactual 1: Water = 0

I remove the fitted contribution of the uncertainty-policy space interaction terms to obtain a counterfactual predictor under zero policy space:

$$xb_{ijpt}^{cf0} = xb_{ijpt} - \hat{\beta}_2 \left[WU_{ipt}\right] - \hat{\beta}_3 \left[WU_{ipt} \times Post2018_t\right] \quad (13)$$

and compute:

$$\mu_{ijpt}^{cf0} = \exp\left(xb_{ijpt}^{cf0}\right) \quad (14)$$

3.4.2 Counterfactual 2: Water reduced by 50%

I scale down the fitted interaction contribution by one-half:

$$xb_{ijpt}^{cf50} = xb_{ijpt} - 0.5\left(\hat{\beta}_2\left[WU_{ipt}\right] + \hat{\beta}_3\left[WU_{ipt} \times Post2018_t\right]\right) \quad (15)$$

and compute:

$$\mu_{ijpt}^{cf50} = \exp\left(xb_{ijpt}^{cf50}\right) \quad (16)$$

3.4.3 Counterfactual summary metric

For each counterfactual scenario $c \in \{cf0, cf50\}$, I summarize model-implied percentage changes in imports as:

$$PctChange_{ijpt}^{c} = 100 \times \left(\frac{\mu_{ijpt}^{c}}{\mu_{ijpt}} - 1\right) \quad (17)$$

For year-by-year reporting, I summarize the counterfactual as the percentage change in total predicted imports within year (t).

3.5 Matched-control DDD design: climate-smart and non-climate-smart goods

3.5.1 Treatment and control product sets

The DDD design compares the five CSG to a matched set of 15 non-CSG HS6 controls drawn from closely related product families in HS chapters 39, 84, and 85. These controls are selected from neighbouring HS6 product lines within the same broad product families as the treated climate-smart goods, so as to ensure comparability in customs classification, tariff administration, and manufacturing and trade environment, while remaining outside the study's UNESCAP-based climate-smart treatment group. Table B2 reports the full list of matched control codes, product descriptions, and matching rationale. This matched-control construction provides a within-family counterfactual for testing whether the post-2018 reconfiguration of the uncertainty-policy space slope is specific to CSG rather than a general import response across related manufactured products.

3.5.2 DDD PPML specification

On the pooled sample of treated and matched controls, define $CSG_p = 1$ for the five CSG HS6 codes and $CSG_p = 0$ for the matched non-CSG controls. The preferred specification retains the same triple-difference logic (Olden and Møen, 2022), but anchors exposure in pre-2018 policy space:

$$\begin{aligned}\mathbb{E}\left[Imports_{ijpt} \mid X\right] \\ = \exp\big(\theta_1 \ln(1 + MFN)_{ipt} + \theta_2 WU_{ipt}^{pre} + \theta_3\big(CSG_p \times WU_{ipt}^{pre}\big) \\ + \theta_4\big(Post2018_t \times WU_{ipt}^{pre}\big) + \theta_5\big(CSG_p \times Post2018_t\big) \\ + \theta_6\big(CSG_p \times Post2018_t \times WU_{ipt}^{pre}\big) + \alpha_{ij} + \delta_{it} + \gamma_{jt} + \eta_p\big)\end{aligned} \tag{18}$$

The coefficient of interest is θ_6, the DDD estimand, which captures whether the post-2018 change in the (Water×Uncertainty) slope is different for climate-smart goods relative to matched non-CSG products when exposure is anchored in pre-2018 policy space.

The implied uncertainty-policy space slopes are matched controls pre-2018 (θ_2), matched controls post-2018 ($\theta_2 + \theta_4$), climate-smart goods pre-2018 ($\theta_2 + \theta_3$), CSG post-2018 ($\theta_2 + \theta_3 + \theta_4 + \theta_6$).

The coefficient θ_5 captures the post-2018 relative level shift for climate-smart goods compared with matched controls, conditional on exposure, whereas θ_6 identifies whether the post-2018 change in slopes differs between CSG and matched non-CSG.

For completeness, I also report a contemporaneous exposure variant using (WU_{ipt}) as a robustness comparison.

3.5.3 DDD placebo timing tests

To assess whether the estimated CSG differential emerges before the intended regime timing, I conduct placebo timing tests in the DDD specification by replacing $Post2018_t$ with earlier pseudo-break indicators while retaining the predetermined exposure **(**WU_{ipt}^{pre}) used in the preferred DDD specification. Specifically, I estimate:

I. a **Lead2017 placebo (**$1[t \geq 2017]$) under the baseline DDD fixed-effects structure with pair clustered standard errors, and

II. a **Lead2016 placebo** ($1[t \geq 2016]$) estimated as a stricter diagnostic with multiway clustering (following Cameron et al., 2011) by importer and exporter which allows arbitrary within-importer and within-exporter correlation in shocks, and provides a more conservative inference check.

I keep pair clustering for Lead2017 to preserve comparability with the preferred DDD table, while Lead2016 tightens inference as a stress test. Insignificant placebo triple interactions in these specifications would support the interpretation that the post-2018 DDD effect is not driven by pre-existing differential timing patterns.

3.6 Robustness framework and additional diagnostics

The empirical results are evaluated against a broad robustness battery designed to test functional form, inference, timing, over-absorption, economic magnitude, and product-specific interpretation.

3.6.1 PPML robustness tests

I treat the following tests as robustness specifications around the preferred baseline:

- Pooled PPML with standardized WTUI interaction and no break - As a robustness check on the scaling of the uncertainty measure, I replace the baseline log-transformed annual WTUI with a standardized annual WTUI series ($WTUI_Z$), defined as the z-score transformation of annual WTUI, and interact it with tariff policy space ($Water \times WTUI_Z$).
- Pooled PPML with raw WTUI interaction and no break.
- Baseline model with alternative clustering (importer×HS6).
- Break-based PPML using raw WTUI instead of $\ln(1 + WTUI_t)$.

These models assess attenuation in pooled specifications, inference sensitivity, and dependence on the uncertainty scaling choice.

3.6.2 Marginal effect diagnostics

I report marginal effect calculations (nlcom) at representative uncertainty levels (such as median and upper-percentile WTUI values) to quantify the conditional semi-elasticities of tariff policy space before and after 2018. This follows standard practice for evaluating interaction effects in nonlinear models (Karaca-Mandic et al., 2012).

3.6.3 MFN-policy response diagnostics

Because tariff policy space is defined as ($Water_{ipt} = Bound_{ipt} - MFN_{ipt}$), I test whether the main interaction may be mechanically driven by contemporaneous MFN tariff adjustments. Using importer–product–year collapsed data, I estimate fixed-effects regressions of ΔMFN_{ipt}, $|\Delta MFN_{ipt}|$, and $1[\Delta MFN_{ipt} > 0]$ on the uncertainty-policy space exposure term (and corresponding variants). These diagnostics assess whether the trade results are confounded by systematic tariff changes.

3.6.4 Market-level decomposition

To distinguish market-wide contraction from bilateral reallocation, I aggregate to importer–product–year and estimate analogous specifications for total imports, the extensive margin (number of exporters), concentration (HHI across exporters), and dominance (top-1 exporter share).

3.6.5 DDD robustness and placebo timing

I complement the baseline DDD with placebo timing tests, including the Lead2016 specification with multiway importer–exporter clustering, to assess whether the estimated climate-smart differential appears spuriously before the intended post-2018 regime timing.

Taken together, the robustness exercises cover functional-form dependence (standardized versus raw WTUI; log versus raw scaling), inference sensitivity (alternative clustering), timing discipline, high-dimensional fixed-effects saturation, economic magnitudes (marginal effects and counterfactual quantification), potential MFN-policy mechanical channels, market-level decomposition, and DDD placebo timing. This battery is designed to show that the estimated

uncertainty–policy-space pattern is not an artifact of one breakpoint choice, one functional form, one clustering scheme, or one product composition.

The empirical strategy combines three layers of variation: (i) cross-sectional differences in importer-product tariff policy space, (ii) a common time-varying global uncertainty shock (WTUI), and (iii) regime timing discipline (post-2018 slope change, break-year sensitivity, and event-study dynamics), further strengthened by matched non-CSG DDD comparisons. In the preferred DDD specification, exposure is anchored in pre-2018 policy space via WU_{ipt}^{pre}, strengthening the quasi-experimental interpretation. The central result therefore tests whether the interaction between uncertainty and tariff policy space is economically meaningful and whether its post-2018 reconfiguration is specific to climate-smart goods.

4. Results and Discussion

I begin with the baseline PPML gravity model using the post-2018 onset definition in Table 2 because the core question is whether tariff policy space changes how uncertainty affects climate-smart imports once the high-uncertainty regime begins. The main coefficients are the interaction terms. The coefficient on Water × ln(1+WTUI) is negative and statistically significant at −0.0186, indicating that imports are lower during periods of higher uncertainty in importer-product markets with larger tariff policy space. The post-2018 interaction ([Water × ln(1+WTUI)] × Post2018) is positive and statistically significant at 0.0138, showing that the negative uncertainty–policy space slope attenuates after 2018. The post-2018 net slope remains negative at −0.00480, but statistically insignificant. The evidence, therefore supports a post-2018 slope reconfiguration. The pooled no-break specifications are useful as a contrast because they impose a single uncertainty–policy-space slope over the full sample and do not capture the regime-dependent change documented in Table 2.

Table 2. Baseline gravity PPML: Water × ln(1+WTUI) with post-2018 slope break

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.1880 (1.9887)
Water × ln(1+WTUI)	-0.0186** (0.00923)
[Water × ln(1+WTUI)] × Post2018	0.0138** (0.00620)
Post-2018 net slope ($\beta_2 + \beta_3$)	-0.00480 (0.00331)
Constant	19.3092*** (0.0632)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8756
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.* $Water_{ipt} = Bound_{ipt} - MFN_{ipt}$. $WU_{ipt} = Water_{ipt} \times ln(1 + WTUI_t)$. $Post2018_t = 1[t \geq 2018]$.

I then report Table 3 to show that this result is not driven by the log scaling of uncertainty. When ln(1+WTUI) is replaced with raw WTUI and keep the same break structure, the water interaction remains negative and significant and the post interaction remains positive and significant. This confirms that the baseline pattern reflects the uncertainty policy space channel rather than a particular functional form choice for WTUI.

Table 3. Robustness: Raw WTUI × Water with post-2018 slope break

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.0651 (2.0032)
Water × WTUI (raw)	-0.00547** (0.00275)
[Water × WTUI] × Post2018	0.00534** (0.00264)
Post-2018 net slope ($\beta_2 + \beta_3$)	-0.000128 (0.000115)
Constant	19.2811*** (0.0587)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8754
N	128,117

*Notes: Dependent variable is bilateral imports in levels. This specification replaces ln(1+WTUI) with raw WTUI to show results are not driven by the log transform. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

I then run the near-leads event study with predetermined exposure in Table 4 because credibility depends on ruling out differential movements just before the regime change. The corrected specification includes tail-bin interactions for years ≤2014 and ≥2022, making 2017 the omitted reference year. The near-lead interactions for 2015 and 2016 are not statistically significant, and the joint pre-test gives a p-value of 0.623. This provides no evidence of anticipatory differential movement immediately before the post-2018 regime. The post-year interactions for 2018, 2019, and 2020 are positive and statistically significant, and the post interactions are jointly significant with a p-value of 0.014. The event-study evidence therefore supports a post-onset reconfiguration of the uncertainty–policy-space slope rather than an anticipatory pre-trend.

Table 4. Event-study near-leads using predetermined exposure (pre-2018 mean water)

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.230* (1.957)
Predetermined exposure base slope	-0.0119* (0.00662)
Predetermined exposure × 1[2015]	-0.0152 (0.0158)
Predetermined exposure × 1[2016]	-0.000660 (0.00426)
Predetermined exposure × 1[2018]	0.00624** (0.00303)
Predetermined exposure × 1[2019]	0.0101** (0.00486)
Predetermined exposure × 1[2020]	0.00933** (0.00396)
Predetermined exposure × 1[2021]	0.00712 (0.00632)
Estimator	PPML
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair
Pseudo R^2	0.876
N	128,117
Omitted reference year	2017
Tail bins	≤2014 and ≥2022 included but not reported
Pre-joint test p-value	0.6187
Post-joint test p-value	0.0149

*Notes: Dependent variable is bilateral imports in levels. Predetermined exposure is importer×HS6 mean water over 2005-2017 multiplied by ln(1+WTUI). The omitted reference year is 2017. Tail bins for years ≤2014 and ≥2022 are included but not reported, so the reported near-lead and post-year coefficients are interpreted relative to 2017. Standard errors clustered by pair are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

The DDD asks whether the post-2018 change in the uncertainty-policy-space slope differs for CSG relative to closely related non-CSG controls. In Table 5, the matched-control slope is −0.02282

before 2018 and −0.00568 after 2018 (−0.02282 + 0.01714). The corresponding CSG slope is −0.01625 before 2018 (−0.02282 + 0.00657) and −0.00358 after 2018 (−0.02282 + 0.00657 + 0.01714 − 0.00447). Thus, CSG have less negative slopes than matched controls in both periods. The negative and significant triple interaction, (CSG × Post2018 × WU_{ipt}^{pre}), does not imply a more negative level slope for CSG. Instead, it shows that the post-2018 attenuation of the uncertainty–policy space slope is smaller for CSG: the matched-control slope shifts upward by 0.01714, whereas the CSG slope shifts upward by 0.01267 (0.01714 + (− 0.00447)). This indicates a differential post-2018 slope reconfiguration for CSG relative to matched controls, rather than a larger level effect.

Table 5. Matched-control DDD (PPML): predetermined exposure (pre-2018 mean water)

Variable	Estimate (Std. Err.)
ln(1+MFN)	-2.9958 (2.0032)
WU_{ipt}^{pre}	-0.02282** (0.00989)
CSG × WU_{ipt}^{pre}	0.00657** (0.00278)
Post2018 × WU_{ipt}^{pre}	0.01714** (0.00723)
CSG × Post2018	0.24387*** (0.06373)
CSG × Post2018 × WU_{ipt}^{pre}	-0.00447** (0.00223)
Constant	19.2130*** (0.0640)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,444 clusters)
Pseudo R^2	0.9052
N	328,178
Treatment HS6 (CSG=1)	392690, 847989, 850440, 853710, 854140
Matched controls (CSG=0)	392610, 392620, 392640, 847920, 847940, 847990, 850431, 850432, 850433, 850490, 853720, 854110, 854130, 854150, 854190

*Notes: Dependent variable is bilateral imports in levels. The triple interaction is the DDD estimand. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

I then report placebo timing checks in the combined Table 6 using Lead2017 and Lead2016 indicators. The purpose is to assess whether a similar climate-smart differential change in the uncertainty-policy space slope would be detected under earlier pseudo-break dates. The Lead2017 placebo triple interaction is marginal at the 10% level, but the evidence is not stable across placebo cut-offs and it disappears in the stricter Lead2016 specification with multiway clustering. This weak placebo signal is also not mirrored in the predetermined near-leads event study, where the 2015 and 2016 interactions are small and jointly insignificant, which supports the view that the post-2018 pattern is unlikely to be driven by a systematic pre-regime differential slope trend between climate-smart and matched non-CSG control products.

Table 6. DDD placebo timing (PPML): predetermined exposure with Lead2017 and Lead2016

Variable	Lead2017 (year ≥ 2017)	Lead2016 (year ≥ 2016)
ln(1+MFN)	-3.0291 (1.9916)	-3.1100 (2.6134)
WU_{ipt}^{pre}	-0.02864** (0.01449)	-0.04523* (0.02457)
CSG × WU_{ipt}^{pre}	0.00774** (0.00379)	0.00986 (0.01027)
Lead × WU_{ipt}^{pre}	0.02218* (0.01170)	0.03837* (0.02153)
CSG × Lead	0.25995*** (0.05870)	0.29231*** (0.02474)
CSG × Lead × WU_{ipt}^{pre}	-0.00558* (0.00324)	-0.00770 (0.00845)
Constant	19.1910*** (0.0635)	19.1664*** (0.0684)
Estimator	PPML (ppmlhdfe)	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,444 clusters)	Multiway: importer (26) and exporter (239)
Pseudo R^2	0.9052	0.9053
N	328,178	328,178

*Notes: Dependent variable is bilateral imports in levels. Placebo regressions replace Post-2018 with earlier pseudo-break indicators while retaining predetermined exposure. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01. Lead2016 (year ≥ 2016) uses*

multiway clustering by importer and exporter. Stata applies a Cameron–Gelbach–Miller adjustment when the VCV is not positive semi-definite under multiway clustering.

I then quantify economic magnitude using model-implied counterfactual predictions because interaction coefficients alone are hard to interpret. Table 7 reports two exercises by setting water to zero and reducing water by 50%. Eliminating tariff policy space implies predicted CSG imports would have been about 10% higher in 2018, 15% higher in 2019, and 7% higher in 2020. Halving tariff policy space implies predicted imports would have been about 4% higher in 2018, 6% higher in 2019, and 3% higher in 2020. The counterfactual gains are also large in some pre-2018 years, especially 2016 and 2017, consistent with the stronger pre-period slope estimated in the baseline model. These exercises show that the uncertainty–policy space channel is economically meaningful, serving as model-implied magnitude diagnostics rather than policy reform estimates.

Table 7. Counterfactual predictions: percent change in imports under Water = 0 and Water reduced by 50%

Year	Water = 0	Water reduced 50%
2005	3.116	1.444
2006	3.908	1.793
2007	11.109	4.530
2008	0.208	0.104
2009	2.316	1.104
2010	0.280	0.139
2011	0.834	0.409
2012	2.668	1.253
2013	4.310	1.969
2014	4.162	1.949
2015	5.224	2.405
2016	19.993	7.532
2017	25.900	9.316
2018	9.569	4.303
2019	15.260	6.347
2020	6.921	3.052
2021	1.137	0.554
2022	2.545	1.258
2023	25.196	11.701

Notes: Table 7 reports model-implied percent changes in total predicted imports by year. The Water = 0 scenario removes the fitted contribution of the uncertainty–policy-space interaction terms. The Water reduced 50% scenario scales that fitted contribution by one half. MFN tariffs and the estimated fixed-effect structure are held at their baseline fitted values. These are economic-magnitude diagnostics implied by the fitted model, not literal policy reform estimates.

I then add HS6 × Year fixed effects in Table 8 as a demanding robustness check because global product year shocks could otherwise drive the interaction pattern. With HS6 × Year absorbed, the main interaction remains negative and the post interaction remains positive with similar magnitudes and conventional significance, so the results are not explained by worldwide HS6 cycles. This strengthens the interpretation that cross market differences in tariff policy space shape how uncertainty shocks translate into climate smart imports.

Table 8. Stringent FE robustness: add HS6×Year fixed effects

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.2558* (1.8611)
Water × ln(1+WTUI)	-0.01685* (0.00916)
[Water × ln(1+WTUI)] × Post2018	0.01066* (0.00630)
Post-2018 net slope ($\beta_2 + \beta_3$)	-0.00619* (0.00323)
Constant	19.3268*** (0.0621)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6×Year FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8800
N	128,117

*Notes: Dependent variable is bilateral imports in levels. HS6×Year fixed effects absorb global product-year shocks common to a product in a given year. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

I finally report Table 9 because it is important to show that the effect is visible at the market level and not only through bilateral reallocation across partners. This table aggregates trade to importer product year total imports and still finds a negative and significant water × uncertainty term and a positive post interaction, with a negative and significant post period net slope. In simple words the mechanism shows up in total climate smart imports for a market, which supports an overall contraction channel rather than only a reshuffling of exporters.

Table 9. Decomposition (PPML): total imports at importer×HS6×year level

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.2281* (1.8233)
Water × ln(1+WTUI)	-0.01681** (0.00798)
[Water × ln(1+WTUI)] × Post2018	0.01074* (0.00582)
Post-2018 net slope ($\beta_2 + \beta_3$)	-0.00607** (0.00265)
Constant	21.7402*** (0.0713)
Estimator	PPML (ppmlhdfe)
Fixed effects	Importer×Year FE and HS6×Year FE
Clustered SE	Importer×HS6 (126 clusters)
Pseudo R^2	0.9138
N	1,823

*Notes: Dependent variable is total imports aggregated to importer–product–year. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Taken together, tariff policy space systematically conditions the import response to uncertainty, the timing matches a post 2018 regime shift rather than pre trends, and the matched-control evidence shows that the post-2018 change in the uncertainty-policy space slope differs systematically between CSG and close HS-family controls, with CSG exhibiting a smaller attenuation of the slope than the matched controls. The results imply that tightening bindings toward applied rates and limiting discretionary tariff changes can make clean tech supply chains more resilient in periods of elevated uncertainty.

5. Robustness and Additional Diagnostics

5.1 Pooled Specifications and the Need for a Regime Design

I begin with the pooled constant effect specifications in Tables A1 and A2 to assess whether the uncertainty-policy space channel is visible on average when the model is forced to estimate a single common slope over the full 2005–2023 period. In Table A1, the coefficient on ($Water \times WTUI_Z$) is 0.000547 with a standard error of 0.00160, while in Table A2 the coefficient on Water

× WTUI is −0.000148 with a standard error of 0.000128. In both cases, the estimated effect is very small and statistically weak. The implication is that a pooled constant-slope specification averages across distinct regimes and therefore washes out the underlying relationship. This is precisely why the analysis cannot rely on a pooled interpretation and instead focuses on the post-2018 regime design in the main results.

I then examine whether this weak pooled conclusion is merely an inference artifact by changing the clustering structure in Table A3. The point estimate remains exactly 0.000547, and the standard error changes only slightly, from 0.00160 to 0.00154. The inference is therefore unchanged. This is important because it shows that the attenuation in pooled models is not being generated by one convenient clustering choice, rather, it is a feature of the pooled restriction itself. Taken together, Tables A1-A3 justify the use of the break-based specification as the preferred empirical design.

5.2 Break Timing and Regime Sensitivity

Break timing and regime sensitivity tests are reported in Tables A4-A7. Once the baseline model allows the uncertainty-policy space slope to change after 2018, a natural concern is whether the result is mechanically driven by the choice of that particular breakpoint. Tables A4-A6 show that it is not. With a 2017 break, the coefficient on Water × ln(1+WTUI) is −0.0246 and the post interaction is 0.0191, implying a post-break slope of about −0.0055. With the baseline 2018 break in Table A5, the corresponding coefficients are −0.0186 and 0.0138, implying a post-break slope of about −0.0048. With a 2019 break in Table A6, they are −0.0124 and 0.00794, implying a post-break slope of about −0.0044. Across all three specifications, the pre-break slope is negative, the post interaction is positive, and the post-period net slope remains negative and very similar in magnitude. The central result therefore does not depend on a single cut-off year.

Table A7 complements these regressions with an external timing diagnostic based on segmented trends in WTUI itself. The clearest statistical break appears in 2019, with a large post-2019 level term, a negative slope change, and a joint test p-value of 0.0752, whereas the 2017 and 2018 alternatives are weaker. This does not undermine the 2018 design. Rather, it supports the interpretation that 2018 is an onset anchor for a rising uncertainty regime, while 2019 captures the sharper break in the WTUI series itself. In a trade setting with contracting, sourcing, and

adjustment frictions, such a pattern is economically plausible. Uncertainty can begin rising earlier, while realized trade effects become sharper with some delay. These tables show that the regime narrative is stable across nearby break dates and consistent with the underlying timing of the uncertainty series.

5.3 Economic Magnitude and the MFN Mechanical Channel

I next assess marginal effect magnitudes in Table A8 because interaction coefficients are hard to map into economic meaning without a reference uncertainty level. At the median uncertainty level, the pre period marginal effect is −0.0110. At the high uncertainty level near the 90th percentile, the pre period marginal effect is much larger in magnitude at −0.06289. In the post period the marginal effects are smaller at −0.00286 at the median and −0.0162 at the 90th percentile. These numbers show state dependence. Policy space matters most when uncertainty is high. This aligns closely with the interpretation, that policy space amplifies uncertainty shocks and that the economic cost is concentrated in high uncertainty episodes.

I also examine whether the estimated trade effect is mechanically driven by contemporaneous changes in applied MFN tariffs. This diagnostic is important because water is defined as the difference between bound and applied MFN tariffs. Using importer-product-year collapsed data, Tables A9 to A11 regress changes in MFN tariffs, absolute changes in MFN tariffs, and an indicator for MFN tariff increases on the uncertainty-policy-space exposure term. In Table A9, the coefficient on Water × Uncertainty in the ΔMFN regression is −0.00297 with a standard error of 0.00153. In Table A10, the coefficient in the |ΔMFN| regression is −0.00133 with a standard error of 0.00168 and is not statistically significant. In Table A11, the coefficient in the 1[ΔMFN>0] regression is −0.000406 with a standard error of 0.000444 and is also not statistically significant. These estimates provide little evidence that the main trade results are driven by systematic contemporaneous MFN tariff increases or by greater tariff volatility. The diagnostics therefore support the interpretation that water captures tariff policy space and credibility risk rather than active tariff changes coinciding with uncertainty.

5.4 Market-Structure and Supply-Chain Mechanism

I next examine market structure responses in Tables A12 to A14 because beyond total trade effects, it helps to understand whether the channel reflects supplier exit and concentration. In Table A12, the post period net slope for the number of exporters is negative at about −0.000717, so higher uncertainty combined with larger policy space is associated with fewer exporting partners serving a market. In Table A13, the post period net slope for HHI is positive at about 0.000974, which means sourcing becomes more concentrated. In Table A14, the post period net slope for the top exporter share is also positive at about 0.000906, which indicates a stronger dominance of the largest supplier. Economically, this pattern points to an extensive margin contraction and increased concentration under uncertainty in high policy space markets. It is consistent with a broader supply-chain fragility channel rather than only a price or quantity response among the same set of suppliers.

5.5 Additional DDD Robustness

Finally, I present additional DDD robustness checks in Tables A15 and A16. Table A15 reports a contemporaneous-exposure DDD specification as a robustness comparison to the preferred DDD model, which is based on predetermined exposure using pre-2018 mean water. The contemporaneous triple interaction is negative and statistically meaningful at about −0.00420. This indicates that the post-2018 change in the uncertainty-policy space slope differs between climate-smart and matched non-climate products even when exposure is measured contemporaneously.

Further, I also conduct contemporaneous DDD placebo timing checks in Table A16 because the key credibility issue for any DDD is whether a similar differential appears when the treatment date is shifted earlier. In the contemporaneous Lead2017 placebo, the triple interaction is −0.00503 and not significant. In the Lead2016 multiway version, the triple interaction is −0.00626 and not significant. These estimates are not consistent with a stable pre period differential. This supports the timing story and reinforces the narrative that the post period pattern is not driven by pre-existing differences between climate smart and matched control products.

Taken together, these robustness exercises show that the main findings are not artifacts of pooled averaging, one clustering choice, one breakpoint, one functional form, or one product composition. They show that the effect is strongest at high uncertainty levels, is not explained by systematic MFN adjustments, and is consistent with supplier exit and increased market concentration. Overall, the robustness battery strengthens the interpretation that tariff policy space amplifies uncertainty shocks for climate-smart imports and that tighter tariff commitments can reduce the vulnerability of clean-technology supply chains in periods of elevated uncertainty.

6. Conclusion and Policy Implications

This paper asks whether clean technology imports decline more steeply when trade uncertainty rises in markets where governments retain greater tariff policy space. When governments retain large gaps between bound and applied tariffs, firms face not only current trade costs but also the risk that future tariffs may rise. For clean technologies, this risk is economically important because these imports are often inputs into clean capital formation, energy-system upgrading, grid reliability, and infrastructure investment. Predictable access to these goods therefore matters not only for trade flows, but also for the ability of countries to build cleaner and more resilient production systems over time.

Using tariff-line bilateral trade data for five UNESCAP's climate-smart goods and technologies products over 2005–2023 matched with the World Trade Uncertainty Index, I estimate gravity models with PPML high-dimensional fixed effects and allow the uncertainty–tariff policy space relationship to change after 2018. I then test timing using an event study built on predetermined exposure and a matched-control triple-difference method that compares climate smart goods (CSG) to closely related non-climate products.

Three results stand out. First, larger tariff policy space is associated with a more negative uncertainty-related import response, and this relationship remains negative after 2018 but becomes substantially attenuated. The event study shows no detectable near-lead effects in 2015 and 2016, while the post-2018 interactions are jointly significant after including tail bins that make 2017 the omitted reference year. Second, the matched-control triple-difference design indicates that the post-2018 change in the uncertainty–policy space slope differs significantly between CSG and

closely related non-climate products. Specifically, the attenuation of the slope after 2018 is smaller for CSG than for matched controls. Third, the mechanism is consistent with supply-chain fragility. Under higher uncertainty in high-tariff-policy-space markets, the number of exporters falls and sourcing becomes more concentrated, with greater dominance by the top supplier. This pattern is consistent with market exit and consolidation rather than only a reallocation across partners.

The economic magnitudes are meaningful. Model-implied counterfactual predictions imply that setting tariff policy space to zero would have raised climate-smart imports by about 10% in 2018, 15% in 2019, and 7% in 2020. Reducing policy space by half would have raised imports by about 4% in 2018, 6% in 2019, and 3% in 2020. Taken together, the evidence implies that large gaps between WTO bindings and applied tariffs can make clean-technology imports more vulnerable when uncertainty rises. For CSG, binding tariffs closer to applied rates and adopting rules that limit sudden discretionary tariff changes may reduce the incentive to delay orders, lower supplier exit risk, and help keep clean-technology supply chains more resilient during uncertainty spikes. The policy implication is not that countries should eliminate all tariff flexibility. Tariff overhang can preserve useful policy autonomy, particularly where governments value room to respond to shocks. The evidence instead points to a more targeted trade-off. For climate-smart intermediate and capital goods, large bound–applied gaps can create a hidden cost: they raise the perceived risk of future tariff increases and may discourage supplier participation precisely when reliable access to clean-technology inputs is most valuable. In this setting, tariff policy space is not only a legal reserve of discretion; it can also become a source of import fragility.

A first policy lever is selective tariff-binding discipline for CSG. Countries could consider binding tariffs closer to applied rates for clean-technology inputs that are central to energy-system upgrading, power conversion, grid reliability, and infrastructure investment. This would not require a general surrender of policy space across all sectors. Rather, it would prioritize credibility in sectors where delays in imported inputs can slow clean-capital accumulation and technology diffusion.

A second policy lever is to strengthen predictability provisions in trade agreements. Rules that limit sudden discretionary tariff increases, require advance notice, or impose justification requirements for changes in climate-smart tariffs could reduce the option value of waiting that

drives the uncertainty channel. Such provisions would be especially relevant for goods purchased under long-term contracts, procurement schedules, and project-finance conditions, where policy uncertainty can delay orders or narrow supplier participation.

A third policy lever is multilateral. Forums such as the WTO can treat tariff bindings not only as market-access commitments, but also as instruments of supply-chain resilience. For clean technology imports, credible tariff commitments can support the reliability of imported inputs needed for cleaner energy systems, stronger infrastructure, and broader technology diffusion. The central lesson is that when uncertainty is high, the credibility of tariff commitments matters. Narrowing excessive tariff overhang for climate technologies can reduce the risk premium attached to sourcing these products and make clean-technology supply chains less fragile when predictable access is most needed.

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Appendix A

Table A1: Pooled PPML: standardized WTUI interaction (no break)

Variable	Estimate (Std. Err.)
ln(1+MFN)	-2.9471 (2.0109)
Water × $WTUI_Z$	0.000547 (0.00160)
Constant	19.2459*** (0.0568)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8750
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Pooled constant-slope specification without any regime break. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A2: Pooled PPML: raw WTUI interaction (no break)

Variable	Estimate (Std. Err.)
ln(1+MFN)	-2.9437 (2.0151)
Water × WTUI (raw)	-0.000148 (0.000128)
Constant	19.2549*** (0.0569)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8750
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Pooled constant-slope specification without any regime break, using raw WTUI. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A3: Inference robustness: pooled PPML clustered by importer×HS6

Variable	Estimate (Std. Err.)
ln(1+MFN)	-2.9471 (1.9877)
Water × $WTUI_Z$	0.000547 (0.00154)
Constant	19.2459*** (0.0699)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Importer×HS6 (126 clusters)
Pseudo R^2	0.8750
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Same as Table A1 but standard errors clustered by importer×HS6. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A4: Break-year sensitivity: post defined as year ≥ 2017

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.2494 (1.9774)
Water × ln(1+WTUI)	-0.02459* (0.01276)
[Water × ln(1+WTUI)] × Post2017	0.01906** (0.00968)
Post-break net slope ($\beta_2 + \beta_3$)	-0.00552 (0.00363)
Constant	19.3137*** (0.0643)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8756
N	128,117

Notes: Dependent variable is bilateral imports in levels. Shifts the break earlier to test sensitivity. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01. $Post2017_t = 1[t \geq 2017]$.

Table A5: Break-year sensitivity: post defined as year ≥ 2018

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.1880 (1.9887)
Water × ln(1+WTUI)	-0.0186** (0.00923)
[Water × ln(1+WTUI)] × Post2018	0.0138** (0.00620)
Post-break net slope ($\beta_2 + \beta_3$)	-0.00480 (0.00331)
Constant	19.3092*** (0.0632)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8756
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Baseline break definition shown for loop completeness. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.* $Post2018_t = 1[t \geq 2018]$.

Table A6: Break-year sensitivity: post defined as year ≥ 2019

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.0873 (1.9960)
Water × ln(1+WTUI)	-0.01238* (0.00677)
[Water × ln(1+WTUI)] × Post2019	0.00794** (0.00399)
Post-break net slope ($\beta_2 + \beta_3$)	-0.00444 (0.00313)
Constant	19.3001*** (0.0620)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,097 clusters)
Pseudo R^2	0.8755
N	128,117

*Notes: Dependent variable is bilateral imports in levels. Shifts the break later to test sensitivity. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.* $Post2019_t = 1[t \geq 2019]$.

Table A7: WTUI segmented-trend break diagnostics: candidate break years 2017, 2018, 2019

Variable	Break at 2017	Break at 2018	Break at 2019
PostB	39.464 (31.775)	55.966 (39.952)	73.925** (30.023)
(t − B) × PostB	-5.262 (5.894)	-12.375 (9.952)	-25.555** (10.897)
Joint test p-value (PostB = 0 and slope change = 0)	0.3455	0.3442	0.0752
R^2	0.2578	0.4249	0.6997
Estimator	OLS with robust SE	OLS with robust SE	OLS with robust SE
N (years)	19 (2005–2023)	19 (2005–2023)	19 (2005–2023)

*Notes: These segmented-trend regressions provide external timing diagnostics for annual WTUI. The baseline trade regressions treat 2018 as the onset of the higher-uncertainty regime, while Tables A4–A6 assess sensitivity to alternative 2017, 2018, and 2019 break definitions and Table 4 examines dynamic timing around the omitted 2017 reference year. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

$$WTUI_t = a_0 + a_1 t + a_2 PostB_t + a_3[(t - B) \times PostB_t] + u_t$$

Table A8: Economic magnitudes (nlcom): marginal effects of Water at ln(1+WTUI) percentiles

Variable	Estimate (Std. Err.)
ME_pre at lnWTUI p50	-0.01107** (0.00549)
ME_pre at lnWTUI p90	-0.06289** (0.03118)
ME_post at lnWTUI p50	-0.00286 (0.00197)
ME_post at lnWTUI p90	-0.01624 (0.01118)
Estimator	Derived via nlcom from baseline PPML
Clustered SE	Pair (inherits baseline clustering)
N	128,117

*Notes: Dependent variable is bilateral imports in levels (baseline PPML). Marginal effects are semi-elasticities evaluated at representative uncertainty levels. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A9: Mechanism diagnostic: ΔMFN on Water×Uncertainty (collapsed importer×HS6×year)

Variable	Estimate (Std. Err.)
Water × Uncertainty	-0.002965* (0.001532)
Constant	-0.02042 (0.01899)
Estimator	OLS (reghdfe)
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6 (125 clusters)
R^2	0.1081
Within R^2	0.0023
N	1,552

Notes: Dependent variable is ΔMFN. Standard errors are in parentheses. Significance: p<0.10, ** p<0.05, *** p<0.01.*

Table A10: Mechanism diagnostic: |ΔMFN| on Water×Uncertainty (collapsed importer×HS6×year)

Variable	Estimate (Std. Err.)
Water × Uncertainty	-0.001329 (0.001681)
Constant	0.3032*** (0.02084)
Estimator	OLS (reghdfe)
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6 (125 clusters)
R^2	0.1847
Within R^2	0.0005
N	1,552

*Notes: Dependent variable is |ΔMFN|. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A11: Mechanism diagnostic: 1[ΔMFN>0] on Water×Uncertainty (collapsed importer×HS6×year)

Variable	Estimate (Std. Err.)
Water×Uncertainty	-0.000406 (0.000444)
Constant	0.05787*** (0.00551)
Estimator	OLS (reghdfe)
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6 (125 clusters)
R^2	0.1589
Within R^2	0.0013
N	1,552

*Notes: Dependent variable is 1[ΔMFN>0]. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A12: Decomposition (PPML): extensive margin (number of exporters) at importer×HS6×year

Variable	Estimate (Std. Err.)
ln(1+MFN)	0.1853 (0.2227)
Water × ln(1+WTUI)	0.000672* (0.000365)
[Water × ln(1+WTUI)] × Post2018	-0.001389*** (0.000490)
Post-2018 net slope ($\beta_2 + \beta_3$)	-0.000717* (0.000380)
Constant	4.3073*** (0.0108)
Estimator	PPML (ppmlhdfe)
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6 (126 clusters)
Pseudo R^2	0.5114
N	1,823

*Notes: Dependent variable is the number of exporters in an importer–product–year market. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A13: Decomposition (OLS): concentration (HHI)

Variable	Estimate (Std. Err.)
ln(1+MFN)	0.02686 (0.35888)
Water × ln(1+WTUI)	0.001313*** (0.000437)
[Water × ln(1+WTUI)] × Post2018	-0.000339 (0.000258)
Post-2018 net slope	0.000974** (0.000381)
Constant	0.20935*** (0.01590)
Estimator	OLS
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6
R^2	0.5626
Within R^2	0.0304
N	1,823

*Notes: Dependent variable is the Herfindahl–Hirschman Index (HHI) of sourcing concentration. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A14: Decomposition (OLS): dominance (top-1 exporter share) within importer×HS6×year

Variable	Estimate (Std. Err.)
ln(1+MFN)	-0.04055 (0.39083)
Water × ln(1+WTUI)	0.001389*** (0.000392)
[Water × ln(1+WTUI)] × Post2018	-0.000483** (0.000222)
Post-2018 net slope ($\beta_2 + \beta_3$)	0.000906*** (0.000334)
Constant	0.36599*** (0.01728)
Estimator	OLS (reghdfe)
Fixed effects	Importer×HS6 FE; Year FE
Clustered SE	Importer×HS6 (126 clusters)
R^2	0.6067
Within R^2	0.0248
N	1,823

*Notes. Dependent variable is the largest exporter's import share in an importer–product–year market. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.*

Table A15: Matched-control DDD (PPML): contemporaneous exposure (robustness)

Variable	Estimate (Std. Err.)
ln(1+MFN)	-3.1876 (1.9880)
WU_{ipt}	-0.02489** (0.00999)
CSG × WU_{ipt}	0.00629** (0.00271)
Post2018 × WU_{ipt}	0.01800** (0.00720)
CSG × Post2018	0.2411*** (0.0653)
CSG × Post2018 × WU_{ipt}	-0.00420* (0.00223)
Constant	19.2308*** (0.0670)
Estimator	PPML (ppmlhdfe)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,444 clusters)
Pseudo R^2	0.9054
N	328,178

*Notes. Dependent variable is bilateral imports in levels. Robustness comparison using contemporaneous exposure. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.* $WU_{ipt} = Water_{ipt} \times ln(1 + WTUI_t)$.

Table A16: DDD placebo timing (PPML): contemporaneous exposure with Lead2017 and Lead2016

Variable	Estimate (Std. Err.) (Lead2017)	Estimate (Std. Err.) (Lead2016)
ln(1+MFN)	-3.2490 (1.9767)	-3.4193 (2.5869)
WU	-0.03175** (0.01451)	-0.05069** (0.02372)
CSG × $\boldsymbol{WU_{ipt}}$	0.00717* (0.00374)	0.00842 (0.01035)
Lead2017 × $\boldsymbol{WU_{ipt}}$	0.02408** (0.01159)	
CSG × Lead2017	0.2566*** (0.0600)	
CSG × Lead2017 × $\boldsymbol{WU_{ipt}}$	-0.00503 (0.00324)	
Lead2016 × $\boldsymbol{WU_{ipt}}$		0.04262** (0.02057)
CSG × Lead2016		0.2884*** (0.0327)
CSG × Lead2016 × $\boldsymbol{WU_{ipt}}$		-0.00626 (0.00867)
Constant	19.2109*** (0.0669)	19.1901*** (0.0723)
Fixed effects	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE	Pair FE; Importer×Year FE; Exporter×Year FE; HS6 FE
Clustered SE	Pair (4,444 clusters)	Multiway: importer (26) & exporter (239)
Pseudo R^2	0.9054	0.9055
N	328,178	328,178

*Notes: Dependent variable is bilateral imports in levels. Placebo regressions replace Post2018 with earlier pseudo-break indicators, reported separately for Lead2017 and Lead2016 under contemporaneous exposure. Standard errors are in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.* $\boldsymbol{Lead2017_t = 1[t \geq 2017]}$*;* $\boldsymbol{Lead2016_t = 1[t \geq 2016]}$. $\boldsymbol{WU_{ipt} = Water_{ipt} \times ln(1 + WTUI_t}$. *Estimator is PPML (ppmlhdfe).*

Appendix B

Table B1: Reporting economies (importers) in the final estimation sample

Argentina	Colombia	Korea, Rep.	Philippines	Switzerland	Vietnam
Australia	India	Malaysia	Russian Federation	Thailand	
Brazil	Indonesia	Mexico	Saudi Arabia	Turkey	
Canada	Israel	Norway	Singapore	United Arab Emirates	
China	Japan	Pakistan	South Africa	United States	

Notes: This table reports the 26 reporting economies (importers) retained in the final DDD estimation sample. The estimation panel covers 2005–2023 and is unbalanced across reporting economies after imposing the requirements that TradeYear = TariffYear and that both applied MFN and bound tariff observations are non-missing. The exporter dimension comprises 242 partners appearing in the cleaned bilateral panel, including sovereign countries, territories, and source-defined statistical categories.

Table B2: Matched non-CSG HS6 controls used in the DDD design

HS6 code	Product description	HS chapter	Related CSG family	Why valid as control
392610	Plastics; office or school supplies	39	392690	Same plastics chapter and neighbouring product line; shares broad customs and tariff environment but is not climate-smart classified.
392620	Plastics; articles of apparel and clothing accessories (including gloves, mittens and mitts)	39	392690	Same plastics chapter and nearby HS family; provides non-CSG comparison within a similar tariff-administration environment.
392640	Plastics; statuettes and other ornamental articles	39	392690	Same plastics chapter and neighbouring product family; useful as a non-CSG comparator under similar customs treatment.
847920	Machinery; for the extraction or preparation of animal or fixed vegetable fats or oils	84	847989	Same machinery heading family (8479); comparable machinery-class customs environment but not climate-smart classified.
847940	Machines; for making rope or cable	84	847989	Same 4-digit machinery family; provides within-heading non-CSG comparison for specialized machinery trade.
847990	Machines and mechanical appliances; parts, of those having individual functions	84	847989	Same machinery family and closely related parts line; strong within-family non-CSG counterfactual.
850431	Electrical transformers; n.e.c. in item no. 8504.2, having a power	85	850440	Same 4-digit electrical equipment family (8504); similar power-equipment

HS6 code	Product description	HS chapter	Related CSG family	Why valid as control
	handling capacity not exceeding 1kVA			customs environment but outside the climate-smart classification.
850432	Transformers; n.e.c. in item no. 8504.2, having a power handling capacity exceeding 1kVA but not exceeding 16kVA	85	850440	Same heading family as static converters; comparable electrical-manufacturing and tariff setting environment.
850433	Transformers; n.e.c. in item no. 8504.2, having a power handling capacity exceeding 16kVA but not exceeding 500kVA	85	850440	Same heading family and related power-equipment line; useful non-CSG control for power-conversion products.
850490	Electrical transformers, static converters and inductors; parts thereof	85	850440	Same heading family and parts category; especially strong control because it sits very close to the treated converter family.
853720	Boards, panels, consoles, desks and other bases; for electric control or the distribution of electricity, (other than switching apparatus of heading no. 8517), for a voltage exceeding 1000 volts	85	853710	Same 4-digit electrical control-panel family; neighbouring non-CSG line under a very similar customs and tariff environment.
854110	Electrical apparatus; diodes, other than photosensitive or light-emitting diodes	85	854140	Same semiconductor-device family (8541); comparable electronics customs environment but not climate-smart classified.
854130	Electrical apparatus; thyristors, diacs and triacs, other than photosensitive devices	85	854140	Same semiconductor heading family; neighbouring non-CSG electronic component line.

HS6 code	Product description	HS chapter	Related CSG family	Why valid as control
854150	Electrical apparatus; photosensitive semiconductor devices n.e.c. in heading no. 8541, including photovoltaic cells, whether or not assembled in modules or made up into panels	85	854140	Same semiconductor family and technologically related line; useful within-family control.
854190	Electrical apparatus; parts for diodes, transistors and similar semiconductor devices and photosensitive semiconductor devices	85	854140	Same semiconductor family and closely related parts line; strong non-CSG comparator within the same electronics customs environment.

Notes: *Tariff and trade data are extracted from UNCTAD TRAINS via WITS at the HS6 level using HS Combined. The five treated CSG are defined based on the UNESCAP climate-smart goods and technologies list. The 15 matched non-CSG control products are defined based on the UN Statistics Division (UNSD) HS 6-digit 2012 product descriptions. These control products are not part of the UNESCAP climate-smart goods and technologies list and therefore form the non-CSG comparison group.*