International Journal of Applied and Advanced Scientific Research (IJAASR)
Impact Factor: 5.655, ISSN (Online): 2456 - 3080
(www.dvpublication.com) Volume 6, Issue 2, 2021

GREEN SUBSIDIES AND COMPETITIVE DISPLACEMENT IN GLOBAL CLEAN TECHNOLOGY TRADE

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Cite This Article: Kannan Vishwanath & Lloyd Zulu, "Green Subsidies and Competitive Displacement in Global Clean Technology Trade", International Journal of Applied and Advanced Scientific Research, Volume 6, Issue 2, Page Number 64-76, 2021.

Abstract:

This analysis examines whether recorded green support measures are associated with competitive repositioning in international clean technology trade. Using secondary policy records and UN Comtrade exports for 28 European economies over 2010 to 2020, the analysis estimates fixed effects regressions with inference clustered by economy. The estimation sample contains 513 annual share changes across 55 economy and product combinations covering wind generating sets and a broader photovoltaic containing product category. Financial, fiscal, and production and market support coefficients are positive at 0.0421, 0.0209, and 0.0664 percentage points per additional record, respectively, but all confidence intervals include zero. Removing repeated policy entries, restricting observations to complete histories, and fixing reporting pools produces similar estimates. These findings distinguish recorded interventions from economic exposure and relative export movements from demonstrated rival displacement. The contribution is a common empirical assessment of three support dimensions that qualifies automatic links between policy breadth and export competitiveness. International policy evaluation should connect beneficiary assistance to specific trade outcomes before attributing competitive gains to public support.

Key Words: Green Industrial Policy; Clean Technology Trade; Export Market Shares; Policy Measurement; Panel Regression.

1. Introduction:

Government support for clean technology raises a consequential question for international trade: does it strengthen domestic technological capabilities, or does it also redistribute competitive positions among exporters? These outcomes carry different implications for industrial policy and trade assessment. Support that expands renewable energy markets may benefit several suppliers, whereas displacement implies losses for competing exporters. Green industrial policy therefore requires evaluation that separates domestic development objectives from changes in international market positions (Rodrik, 2014). The distinction also matters because competitiveness encompasses trade, productivity, innovation, and industrial location rather than a single interchangeable outcome (Dechezleprêtre & Sato, 2017).

Financial, fiscal, and production and market support may influence export performance through different economic channels. Grants, preferential loans, and guarantees may reduce financing constraints and investment risk. Tax incentives may improve investment returns or reduce effective production costs. Production incentives and market support may encourage deployment, expand demand, and create opportunities for accumulated production experience. These mechanisms do not imply equivalent international effects. Investment can serve domestic demand, imported equipment can benefit from deployment incentives, and supported producers may expand without reducing competitors' sales. Research on renewable technology diffusion and innovation establishes the importance of policy and technological conditions while showing that instruments can operate differently across technologies (Johnstone et al., 2010; Popp et al., 2011). The expected relationship between support and export competitiveness is therefore conditional rather than automatic.

The closest empirical research connects environmental policy, innovation, and renewable technology exports through several distinct approaches. Costantini and Mazzanti (2012) examine environmental policy and innovation in European export competitiveness. Groba and Cao (2015) investigate Chinese renewable technology exports through policy, innovation, and market conditions. Kuik et al. (2019) analyse bilateral renewable technology trade and report policy related competitive advantages that persist differently in wind and photovoltaic industries. Together, these contributions establish that the relationship depends on the policy proxy, technological setting, and trade specification. They do not make documented policy counts equivalent to financial exposure, nor do they make export growth equivalent to rival displacement. These distinctions define the empirical question addressed here.

Policy measurement is particularly consequential when several instruments operate simultaneously. A recorded measure identifies an intervention but does not necessarily identify its expenditure, generosity, coverage, or benefits received by manufacturers. Multiple entries can also represent eligibility conditions or different technology applications within a programme. Policy mix research consequently distinguishes the presence and number of instruments from their design, intensity, consistency, and implementation (Rogge & Reichardt, 2016; Schmidt & Sewerin, 2019). This distinction creates a specific empirical boundary: an

association between policy records and trade outcomes concerns documented policy activity, while an association between financial benefits and trade outcomes concerns economic exposure. Treating these constructs as equivalent can obscure what an estimated coefficient represents.

Outcome measurement introduces a related boundary. An exporter's market share measures its position relative to other observed exporters. Its share can decline even when its export value increases, provided that competing exporters expand more rapidly. Conversely, a share gain need not establish that a particular rival lost sales because of government support. The reviewed evidence does not establish whether counts of financial, fiscal, and production and market support records provide consistent information about annual relative export movements when the three dimensions are examined jointly. The contribution pursued here is therefore a bounded measurement and empirical comparison: assessing these policy indicators against a common trade outcome while examining sensitivity to repeated records, incomplete histories, and reporting pool composition.

This study aims to assess whether recorded financial, fiscal, and production and market support measures are associated with annual changes in exporters' shares of clean technology trade. The research question is whether more documented support within each dimension corresponds to stronger relative export performance after accounting for persistent differences between economy and product combinations and common annual movements within product categories. The specific objectives are to estimate the association for financial support records, estimate the association for fiscal support records, and estimate the association for production and market support records. Complementary analyses examine exporters' own share losses and the sensitivity of the estimated relationships to alternative data constructions.

The empirical analysis links secondary policy records with annual UN Comtrade exports for 28 European economies over 2010 to 2020. It covers wind powered generating sets and a broader photosensitive semiconductor category containing photovoltaic cells and light emitting diodes. The latter category is therefore interpreted as photovoltaic containing trade rather than exclusively solar equipment. The unit of analysis is an economy, product category, and year. Consecutive annual observations yield 513 export share changes across 55 economy and product combinations. The specification includes economy and product fixed effects and product and year fixed effects, with inference clustered by economy. This design estimates associations within the observed panel; it does not identify the causal displacement of rival exporters.

The results provide three contributions. First, the joint specification yields positive but imprecise associations for all three policy dimensions, qualifying the expectation that a larger inventory of recorded support necessarily corresponds to annual export share gains. Second, removing repeated policy content and changing the export denominator produces closely similar estimates, distinguishing sensitivity to construction choices from the substantive meaning of the indicators. Third, the analysis separates policy records, relative export movements, and displacement as different empirical objects. Its international relevance lies in this distinction: comparisons of national support systems require evidence about what interventions measure and which competitive outcomes they can explain. The findings support more precise evaluation of green industrial policy without treating statistical uncertainty as proof of policy ineffectiveness.

2. Theory, Conceptual Framework and Hypotheses Development:

2.1. Theoretical Foundation of Green Subsidies and Competitive Displacement:

International clean technology trade operates through interconnected production systems in which government support influences production costs, technological capabilities, and competition for foreign market shares. Strategic trade theory explains how policy intervention can alter competitive positions when firms face economies of scale, imperfect competition, and barriers to market entry. Green subsidies may strengthen domestic producers by reducing investment costs and financing constraints, but their international effects depend on whether supported firms expand exports, replace competing suppliers, or stimulate additional market demand. This distinction is central to evaluating competitive displacement because increased exports by subsidized producers do not necessarily imply equivalent losses among foreign competitors.

This analysis distinguishes three dimensions of green subsidies: financial subsidies, fiscal subsidies, and production and market support subsidies. Financial subsidies influence access to capital and investment capacity. Fiscal subsidies change the effective cost of production and investment. Production and market support subsidies influence commercial incentives and the scale of market participation. The theoretical outcome is competitive displacement in global clean technology trade, operationally reflected in changes in export market shares and rival exporters' competitive positions. The framework treats subsidy support as a policy exposure and competitive displacement as an observed market outcome rather than assuming that all forms of government intervention produce equivalent trade effects.

Empirical research establishes that environmental policy can influence technological innovation, industrial competitiveness, and international trade, although the direction and magnitude depend on policy design and market conditions. Aghion et al. (2016) demonstrate that policy incentives influence the direction of technological innovation, while Dechezleprêtre and Sato (2017) show that the competitiveness consequences of environmental regulation vary across industries and policy settings. Rodrik (2014) identifies the coordination and information problems underlying industrial policy, and Popp et al. (2011) explain how technology policy

can address barriers to clean energy innovation and diffusion. These findings provide a theoretical basis for examining subsidy exposure and export competition, but they do not establish competitive displacement as an automatic consequence of green subsidies.

2.2. Financial Subsidies and Competitive Displacement:

Financial subsidies comprise direct government grants, preferential loans, and government loan guarantees that reduce the financial constraints facing clean technology producers. Their theoretical relevance arises from capital market imperfections that restrict investment in technologies requiring substantial initial expenditure and uncertain commercialization returns. By reducing financing costs and investment risks, financial support may increase production capacity and improve exporters' ability to compete internationally. Rodrik (2014) identifies investment coordination and information failures as central justifications for green industrial policy, while Popp et al. (2011) demonstrate the importance of technological development and diffusion in renewable energy investment.

Financial support may contribute to competitive displacement when subsidized exporters expand their shares within destination markets at the expense of competing suppliers. However, this mechanism depends on whether additional investment translates into exportable production, whether destination markets can absorb greater supply, and whether competing producers adjust their prices or output. Aghion et al. (2016) establish that technological responses depend partly on existing innovation capabilities, suggesting that financing support alone cannot guarantee improved international competitiveness.

Empirical evidence also indicates that policy effects differ across clean technology industries. Research on renewable energy trade finds that domestic policy support can be associated with international competitive advantages, but the persistence of those advantages differs between wind and solar technologies. Dechezleprêtre and Sato (2017) further demonstrate that environmental policy effects on competitiveness are heterogeneous. These findings support a conditional expectation rather than a universal displacement effect.

H1: Higher financial subsidy exposure is associated with greater competitive displacement of rival exporters in clean technology markets, conditional on comparable products, destinations, and observation periods.

2.3. Fiscal Subsidies and Competitive Displacement:

Fiscal subsidies include corporate tax incentives, investment tax credits, and import duty exemptions intended to reduce the effective costs of clean technology investment and production. Unlike direct financial support, fiscal incentives generally operate through the tax treatment of eligible economic activities. Their competitive effects depend on whether firms can use the incentives and convert the resulting cost reductions into lower export prices, increased capacity, or improved production efficiency. Rodrik (2014) emphasizes that the effectiveness of industrial policy depends on institutional design and the capacity to direct incentives toward activities with economic and environmental benefits.

Fiscal incentives may strengthen export competitiveness by improving investment returns and reducing production costs. Nevertheless, the distribution of these benefits depends on firms' tax positions, imported input requirements, and exposure to international competition. Lower production costs may increase export market shares without necessarily reducing rival exports when destination demand expands. Evidence from renewable energy trade confirms that competitive advantages differ across technologies and market conditions, while research on environmental regulation indicates that policy effects cannot be assumed to operate uniformly across sectors.

The theoretical expectation is therefore that fiscal support may strengthen the market position of eligible producers, with potential displacement effects where competing exporters supply substitutable products to the same destinations. This relationship remains an empirical proposition rather than an established result.

H2: Higher fiscal subsidy exposure is associated with greater competitive displacement of rival exporters in clean technology markets, conditional on comparable products, destinations, and observation periods.

2.4. Production and Market Support Subsidies and Competitive Displacement:

Production and market support subsidies include production-based assistance, renewable energy feed in tariffs, and government procurement support. These instruments influence producers through output incentives, expected market demand, and opportunities for commercial expansion. Their theoretical mechanism differs from financial and fiscal subsidies because support may affect both production decisions and domestic market development. Bougette and Charlier (2015) demonstrate that feed in tariff policies can influence relationships between upstream suppliers and renewable energy markets, with implications for international trade and welfare.

Production incentives may improve competitiveness when firms use increased output and accumulated experience to reduce costs. Market support can also encourage investment by providing more predictable demand. However, the resulting trade effects depend on the relationship between domestic deployment and export production. Support that expands domestic consumption may not produce proportional export growth, while policies favoring domestic suppliers may redirect demand away from foreign competitors. Research on

wind energy innovation demonstrates that public research support and feed in tariffs can interact in shaping technological development, although innovation outcomes do not directly establish export displacement.

International competitive effects also depend on trade policy responses. Bougette and Charlier (2018) demonstrate theoretically that renewable energy support and antidumping measures can interact in solar panel markets. Evidence on renewable energy export competitiveness further indicates that policy related advantages may vary in duration across technologies. Accordingly, the expected association between production and market support and competitive displacement depends on whether policy incentives translate into increased export participation and changes in rival market shares.

H3: Higher production and market support subsidy exposure is associated with greater competitive displacement of rival exporters in clean technology markets, conditional on comparable products, destinations, and observation periods.

2.5. Conceptual Framework and Empirical Alignment:

The conceptual framework identifies green subsidies as the explanatory construct and competitive displacement in global clean technology trade as the outcome construct. Financial subsidies, fiscal subsidies, and production and market support subsidies represent distinct policy dimensions. Competitive displacement is conceptually represented by changes in export market shares, rival export market share losses, export competitiveness, market concentration, and export market entry and exit.

The proposed relationships are theoretical associations, not established causal effects. Export market share changes provide the most direct available trade-based representation of competitive displacement. Market concentration and market entry or exit provides supplementary descriptions of competitive restructuring but are not interchangeable measures of displacement.

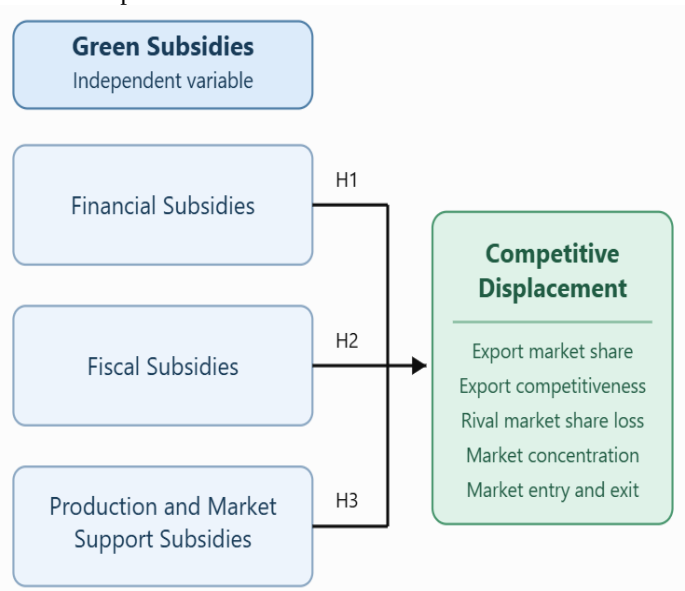


Figure 1: Proposed conceptual framework for green subsidies and competitive displacement in global clean technology trade

The three hypotheses require separate historical measures of financial, fiscal, and production and market support subsidy exposure linked to the same economies, products, and periods as the trade outcomes. The available source audit has not established those complete numerical series. Consequently, H1, H2, and H3 remain prespecified theoretical hypotheses rather than hypotheses currently supported by an estimation ready dataset. Their empirical testing must not be represented as completed until the corresponding subsidy observations have been verified.

3. Data:

This analysis documents data provenance, constructs the analytical sample, and defines the policy and trade indicators. The annual panel supports descriptive comparisons of recorded renewable support and changes in exporters' relative market positions.

3.1 Data Sources, Population, and Sample Construction:

The analysis combines annual UN Comtrade exports with renewable electricity support records from Climate Policy Atlas. Merchandise trade follows the statistical scope documented by United Nations (2011). The empirical framework distinguishes environmental policy instruments from traded technology products, consistent with the OECD (2011).

The trade extract covers HS850231, wind powered generating sets, and HS854140, photosensitive semiconductor devices containing photovoltaic cells and light emitting diodes. HS854140 therefore represents a broader category than solar technology alone (United Nations Statistics Division, 2012).

UN Comtrade supplies annual exports to the world through its public API. The extraction uses annual frequency, export flow X, partner code 0, and the primary Value field in current US dollars. These observations represent annual flows. Reporter identifiers, product codes, classification revisions, quantities, and estimation flags remain attached to the records. The database provides a live historical extract rather than a numbered release, and its use remains subject to United Nations attribution and redistribution terms (United Nations Statistics Division, n.d.).

Climate Policy Atlas supplies the RE Policies worksheet from repository version 1.1. Its policy records are available under the Creative Commons Attribution Share Alike 4.0 licence. The repository identifies version 1.1, although the downloadable workbook retains an internal version 1 label (Weko et al., 2026). The recorded extraction date is 26 October 2026. This date identifies the data vintage; the observation period remains 2010 to 2020.

The target population comprises economies participating in international clean technology trade. The accessible trade extract contains 179 reporting economies and 2,150 observations across the two product categories. The linked policy frame covers 28 European economies. Selection retains records meeting the temporal, instrument, technology, and geographical boundaries.

The unit of analysis is an economy, product category, and calendar year. The constructed panel contains 56 economy and product combinations over eleven annual periods. Its 616 positions form a balanced framework, while the 582 observed trade values form an unbalanced analytical sample. Forty-six combinations have complete trade coverage.

Table 1: Sample construction

Stage	Units	Observations	Reason or rule
Policy records within the observation period	28 economies	2,337 policy records	Records dated 2010 to 2020
Excluded carbon tax records	28 economies remain	74 records excluded	Outside the selected support instruments
Excluded other technology records	28 economies remain	514 records excluded	Outside wind, photovoltaic, and all renewables categories
Retained policy extract	28 economies	1,749 policy records	Eligible instruments and technologies
Retrieved trade extract	179 economies	2,150 trade observations	Annual exports to the world
Constructed panel framework	56 economy and product combinations	616 positions	28 economies, two products, eleven years
Positions without returned trade values	56 combinations remain	34 positions unavailable	Missing records retained as unavailable
Available trade levels and shares	56 combinations	582 observations	Observed exports and valid denominators
Initial observations excluded from annual changes	56 combinations	53 observations excluded	No preceding observation within the study window
Additional observations excluded from annual changes	55 combinations remain	16 observations excluded	Preceding annual value unavailable
Available annual changes and share losses	55 combinations	513 observations	Consecutive annual shares available

3.2 Data Integration, Cleaning, and Quality Assurance:

Integration matches numerical reporter codes, calendar years, and HS product codes. Policy records are aggregated by economy, year, technology, and support dimension before attachment to the panel. This procedure preserves one panel position per merge key. The audit identifies no duplicate trade keys or duplicate panel keys. Trade values retain their classification revisions and estimation flags. Annual exports remain in current US dollars without inflation adjustment or additional currency conversion. The extraction preserves exporter values rather than constructing reconciled bilateral flows. Trade compilation conventions and bilateral reconciliation involve distinct procedures and assumptions (Gaulier & Zignago, 2010; United Nations, 2017).

Policy aggregation matches wind, onshore wind, and offshore wind to HS850231. Photovoltaic, rooftop photovoltaic, and field photovoltaic records match HS854140. Records classified as all renewables enter both categories. Consequently, 1,749 source records generate 2,153 matched record incidences. This replication reflects technology matching rather than additional programmes.

The policy extract contains 1,747 distinct serial identifiers. Twenty records repeat other records across the retained content fields when serial identifiers and source row numbers are excluded. Two serial identifiers

each occur twice. These entries remain in the workbook, so the policy measures describe recorded entries rather than unique programmes.

All 34 unavailable trade values concern wind generating sets. Cyprus accounts for eight; Latvia, Luxembourg, Malta, Slovakia, and Slovenia account for four each; Lithuania and Romania account for two each; Croatia and Hungary account for one each. Annual availability reaches 54 observations in 2013, falls to 52 in 2016 and 2018, and equals 53 in every other year.

Unavailable values remain distinct from zero. No interpolation or imputation replaces them. Missing data treatment requires explicit assumptions, and selective observation can affect interpretation (Ware et al., 2012; Westreich, 2012). The descriptive sample therefore represents observed reporting coverage.

The audit confirms positive export values, shares within zero and one, and shares summing to one within each retrieved product and year pool. Reported values remain unchanged, including large observations. Policy rates retain their currencies, units, and eligibility conditions. Heterogeneous rates and repeated budget entries are not combined into expenditure totals. This treatment preserves the distinction between policy indicators and economic outcomes emphasized by the OECD (2017).

3.3 Variable Measurement, Construction, and Validation:

The explanatory indicators preserve three policy dimensions: financial support, fiscal support, and production and market support. Their separation reflects differences between investment financing, tax treatment, and deployment incentives (Popp et al., 2011; Rodrik, 2014). Policy relevance can also differ across renewable technologies (Johnstone et al., 2010).

Financial support counts grants, soft loans, and loan guarantees. Fiscal support counts tax incentives. Production and market support counts feed in tariffs, premiums, tenders, and tradable green certificates. Market support remains conceptually distinct from direct producer assistance (Bougette & Charlier, 2015). These counts measure recorded policy entries, while technological responses represent separate outcomes (Aghion et al., 2016). Equation 1 defines the export share used in the workbook.

$$s_{ipt} = \frac{x_{ipt}}{\sum_{j \in R_{pt}} x_{jpt}}$$

Here, s_{ipt} is economy i's share for product pin year t; x_{ipt} is its export value; j indexes reporting economies; and R_{pt} contains the economies observed for that product and year. The denominator measures the retrieved export pool rather than a verified complete world total. Equation 2 calculates the annual share change in percentage points.

$$\Delta s_{ipt} = 100\left[s_{ipt} - s_{ip,t-1}\right]$$

Here, Δs_{ipt} is the annual share change, and $s_{ip,t-1}$ is the preceding annual share for the same economy and product. The calculation requires both observations. Equation 3 defines the magnitude of a share loss.

$$L_{ipt} = \max\{0, -\Delta s_{ipt}\}$$

Here, L_{ipt} equals the absolute percentage point decline when the share falls and zero otherwise. It describes the exporter's relative loss without identifying its cause.

Table 2: Variable dictionary

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
Financial support records	Policy indicator	Count of grant, soft loan, and loan guarantee entries	Climate Policy Atlas version 1.1; measure field	Records annually	Higher values indicate more recorded entries	Zero means no matching source entry	616 positions; repeated entries remain
Fiscal support records	Policy indicator	Count of tax incentive entries	Climate Policy Atlas version 1.1; tax incentive	Records annually	Higher values indicate more recorded entries	Same counting rule	616 positions; does not measure tax expenditure
Production and market support records	Policy indicator	Count of tariff, premium, tender, and certificate entries	Climate Policy Atlas version 1.1; fit, premium, tender, tgc	Records annually	Higher values indicate more recorded entries	Same counting rule	616 positions; beneficiaries can include generators or consumers
Export value	Trade level	Annual exports to the world	UN Comtrade; primary Value, X, partner 0	Current US dollars annually	Original nominal value	Unavailable records remain missing	582 panel observations; HS854140 includes non photovoltaic goods
Observed export pool	Share denominator	Sum of retrieved exporter values by product and year	UN Comtrade; primary Value	Current US dollars annually	Original values summed	Requires a positive denominator	22 product and year totals; reporting composition varies
Export share	Relative	Equation 1	UN Comtrade	Ratio	Higher values	Requires	582 observations

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
	market position		derived measure	annually	indicate a larger observed pool share	observed exports and a valid denominator	
Annual share change	Relative market movement	Equation 2	UN Comtrade derived measure	Percentage points annually	Positive values indicate gains	Requires consecutive annual shares	513 observations
Share loss	Relative decline	Equation 3	UN Comtrade derived measure	Percentage points annually	Higher values indicate larger losses	Inherits missingness from annual changes	513 observations; does not identify rival displacement

Table 3: Descriptive statistics for the consolidated panel

Indicator	Valid Observations	Mean	SD	Median	Minimum	Maximum
Financial support records	616	0.977	1.289	1	0	7
Fiscal support records	616	0.664	0.802	0	0	3
Production and market support records	616	1.844	2.182	1	0	22
Exports, USD millions	582	275.042	783.591	18.865	0.000128	8,522.051
Export share, percent	582	1.9423	6.7490	0.0713	0.000002	44.0055
Annual share change, percentage points	513	−0.0468	2.0183	−0.000469	−14.5777	18.8019
Share loss, percentage points	513	0.3023	1.3922	0.000469	0	14.5777

Standard deviations use the sample formula. Dollar values and shares are rescaled only for presentation in Table

3. The Workbook Retains Dollars and Share Ratios:

3.4 Analytical Framework, Identification, and Reproducibility:

This analysis applies a descriptive framework to recorded policy support and exporters' relative trade positions. It distinguishes measurement from causal explanation, consistent with Shmueli (2010). The observed quantities are export levels, shares, annual share changes, and share losses. The interpretation separates domestic support, technological capability, and export performance. These relationships involve distinct mechanisms and empirical requirements (Costantini & Mazzanti, 2012; Groba& Cao, 2015). Policy counts and aggregate exports provide descriptive alignment across economies, products, and years but do not isolate a subsidy effect.

A falling export share can reflect slower growth relative to other exporters even when the exporter's sales increase. Changes in reporting coverage can also alter measured shares. Competitiveness indicators therefore require careful interpretation, while causal conclusions depend on research design (Angrist & Pischke, 2010; Dechezleprêtre & Sato, 2017). The reported share losses describe relative market movement rather than sales displaced by a subsidized rival.

Reproducibility rests on the workbook's API queries, reporter codes, product identifiers, source row numbers, policy serial identifiers, coverage records, and calculation formulas. Annual matching aligns policy records and trade observations to the same calendar year. The extraction represents a retrospective historical data vintage. Consistent definitions preserve the distinction between recorded support, nominal export flows, relative shares, and percentage point movements.

4. Methods:

4.1 Research Design and Identification Strategy:

The analysis uses an annual observational panel to estimate conditional associations between recorded renewable support measures and changes in exporters' relative market positions. The unit of analysis is an economy, product category, and calendar year. The observation period covers 2010 to 2020. The primary outcome is the annual export share change defined in Equation 2. The alternative outcome is the exporter's own share loss defined in Equation 3.

The estimand is the difference in annual export share movement associated with one additional recorded support entry, conditional on the other support dimensions and the specified fixed effects. Useful variation arises from changes in recorded support within economy and product combinations. Economy and product fixed effects absorb persistent differences between these combinations. Product and year fixed effects absorb annual movements shared by economies within each product category. This specification follows established panel regression principles while preserving the distinction between statistical adjustment and causal identification (Wooldridge, 2010).

The estimated relationships are associational. Policy adoption may respond to industrial performance, while changing demand, production capabilities, and concurrent interventions may influence both support and exports. Fixed effects address the specified persistent and common differences but do not remove every source of confounding or reverse causality. Moreover, changes in an exporter's own share do not identify losses caused

to particular competitors. The analysis therefore evaluates observable policy and trade relationships without interpreting the coefficients as causal displacement effects.

4.2 Model Specification and Measurement Alignment:

The baseline specification jointly includes the three recorded support dimensions:

$$\Delta s_{ipt} = \beta_F F_{ipt} + \beta_T T_{ipt} + \beta_M M_{ipt} + \alpha_{ip} + \lambda_{pt} + \varepsilon_{ipt}.$$

Here, Δs_{ipt} is the annual export share change in percentage points for economy i, product p, and year t. F_{ipt}, T_{ipt}, and M_{ipt} are the counts of financial, fiscal, and production and market support records. The coefficients β_F, β_T, and β_M measure the corresponding conditional associations. α_{ip} denotes economy and product fixed effects, λ_{pt} denotes product and year fixed effects, and ε_{ipt} is the regression disturbance.

The predictors enter contemporaneously because the implemented comparison aligns recorded support and trade movements within the same calendar year. No restrictions constrain coefficient signs. Each coefficient represents percentage points associated with an additional recorded entry rather than a monetary increase in assistance. The specification includes the three dimensions jointly and applies no observation weights.

The alternative outcome replaces Δs_{ipt} in Equation 4 with the share loss measure L_{ipt}. Its coefficients describe differences in the magnitude of exporters' own relative declines. Separate product specifications retain the three predictors and include economy and year fixed effects within each product category.

The sample construction in Table 1 and the measurement dictionary in Table 2 define eligibility and indicator construction. Of the 582 available export observations, 513 support consecutive annual share comparisons. The estimation panel contains 55 economy and product combinations across 28 economies and remains unbalanced. The wind specification contains 233 observations across 27 economies; the broader photovoltaic containing specification contains 280 observations across 28 economies.

Measurement interpretation remains consistent across specifications. A zero-policy count indicates no matching record in the extract rather than verified absence of support. The broader photovoltaic containing trade category also includes other photosensitive devices and light emitting diodes. Consequently, its coefficients cannot be interpreted exclusively as solar equipment relationships.

4.3 Estimation, Inference, and Numerical Verification:

Ordinary least squares estimate Equation 4 because the objective is an additive conditional association with a continuous outcome measured in percentage points. Fixed effects enter through indicator variables. Estimation uses NumPy's least squares routine with its default numerical rank criterion. Covariance calculations use the Moore Penrose inverse where redundant fixed effect indicators make the design matrix singular. The baseline design has rank 76.

The primary covariance estimator clusters disturbances by economy, allowing heteroskedasticity and dependence across years and products within each economy. This choice recognizes that observations from the same economy can share policy institutions and economic conditions. Clustered inference follows Cameron and Miller (2015), with an explicit finite sample adjustment.

$$\widehat{V}_C = \frac{G}{G-1}\frac{N-1}{N-K} B \left[\sum_{g=1}^{G} X_g' \hat{u}_g \hat{u}_g' X_g\right] B, \qquad B = [X'X]^{+}.$$

Here, $\widehat{V}_C$ is the estimated clustered covariance matrix, G is the number of economy clusters, N is the number of observations, and K is the rank of the design matrix. X contains the predictors and fixed effect indicators; X_g contains its observations for economy g, $\hat{u}_g$ is the corresponding residual vector; and the superscript \(+\) denotes the Moore Penrose inverse.

The baseline uses 28 clusters. Two-sided probability values and 95 percent confidence intervals use a Student distribution with 27 degrees of freedom. The joint test evaluates whether the three policy coefficients equal zero using an F reference distribution with three numerator and 27 denominator degrees of freedom. Product specific inference uses the corresponding number of economy clusters.

Because exporters share product specific market denominators, an additional inference procedure permits clustering by both economy and product and year group:

$$\widehat{V}_{C,P} = \widehat{V}_C + \widehat{V}_P - \widehat{V}_{C\cap P}.$$

Here, $\widehat{V}_{C,P}, \widehat{V}_{C,P}$ is the covariance estimate allowing both clustering dimensions, $\widehat{V}_P$ clusters by product and year group, and $\widehat{V}_{C\cap P}$ clusters by their intersections with economies. Each component receives the adjustment specified in Equation 5 using its own cluster count. The baseline contains 20 product and year groups, so this sensitivity analysis uses 19 reference degrees of freedom. The construction follows Cameron et al. (2011) and addresses the specified dependence patterns without assuming that all international dependence has been removed.

Numerical verification independently residualizes the outcome and predictors against the fixed effects and recovers the focal coefficients from the residualized regression. The three residualized predictors retain full joint rank. Collinearity assessment uses variance inflation factors calculated from their residualized correlation matrix. These checks assess numerical identification and predictor overlap rather than causal validity.

Computation uses Python 3.12.14, NumPy 2.3.5, pandas 2.2.3, SciPy 1.17.0, and openpyxl 3.1.5. The procedures are deterministic and require no random seed or iterative optimization.

4.4 Analytical Sequence, Sensitivity, and Replicability:

Processing first converts unavailable trade inputs and undefined changes to missing values while preserving valid numerical zeros. Observations are ordered by economy, product, and calendar year. Annual shares and consecutive changes follow Equations 1 and 2. The baseline retains observations with an available outcome and all three recorded support counts. Missing trade observations are neither interpolated nor imputed. Reported extreme values remain unchanged.

Sensitivity analyses address specific construction and sample choices. First, repeated policy content is removed using equality across the retained fields after excluding serial identifiers and source row numbers. This procedure removes 20 records. Policy counts are then reconstructed using the original economy, year, dimension, and technology matching rules. The resulting specification retains the baseline's 513 trade observations, separating the consequences of policy record construction from changes in the trade sample.

Second, estimation is restricted to the 46 economy and product combinations with complete export histories. This produces 460 annual changes. Third, export shares are reconstructed using fixed reporting pools consisting of economies observed in every year for each product. These pools contain 32 wind exporters and 82 exporters in the broader photovoltaic containing category. The original and fixed denominator specifications use the same 460 observations, allowing denominator sensitivity to be examined without changing the estimation sample.

Further comparisons estimate the alternative share loss outcome, separate product relationships, and the covariance procedure in Equation 6. All sensitivity analyses are exploratory. Interpretation considers coefficient direction, magnitude, and confidence intervals rather than treating repeated statistical significance as sufficient evidence of robustness.

Replication follows the workbook's query URLs, reporter identifiers, product codes, source row references, serial identifiers, and construction formulas. The analytical sequence links these records to the estimation samples and specifications described here. Together, the procedures provide a reproducible assessment of conditional policy and trade associations using established methods. They do not identify subsidy intensity, causal transmission mechanisms, or displacement of individual rival exporters.

5. Findings:

This analysis examines the relationships between recorded financial, fiscal, and production and market support measures and annual export share movements. It estimates adjusted associations and assesses their sensitivity to repeated policy records, incomplete reporting, and alternative export denominators. The findings distinguish observed market repositioning from subsidy induced displacement.

The analytical sample contains 513 annual export share changes across 55 economy and product combinations in 28 economies. These observations comprise 233 wind generating set observations and 280 observations for the broader photovoltaic containing product category. The underlying observation period covers 2010 to 2020. The sample records 233 export share gains and 280 declines.

The policy indicators count documented support entries rather than expenditure, subsidy generosity, or assistance received by exporting manufacturers. This distinction matters because investment financing, technological development, and industrial policy implementation represent separate mechanisms influencing competitive performance (Popp et al., 2011; Rodrik, 2014).

Table 1: Descriptive statistics for the analytical sample

Indicator	Observations	Mean	SD	Median	Minimum	Maximum
Financial support records	513	0.938	1.285	0	0	7
Fiscal support records	513	0.684	0.816	0	0	3
Production and market support records	513	1.971	2.326	1	0	22
Annual export share change, percentage points	513	−0.0468	2.0183	−0.000469	−14.5777	18.8019
Export share loss, percentage points	513	0.3023	1.3922	0.000469	0	14.5777

Note. Calculations use the supplied workbook. Share loss equals the absolute decline when an exporter's share falls and zero otherwise. Standard deviations use the sample formula.

Annual share movements concentrate around zero but include substantial changes at both extremes. The median annual change equals −0.000469 percentage points, compared with a mean of −0.0468 percentage points. Larger movements therefore influence the average more strongly than the typical observation. This distribution supports reporting uncertainty and sensitivity alongside mean relationships.

The main specification estimates annual export share changes using the three contemporaneous policy counts, economy and product fixed effects, and product and year fixed effects. Ordinary least squares estimation uses standard errors clustered across 28 economies with a finite sample correction. Confidence intervals and probability values use a student distribution with 27 degrees of freedom. These exploratory estimates use

changes within economy and product combinations after accounting for common annual movements within each product category.

Table 2: Policy records and annual export share changes

Policy indicator	Coefficient	Standard Error	Lower Confidence Limit	Upper Confidence Limit	Probability Value
Financial support records	0.0421	0.0576	−0.0761	0.1603	0.472
Fiscal support records	0.0209	0.0937	−0.1714	0.2132	0.825
Production and market support records	0.0664	0.0855	−0.1090	0.2418	0.444

Note. The sample contains 513 observations across 55 economy and product combinations and 28 economies. Confidence limits represent 95 percent intervals. Coefficients measure percentage point changes associated with one additional recorded policy entry. All specifications include economy and product fixed effects and product and year fixed effects.

Financial support records have a positive coefficient of 0.0421 percentage points. One additional entry is associated with an estimated annual share gain of approximately 4.2 basis points. However, the confidence interval extends from −0.0761 to 0.1603 percentage points. The estimate does not distinguish a positive relationship from zero or a negative relationship.

Fiscal support records have a coefficient of 0.0209 percentage points, with a confidence interval from −0.1714 to 0.2132 percentage points. Fiscal counts vary over time in only 14 of the 55 analytical economy and product combinations. This limited variation constrains estimation precision. The result establishes neither a positive association nor the absence of an economically relevant relationship.

Production and market support records have the largest positive point estimate, at 0.0664 percentage points per additional entry. Its confidence interval extends from −0.1090 to 0.2418 percentage points. The estimate remains imprecise despite temporal variation in 45 economy and product combinations. The three policy coefficients are jointly indistinguishable from zero, with an F statistic of 0.394 and a probability value of 0.759.

The coefficient signs do not provide sufficient evidence to support the proposed positive relationships at the 5 percent significance level. For H1, H2, and H3, the available proxy estimates provide no statistically distinguishable positive association with annual export share changes. This assessment concerns recorded support entries and exporters' own relative positions. It does not directly test whether measured subsidy exposure displaces rival exporters.

Using exporters' own share losses as an alternative outcome produces financial, fiscal, and production and market support coefficients of −0.0140, −0.0246, and −0.0722 percentage points. Their confidence intervals extend from −0.1516 to 0.1237, −0.1540 to 0.1049, and −0.2348 to 0.0904 percentage points, respectively. These estimates do not establish that additional support records protect exporters against relative market losses.
Sensitivity analysis examines repeated policy content, incomplete exporter histories, and changing export pool composition. Removing 20 repeated content records produces coefficients close to the main estimates. Restricting the sample to complete exporter histories yields 460 annual changes across 46 economy and product combinations. Recalculating shares using continuously reporting exporters also leaves the estimates largely unchanged.

Table 3: Sensitivity of annual export share change estimates

Specification	Observations	Financial Support	Fiscal Support	Production and Market Support
Main specification	513	0.0421	0.0209	0.0664
Repeated policy content removed	513	0.0459	0.0230	0.0615
Complete histories, original denominators	460	0.0391	0.0232	0.0691
Complete histories, fixed reporting pools	460	0.0379	0.0254	0.0694

Note. Coefficients measure percentage points per additional recorded policy entry. Every coefficient has a 95 percent confidence interval containing zero. The final two specifications use identical observations. Fixed reporting pools contain 32 wind exporters and 82 exporters in the broader photovoltaic containing category.

The similarity between the final two specifications indicates that changing denominator composition does not materially alter the estimates within the common sample. Removing repeated policy content produces the same substantive assessment. These checks address specific construction choices without establishing complete global coverage or validating policy counts as measures of subsidy intensity.

Allowing dependence within both economies and product and year groups also preserves the assessment. The resulting confidence intervals are −0.2641 to 0.3482 for financial support, −0.0606 to 0.1025 for fiscal support, and −0.0806 to 0.2134 for production and market support. None excludes zero.

Separate product estimates show variation in direction and magnitude. Financial support coefficients equal 0.0957 percentage points for wind and 0.0104 percentage points for the broader photovoltaic containing category. Fiscal coefficients equal 0.1130 and −0.0525 percentage points, while production and market support coefficients equal 0.1982 and 0.0242 percentage points. Every confidence interval includes zero. These estimates do not establish differences between technologies. They nevertheless support interpreting pooled relationships cautiously because policy instruments can operate differently across renewable technologies (Johnstone et al., 2010).

The findings do not establish that renewable support lacks competitive relevance. Research examining specific financing, innovation, and market mechanisms identifies relationships that aggregate policy counts may not capture (Groba & Cao, 2015). The supported conclusion is narrower: the recorded support indicators do not provide precise evidence of annual export share gains in this sample.

A declining export share can accompany increasing export sales when competing exporters expand more rapidly. It therefore cannot independently establish sales displaced by a subsidized rival. The distinction between a competitiveness indicator and an identified policy effect remains essential when interpreting international environmental policy evidence (Dechezleprêtre & Sato, 2017).

6. Discussion:

More recorded green support does not, by itself, establish stronger export competitiveness. Table 2 shows positive associations between the three policy indicators and annual export share changes, but none is statistically distinguishable from zero. The unadjusted correlations are also close to zero, ranging from approximately 0.002 to 0.027. These findings qualify the expectation that a broader inventory of support measures translates into stronger international market positions. The contribution lies in jointly examining three policy dimensions against the same trade outcome and testing whether their interpretation survives changes in data construction. Equation 2 measures relative market movement, so its positive coefficients cannot establish increased export volumes or displaced rival sales. The evidence gives empirical importance to distinguishing policy density from policy intensity, a distinction developed by Schmidt and Sewerin (2019). It does not establish that support is ineffective; it shows that record counts alone provide imprecise evidence of competitive gains.

The results also sharpen the distinction between policy instruments and their anticipated transmission mechanisms. Financial assistance may relax investment constraints, fiscal incentives may change investment returns, and market support may strengthen demand. However, the coefficients in Table 2 connect recorded instruments directly to annual share movements without observing these intermediate responses. They therefore cannot establish investment, innovation, or demand as the pathway producing competitive change. Rogge and Reichardt (2016) explain why policy consistency, credibility, and implementation matter alongside instrument selection. Moreover, Jenner et al. (2013) evaluate support strength against renewable electricity deployment, an outcome distinct from equipment export performance. The present evidence adds a boundary to that relationship: deployment-oriented support records cannot automatically serve as measures of assistance to exporting manufacturers. This distinction changes how positive policy coefficients should be interpreted, separating a plausible theoretical channel from an empirically identified mechanism.

The larger point estimate for production and market support does not establish that this dimension dominates financial or fiscal support. Table 2 reports an association of approximately 0.066 percentage points per additional market support entry, but its confidence interval spans both negative and positive values. Instrument categories also contain different eligibility conditions, beneficiaries, and support arrangements. Their coefficients consequently cannot be converted into proportional contributions to a common subsidy effect. Borrás and Edquist (2013) emphasize that instrument choice derives meaning from the problems, targets, and implementation settings it addresses. The theoretical implication is that the financial, fiscal, and market dimensions remain useful distinctions without constituting interchangeable units of intervention. The analysis redirects attention from the numerical breadth of a policy portfolio toward the economic exposure represented by each instrument. Its evidence supports neither a hierarchy of mechanisms nor the assumption that adding instruments produces a proportional competitive return.

The construction checks reveal where the empirical interpretation is stable and where its boundaries remain substantive. Table 3 shows that removing repeated policy content and replacing changing export denominators with fixed reporting pools produces closely similar estimates. These results reduce concern that those specific construction choices explain the imprecise associations. They do not make policy records equivalent to expenditure or turn the retrieved reporting pool in Equation 1 into a complete global market. Equation 3 introduces another consequential distinction: an exporter's own share loss describes relative deterioration, whereas rival displacement requires identifying whose sales or shares were affected by another exporter's support. The analytical contribution is therefore a separation of construction sensitivity from

construct validity. Stable coefficients across alternative datasets strengthen confidence in the reported association, but they cannot resolve a mismatch between the observed indicator and the theoretical outcome.

The international relevance emerges from this distinction between policy presence, economic exposure, and competitive performance. Kuik et al. (2019) identify positive relationships between domestic renewable policy proxies and export competitiveness, with greater persistence in wind than in photovoltaic technologies. Their use of installed capacity and bilateral trade differs from the record counts and annual aggregate share changes examined here. The less precise relationships in Table 2 therefore indicate sensitivity to the measured policy construct and trade outcome rather than a direct contradiction. For decision makers, the evidence does not justify expanding or withdrawing support based on instrument counts alone. Evaluation should distinguish documented measures from beneficiary exposure and distinguish domestic deployment from international sales outcomes. The resulting research question is more specific: under what conditions do identifiable financial benefits to producers translate into gains against particular competitors? This framing connects the findings to international debates while keeping their contribution proportional to the evidence.

7. Conclusion and Implications:

Expanding green support does not automatically secure a stronger position in international technology markets. This analysis shows that a broader inventory of government interventions provides insufficient evidence of annual competitive gains, even when different forms of assistance are examined jointly. Its contribution is to distinguish documented policy activity from economic exposure and relative market movement from displacement of competing suppliers. This distinction qualifies industrial policy expectations without implying that support lacks economic value. The theoretical implication is that instrument availability alone cannot establish the investment, production, or demand responses through which competitive advantages might emerge. For managers, the findings caution against using the number of available programmes as a sufficient basis for investment or export strategy. Decisions should instead assess eligibility, financial benefits, implementation conditions, and market opportunities. For policymakers, evaluation should connect assistance received by beneficiaries to clearly defined economic outcomes before attributing international gains or losses to public intervention. Administrative systems can support this assessment through consistent programme identifiers, beneficiary records, and comparable reporting conventions. These practices could improve accountability and resource allocation while reducing unsupported claims about competitive harm. The international contribution is an empirical boundary for interpreting support inventories, rather than a universal verdict on green industrial policy.

The evidence creates specific opportunities for extending measurement and identification. Programme records can be linked to disbursements, tax benefits, and manufacturer participation to distinguish administrative coverage from economic exposure. Bilateral trade data can connect supported suppliers with competing exporters in common destinations. Finer product classifications can isolate photovoltaic equipment, while broader geographical coverage can assess transferability beyond European economies. Designs exploiting policy changes could strengthen causal identification where their assumptions are credible. Future analyses should examine whether financing conditions, production capabilities, and institutional implementation shape competitive responses, using measured intermediate outcomes rather than inferring mechanisms from aggregate policy counts alone.

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