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Muhammad Afnan Arif

muhdafnanarif@gmail.com

Asia-Europe Institute, Universiti Malaya

Fumitaka Furuoka

Asia-Europe Institute, Universiti Malaya

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Posted Date: November 12th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11392844/v1

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Additional Declarations: No competing interests reported.

Clean Energy Trade in an Age of Environmental Policy Divergence: A Three-Dimensional Panel Approach

Muhammad Afnan Arif (corresponding author) [1] and Fumitaka Furuoka [2]

Abstract

Trade in clean energy goods has grown rapidly while governments pursue different environmental policies, and it remains unclear how divergence in policy stringency between trading partners is related to bilateral trade. This paper examines that relationship and the persistence of bilateral clean energy trade. Divergence may raise trading costs or signal technological advantage. Standard system estimators remove only the pair effect. The paper therefore proposes a system generalised method of moments estimator for dynamic three-dimensional bilateral panels, in which each observation is indexed by an exporter, an importer and a year. The proposed estimator also removes exporter-time and importer-time heterogeneity by cross-sectionally demeaning the dependent variable, the regressors and the instruments within each period and combines this transformation with collapsed instruments and two-step efficient weighting. Monte Carlo experiments show that the proposed estimator keeps a small bias and accurate test size when exporter-time and importer-time effects are persistent, a setting in which standard system estimators are inconsistent. An application to bilateral clean energy trade among major economies shows that the correction matters for some parameters and not for others. Persistence changes little relative to the standard estimator while the association between the absolute difference in environmental policy stringency and trade is much smaller. A signed difference is absorbed by exporter-time and importer-time effects so only the absolute difference is identified and its association differs in sign across estimators. The heterogeneity that a two-dimensional estimator leaves in the error term therefore distorts the policy coefficient more than the estimated dynamics.

Keywords: Environmental policy stringency; Energy transition; Gravity model; Three-dimensional panel; Bilateral trade

JEL classification: C23; C26; F14; F18; Q42; Q56

1. Introduction

Bilateral trade in clean energy goods, from solar panels to wind turbines, has grown rapidly alongside the global expansion of renewable capacity. This paper examines a six-product basket covering electric motors and generators, generating sets, transformers, semiconductor devices including photovoltaic cells and insulated cable, the core manufactured components common to most clean energy technologies. The market for mass-manufactured clean energy technologies was worth about $700 billion in 2023 and is projected to exceed $2 trillion by 2035 (International Energy Agency, 2024). The share of China in clean-technology exports to emerging markets rose from 24% to 43% between 2022 and 2024 (BloombergNEF, 2025). Governments meanwhile differ in how strictly they regulate environmental harm. Exporters and importers of these goods therefore often operate under diverging environmental policies.

A central question for climate and trade policy is how persistent these bilateral relationships are and whether divergence in environmental policy stringency (EPS) between partners shapes them. Highly persistent relationships mean the trade effects of a unilateral policy accumulate over years and are easily missed by short-horizon evaluations. The question has a regional side as well. Gasparini et al. (2025) find for 40 Dutch regions that peripheral regions are considerably more vulnerable to the energy transition than central regions.

[1] Asia-Europe Institute, Universiti Malaya, Kuala Lumpur, Malaysia. Email: muhdafnanarif@gmail.com
[2] Asia-Europe Institute, Universiti Malaya, Kuala Lumpur, Malaysia. Email: fumitaka@um.edu.my

The evidence base for trade persistence, however, is unsettled. Persistence estimates in bilateral panels are sensitive to how the estimator treats unobserved heterogeneity, and a low and a high estimate imply different conclusions about how long a policy shock takes to work through trade, which leaves the policy question hard to answer.

The source of the spread is structural. A bilateral observation, indexed at once by an origin country, a destination country and a year, contains three unobserved components. A pair effect covers time-invariant bilateral characteristics such as distance and shared institutions. An origin-time effect covers time-varying exporter conditions, for example a domestic subsidy programme that raises the manufacturing capacity of one country in a given year, and a destination-time effect covers the analogous importer-side conditions, such as a change in the import tariffs of one country or procurement rules. The system generalised method of moments (GMM) estimator of Blundell and Bond (1998), the standard tool for panels with a lagged dependent variable, was built for a single cross-sectional dimension and absorbs only the pair effect. Applied to bilateral data, it leaves the origin-time and destination-time components in the error, biasing the persistence estimate whenever those components correlate with lagged trade.

The size of the panel works in two directions. A panel of N economies carries $N(N-1)$ pair effects and $2NT$ origin-time and destination-time effects, so the number of incidental parameters grows with the sample and a dummy-variable approach faces a curse of dimensionality. Kapetanios et al. (2021) use the term for a related difficulty in three-dimensional panels, where the full set of cross-sectional averages used as proxies for global and local factors would raise multicollinearity. A large N is also an advantage because the origin-time effect of an exporter is removed by averaging over its $N-1$ partners and the remainder left by the transformation vanishes as N grows. This is a blessing of dimensionality in the sense used for factor models of high-dimensional series, where estimation accuracy does not deteriorate and can improve as the cross-sectional dimension increases (Lam et al., 2011; Lam & Yao, 2012; Li et al., 2018).

Existing work addresses the heterogeneity and the dynamics separately, rarely together. Egger and Pfaffermayr (2003) show, for static gravity panels, that bilateral interaction effects explain most of the variation in trade and must be controlled, but their framework is static and silent on persistence. Sargento (2007) tests several econometric specifications of the gravity model and arrives at a three-dimensional error model that is estimated separately for ten products. Hayakawa and Qi (2020) and Kripfganz and Schwarz (2019) refine dynamic panel estimation but only for a single cross-sectional dimension.

Recent applied studies of clean energy trade inherit the same limitation. Brusiło and Tomski (2025) estimate a dynamic panel gravity model of photovoltaic trade yet leave origin-time and destination-time heterogeneity in the error. Hassan et al. (2024) apply the system GMM estimator to the environmental-policy and renewable-energy nexus under the same two-dimensional restriction. Panel studies of the energy transition in the European Union, such as Paul et al. (2026), likewise treat countries as units in a single cross-sectional dimension. Wagner (2026) introduces kernel-regularized least squares to empirical trade research so that the data determine the functional form of export-margin models, a specification concern that is distinct from the unobserved heterogeneity addressed here.

Among dynamic gravity specifications, Costantini and Mazzanti (2012) estimate a three-way system GMM model that retains the exporter-time, importer-time and pair terms. No available estimator for linear dynamic bilateral panels removes the pair, exporter-time and importer-time effects jointly with a system GMM moment set that has derived dynamic asymptotics. Table A1 summarises this literature in full, covering clean energy and environmental goods trade (Panel A), environmental policy and related outcomes (Panel B) and applications of three-dimensional panels (Panel C).

The closest work is Yang and Zhang (2023), who extend the moment conditions of Jochmans (2017) to three-way gravity models with multiplicative pair, exporter-time and importer-time

effects and sketch a linear feedback specification for dynamics. Their moment conditions are built from products over four dyads and pairs of periods, rest on a multiplicative conditional mean and use difference-type moments only, and the asymptotic theory of the dynamic case is omitted. Ye and Wu (2014) propose an iterated GMM estimator for dynamic three-dimensional panels with interactive effects, in which pair-specific loadings multiply a small number of common time factors that are extracted by principal components and combined with first-difference moments, and Ye and Wu (2017) add smooth transition regimes. Both papers support the estimators with Monte Carlo experiments.

Exporter-time and importer-time effects that vary freely over time need not have such a low-rank form, and the cross-sectional demeaning of this paper removes them without a choice of the number of factors. The dynamic general nesting spatial model with common factors reviewed by Elhorst (2022) controls global cross-sectional dependence through cross-sectional averages or principal components with heterogeneous coefficients, a route that generalises unit-specific and time-specific controls. This paper starts instead from an additive dynamic panel, removes exporter-time and importer-time effects by cross-sectional demeaning within each period and combines the transformation with the difference and level equations of system GMM, the standard remedy when persistence is high and difference moments are weak (Blundell & Bond, 1998; Bun & Windmeijer, 2010). The Monte Carlo experiments compare the estimator with difference GMM, forward orthogonal deviations GMM, a bias-corrected least-squares dummy variable estimator and three-way fixed effects.

The gap matters quantitatively. Nouira et al. (2025) report, in a country-level threshold model, that the link between renewable energy and trade is nonlinear in the stringency of climate policy, so a bilateral estimator that misattributes policy-driven heterogeneity to trade persistence risks distorting exactly the margin that policymakers care about. This paper examines whether the trade consequences of environmental policy divergence can be distinguished from ordinary bilateral heterogeneity, by developing a system GMM estimator for dynamic three-dimensional bilateral panels that removes all three unobserved components.

In the application, the corrected estimator places persistence close to the level of the standard two-dimensional estimator, which indicates that removing origin-time and destination-time heterogeneity changes persistence little. Only the absolute difference in EPS is identified and its association with trade is less than half as large under the corrected estimator as under the standard one. The estimator therefore affects the EPS coefficient far more than it affects persistence. The income-pair and product decompositions show that the absolute EPS divergence is associated with less trade in South-South and North-South pairs and with more trade in generation and grid equipment in the Poisson pseudo-maximum likelihood (PPML) specification. The association for semiconductor and photovoltaic goods is specific to the signed measure. Monte Carlo experiments in the Online Supplement show a small bias and rejection frequencies close to the nominal level at the scale of the application, including designs in which standard system GMM is inconsistent.

The literature frames the link between environmental policy and trade through the pollution haven hypothesis (Cherniwchan et al., 2017; Mulatu, 2018), the Porter hypothesis (Jaffe & Palmer, 1997; Porter & van der Linde, 1995) and the lead-market argument (Costantini & Crespi, 2008; Costantini & Mazzanti, 2012; Groba, 2014), and Baltagi et al. (2003) tie new trade theory, the Heckscher-Ohlin-Samuelson model and the Linder hypothesis to gravity regressors. These studies mostly use the stringency of the exporter alone, a level that exporter-time effects absorb in a three-dimensional design, so the analysis of divergence between trading partners here complements them. Losacker et al. (2023) review the regional determinants of environmental innovation and find that environmental regulation spurs eco-innovation although evidence at the regional level is limited.

Two further ideas are relevant to the divergence. The absolute EPS divergence can be read as regulatory distance, a pair-specific cost of selling into a market governed by different rules,

which Kox and Lejour (2005) model as a sunk market-entry cost and which Dechezleprêtre et al. (2015) and Corrocher and Mancusi (2021) find to hinder technology flows although for patents and not for equipment trade. Persistence in bilateral trade is in turn commonly attributed to sunk entry costs and relationship capital (Albornoz et al., 2016; Roberts & Tybout, 1997).

Gravity studies of environment-related policy and trade do not settle the direction of the association. Harris et al. (2002) report that the link between regulatory stringency and bilateral trade among countries of the Organisation for Economic Co-operation and Development (OECD) becomes statistically insignificant once importer-specific and exporter-specific effects enter a triple-indexed model, and Jug and Mirza (2005) report a negative association for European exporters that GMM estimation strengthens. Neither study is specific to clean energy goods. For environmental goods, Cantore and Cheng (2018) relate bilateral exports to the environment-related tax revenue of the importing country and read the negative coefficient as import substitution, importers meeting demand with domestic production, which their data do not observe.

A recent gravity study of renewable energy technology exports applies resource dependence theory to geopolitical risk and finds that environmental taxes in the exporting country strengthen, and environmental expenditure weakens, the negative association between geopolitical risk and exports (Shao & Li, 2025). That study uses country-level fiscal ratios and does not examine stringency or the divergence in stringency between partners.

Two channels motivate the direction of the EPS effect once origin-time and destination-time heterogeneity is removed. Under a compliance-cost channel, related to the pollution haven argument, greater divergence raises the relative cost of production for the more stringent partner and reduces bilateral clean energy trade. Under a Porter-style channel, which includes the lead-market argument, greater divergence signals a technological advantage of the more stringent partner and raises trade, with the effect concentrated in technologically advanced product categories. Because the corrected estimator identifies only the absolute measure, the empirical test can separate a negative from a positive association with the size of the divergence but cannot tell which partner is the stricter one.

2. Model

2.1 The three-dimensional dynamic panel model

The model considers a bilateral panel of N countries, each of which acts both as an origin and as a destination, observed over the periods $t = 0,1, \dots, T$. The directed pairs (i, j) with $i, j \in \{1, \dots, N\}$ and $i \neq j$ number $n = N(N-1)$ and for every pair the outcome follows the dynamic panel data model:

$$y_{ijt} = \rho\, y_{ij,t-1} + \boldsymbol{\beta}'\mathbf{x}_{ijt} + \mu_{ij} + \lambda_{it} + \xi_{jt} + \varepsilon_{ijt}, \qquad i \neq j, \quad t = 1, \dots, T,$$

where $|\rho| < 1$, $\boldsymbol{\beta}$ is a $K \times 1$ vector of slope coefficients, $\mathbf{x}_{ijt}$ contains K observable time-varying regressors, μ_{ij} is the pair fixed effect, λ_{it} is the origin-time fixed effect and ξ_{jt} is the destination-time fixed effect. The idiosyncratic error satisfies $\varepsilon_{ijt} \sim \text{iid}(0, \sigma_\varepsilon^2)$ across i, j and t with $\mathbb{E}(\varepsilon_{ijt}^4) < \infty$, independent of $(\mu_{ij}, \lambda_{it}, \xi_{jt})$ for all i, j and t. Because a constant can be shifted between the three sets of effects, they are separately identified only under normalisations that follow Lu et al. (2021):

$$\textstyle\sum_{j \neq i} \mu_{ij} = 0 \quad (i = 1, \dots, N), \qquad \sum_{t=1}^{T} \xi_{jt} = 0 \quad (j = 1, \dots, N), \qquad \sum_{i=1}^{N} \lambda_{it} = 0 \quad (t = 1, \dots, T).$$

The estimator developed below removes the three sets of effects rather than estimating them, so these normalisations matter only for the static PPML specification, which estimates them. To write the model in matrix form, stack the pairs of period t with i running slowest and, for each i, the destinations $j \neq i$ in increasing order:

$$\mathbf{y}_t = \rho\, \mathbf{y}_{t-1} + \mathbf{X}_t\boldsymbol{\beta} + \boldsymbol{\mu} + \mathbf{E}_O\boldsymbol{\lambda}_t + \mathbf{E}_D\boldsymbol{\xi}_t + \boldsymbol{\varepsilon}_t, \qquad t = 1, \dots, T,$$

where

$$\underset{n\times 1}{\mathbf{y}_t} = \{y_{ijt}\},\ \underset{n\times K}{\mathbf{X}_t} = \{\mathbf{x}'_{ijt}\},\ \underset{n\times 1}{\boldsymbol{\mu}} = \{\mu_{ij}\},\ \underset{n\times 1}{\boldsymbol{\varepsilon}_t} = \{\varepsilon_{ijt}\},\ \underset{N\times 1}{\boldsymbol{\lambda}_t} = (\lambda_{1t},\dots,\lambda_{Nt})',\ \underset{N\times 1}{\boldsymbol{\xi}_t} = (\xi_{1t},\dots,\xi_{Nt})',$$

$$\underset{n\times N}{\mathbf{E}_O} = \mathbf{S}\,(\mathbf{I}_N \otimes \boldsymbol{\iota}_N), \qquad \underset{n\times N}{\mathbf{E}_D} = \mathbf{S}\,(\boldsymbol{\iota}_N \otimes \mathbf{I}_N),$$

$\mathbf{I}_N$ is the $N \times N$ identity matrix, $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones, $\otimes$ is the Kronecker product and $\mathbf{S}$ is the $n \times N^2$ matrix that deletes the N diagonal pairs $i = j$ from the full cross-section of N^2 pairs. The row of $\mathbf{E}_O$ that belongs to pair (i, j) is the ith unit row vector $\mathbf{e}'_i$ and the corresponding row of $\mathbf{E}_D$ is $\mathbf{e}'_j$ so that $\mathbf{E}_O$ and $\mathbf{E}_D$ are the origin and destination indicator matrices of the dummy-variable representation of three-dimensional fixed effects (Lu et al., 2021). Because each country is the origin of $N - 1$ pairs and the destination of $N - 1$ pairs, they satisfy:

$$\mathbf{E}'_O\mathbf{E}_O = \mathbf{E}'_D\mathbf{E}_D = (N-1)\,\mathbf{I}_N, \qquad \mathbf{E}'_O\mathbf{E}_D = \boldsymbol{\iota}_N\boldsymbol{\iota}'_N - \mathbf{I}_N,$$

$$\mathbf{E}_O\boldsymbol{\iota}_N = \mathbf{E}_D\boldsymbol{\iota}_N = \boldsymbol{\iota}_n, \boldsymbol{\iota}'_n\mathbf{E}_O = \boldsymbol{\iota}'_n\mathbf{E}_D = (N-1)\,\boldsymbol{\iota}'_N.$$

The defining feature of the model above is the simultaneous presence of all three fixed-effect dimensions. Standard two-dimensional system GMM (Blundell & Bond, 1998) conditions on μ_{ij} but treats λ_{it} and ξ_{jt} as absorbed into the error term, which invalidates the level-equation moment conditions when λ_{it} or ξ_{jt} are correlated with the lagged dependent variable. The estimator below removes both components from the instrument set directly.

This paper first applies a static PPML estimator of Santos Silva and Tenreyro (2006), reusing the fixed-effect notation of the dynamic panel model above under $\rho = 0$ since the persistence parameter ρ cannot be recovered from a static specification. It then constructs the cross-sectional demeaning transformation that removes origin-time and destination-time heterogeneity within each period. It combines this transformation with the difference and level transformations of dynamic panel GMM proposed by Arellano and Bond (1991) and Blundell and Bond (1998) to form a composed instrument set.

This paper then applies the resulting three-dimensional system GMM estimator (3D-SysGMM) alongside standard system GMM, difference GMM and a two-way fixed-effects benchmark in the empirical application in Table 1. This paper compares all six estimators, including the forward-orthogonal-deviations estimator of Hayakawa and Qi (2020), the three-way fixed-effects estimator of Baltagi et al. (2003) and the bias-corrected least-squares dummy variable estimator of Dhaene and Jochmans (2015), in the Monte Carlo experiments of the Online Supplement. It closes with the two-step estimation procedure and standard-error correction applied throughout.

2.2 Static gravity estimation by PPML

The gravity relationship for bilateral clean energy trade in levels is specified as an exponential conditional mean, reusing the pair, origin-time and destination-time fixed effects of the dynamic panel model under the restriction $\rho = 0$,

$$\mathbb{E}\left[Y_{ijt} \mid \mathbf{x}_{ijt}, \mu_{ij}, \lambda_{it}, \xi_{jt}\right] = \exp\left(\boldsymbol{\beta}'\mathbf{x}_{ijt} + \mu_{ij} + \lambda_{it} + \xi_{jt}\right),$$

where Y_{ijt} is bilateral trade in levels rather than logarithms, avoiding the log-of-zero problem that arises whenever a pair records no trade in a given year. The two-way specification retains only the pair effect μ_{ij} and a year effect common across pairs while the three-way specification adds λ_{it} and ξ_{jt} directly, following Weidner and Zylkin (2021). The parameter vector $\boldsymbol{\beta}$ is estimated by PPML, following Santos Silva and Tenreyro (2006). PPML specifies trade in levels as a multiplicative, rather than log-linear additive, function of the regressors, directly addressing the multiplicative-functional-form concern recently emphasised in the gravity literature. Kwon et al. (2026) generalise PPML by estimating, with iterated GMM, the exponent that links the conditional variance to the conditional mean (Gamma-PML is the special case

in which the exponent equals 2); their estimator is static and therefore leaves persistence unaddressed. The parameter vector is recovered by maximising the Poisson quasi-log-likelihood:

$$\mathcal{L}(\boldsymbol{\beta}, \mu, \lambda, \xi) = \sum_i \sum_{j \neq i} \sum_t \left\{ Y_{ijt} \left(\boldsymbol{\beta}' \mathbf{x}_{ijt} + \mu_{ij} + \lambda_{it} + \xi_{jt} \right) - \exp\left(\boldsymbol{\beta}' \mathbf{x}_{ijt} + \mu_{ij} + \lambda_{it} + \xi_{jt} \right) \right\},$$

which is consistent for $\boldsymbol{\beta}$ under correct specification of the conditional mean regardless of the true conditional distribution of Y_{ijt}, a robustness property that does not extend to the additive fixed effects μ_{ij}, λ_{it}, ξ_{jt} themselves. The first-order condition for $\widehat{\boldsymbol{\beta}}$ is:

$$\sum_i \sum_{j \neq i} \sum_t \left\{ Y_{ijt} - \exp\left(\widehat{\boldsymbol{\beta}}' \mathbf{x}_{ijt} + \hat{\mu}_{ij} + \hat{\lambda}_{it} + \hat{\xi}_{jt} \right) \right\} \mathbf{x}_{ijt} = \mathbf{0},$$

The first-order conditions for the fixed effects, solved jointly with those above, require the residuals $\hat{e}_{ijt} = Y_{ijt} - \exp\left(\widehat{\boldsymbol{\beta}}' \mathbf{x}_{ijt} + \hat{\mu}_{ij} + \hat{\lambda}_{it} + \hat{\xi}_{jt} \right)$ to sum to zero within every pair, every origin-year and every destination-year cell that identifies a fixed effect:

$$\sum_{t=1}^{T} \hat{e}_{ijt} = 0 \text{ for each } (i,j), \qquad \sum_{j \neq i} \hat{e}_{ijt} = 0 \text{ for each } (i,t), \qquad \sum_{i \neq j} \hat{e}_{ijt} = 0 \text{ for each } (j,t).$$

This joint estimation is precisely the source of the incidental-parameter problem examined for the three-way case below: as N grows with T fixed, the number of origin-time and destination-time fixed effects grows with the sample. Following Weidner and Zylkin (2021), the point estimate $\widehat{\boldsymbol{\beta}}$ remains consistent even as this happens, but the cluster-robust variance estimate used for inference inherits a downward bias of order $O_p(T^{-1})$ from the estimation noise in $\hat{\lambda}_{it}$ and $\hat{\xi}_{jt}$. The two-way specification, which fixes the number of nuisance parameters at n pair effects estimated from T observations each, does not suffer from this particular inference problem in the same way. The pair effect is differenced out algebraically in a way the year-varying effects are not. This is why the two-way and three-way PPML columns can disagree sharply on how precisely the absolute EPS divergence is estimated in the results below, even though both remain point-identified for regressors that vary within the exporter-year and importer-year cells.

The static PPML specification and the dynamic panel estimators developed below are complementary rather than competing descriptions of the data. PPML in levels handles the zero-trade cells that a logarithmic dynamic specification must drop. The dynamic panel construction that follows instead targets the persistence parameter ρ that a static specification cannot recover by construction since ρ is not identified without a lagged dependent variable.

2.3 The three-dimensional system GMM estimator

Removing origin-time and destination-time heterogeneity

For each period t, the origin-time, destination-time and grand cross-sectional averages used to remove λ_{it} and ξ_{jt} are:

$$\bar{y}_{i\cdot t} = \frac{1}{N-1} \sum_{j \neq i} y_{ijt}, \qquad \bar{y}_{\cdot jt} = \frac{1}{N-1} \sum_{i \neq j} y_{ijt}, \qquad \bar{y}_{\cdot\cdot t} = \frac{1}{n} \sum_{i=1}^{N} \sum_{j \neq i} y_{ijt}.$$

In the matrix form of the model, the three averages are $(N-1)^{-1} \mathbf{E}'_O \mathbf{y}_t$, $(N-1)^{-1} \mathbf{E}'_D \mathbf{y}_t$ and $n^{-1} \boldsymbol{\iota}'_n \mathbf{y}_t$, and subtracting them from every pair defines the $n \times n$ demeaning operator:

$$\mathbf{Q} = \mathbf{I}_n - \frac{1}{N-1} \mathbf{E}_O \mathbf{E}'_O - \frac{1}{N-1} \mathbf{E}_D \mathbf{E}'_D + \frac{1}{n} \boldsymbol{\iota}_n \boldsymbol{\iota}'_n.$$

Each of the four terms corresponds to one term of the scalar demeaning. The identity leaves y_{ijt} unchanged, $(N-1)^{-1} \mathbf{E}_O \mathbf{E}'_O$ replaces each entry by the average over the destinations of its origin, $(N-1)^{-1} \mathbf{E}_D \mathbf{E}'_D$ replaces it by the average over the origins of its destination, and the last term adds back the grand mean to correct for double subtraction. The operator is symmetric and applying it to $\mathbf{y}_t$ gives, for every pair,

$$\tilde{y}_{ijt} = y_{ijt} - \bar{y}_{i\cdot t} - \bar{y}_{\cdot jt} + \bar{y}_{\cdot\cdot t}, \qquad \tilde{\mathbf{y}}_t = \mathbf{Q}\, \mathbf{y}_t.$$

In the application the panel is unbalanced because only pairs with positive recorded trade enter, and the three averages are taken over the pairs observed in each period. To see why this transformation removes the contaminating fixed effects rather than merely relabelling them, substitute the model for y_{ijt} into each of the three averages. Averaging the model over $j \neq i$ gives:

$$\bar{y}_{i\cdot t} = \rho\, \bar{y}_{i\cdot,t-1} + \boldsymbol{\beta}'\bar{\mathbf{x}}_{i\cdot t} + \bar{\mu}_{i\cdot} + \lambda_{it} + \bar{\xi}_{(-i)t} + \bar{\varepsilon}_{i\cdot t},$$

where $\bar{\mu}_{i\cdot}$ and $\bar{\varepsilon}_{i\cdot t}$ are averages over $j \neq i$ and $\bar{\xi}_{(-i)t} = (N-1)^{-1}\sum_{j\neq i}\xi_{jt} = \big(N\bar{\xi}_t - \xi_{it}\big)/(N-1)$, with $\bar{\xi}_t = N^{-1}\sum_{c=1}^{N}\xi_{ct}$, depends on i only through the excluded diagonal pair. Because λ_{it} does not vary with j, it survives the averaging undiminished, and $\bar{\varepsilon}_{i\cdot t} = O_p\big(N^{-1/2}\big)$ by a law of large numbers across the $N-1$ destinations. In matrix form, the exact effect of $\mathbf{Q}$ on each component of the model follows from the identities for $\mathbf{E}_O$ and $\mathbf{E}_D$ stated with the model. For the origin-time effects,

$$\begin{aligned}
\mathbf{Q}\mathbf{E}_O\boldsymbol{\lambda}_t &= \mathbf{E}_O\boldsymbol{\lambda}_t - \tfrac{1}{N-1}\,\mathbf{E}_O(\mathbf{E}'_O\mathbf{E}_O)\boldsymbol{\lambda}_t - \tfrac{1}{N-1}\,\mathbf{E}_D(\mathbf{E}'_D\mathbf{E}_O)\boldsymbol{\lambda}_t + \tfrac{1}{n}\,\boldsymbol{\iota}_n(\boldsymbol{\iota}'_n\mathbf{E}_O)\boldsymbol{\lambda}_t \\
&= \mathbf{E}_O\boldsymbol{\lambda}_t - \mathbf{E}_O\boldsymbol{\lambda}_t - \tfrac{1}{N-1}\,\mathbf{E}_D(\boldsymbol{\iota}_N\boldsymbol{\iota}'_N - \mathbf{I}_N)\boldsymbol{\lambda}_t + \tfrac{N-1}{n}\,\boldsymbol{\iota}_n\boldsymbol{\iota}'_N\boldsymbol{\lambda}_t \\
&= -\tfrac{N\bar{\lambda}_t}{N-1}\,\boldsymbol{\iota}_n + \tfrac{1}{N-1}\,\mathbf{E}_D\boldsymbol{\lambda}_t + \bar{\lambda}_t\,\boldsymbol{\iota}_n \\
&= \tfrac{\mathbf{E}_D\boldsymbol{\lambda}_t - \bar{\lambda}_t\boldsymbol{\iota}_n}{N-1},
\end{aligned}$$

where $\bar{\lambda}_t = N^{-1}\boldsymbol{\iota}'_N\boldsymbol{\lambda}_t$, the second line uses $\mathbf{E}'_O\mathbf{E}_O = (N-1)\mathbf{I}_N$, $\mathbf{E}'_D\mathbf{E}_O = \boldsymbol{\iota}_N\boldsymbol{\iota}'_N - \mathbf{I}_N$ and $\boldsymbol{\iota}'_n\mathbf{E}_O = (N-1)\boldsymbol{\iota}'_N$, and the third uses $\mathbf{E}_D\boldsymbol{\iota}_N = \boldsymbol{\iota}_n$ and $n = N(N-1)$. Exchanging the roles of the two indicator matrices, and using $\mathbf{E}'_O\boldsymbol{\iota}_n = \mathbf{E}'_D\boldsymbol{\iota}_n = (N-1)\boldsymbol{\iota}_N$ for the common component, gives:

$$\mathbf{Q}\mathbf{E}_D\boldsymbol{\xi}_t = \tfrac{\mathbf{E}_O\boldsymbol{\xi}_t - \bar{\xi}_t\boldsymbol{\iota}_n}{N-1}, \qquad \mathbf{Q}\boldsymbol{\iota}_n = \boldsymbol{\iota}_n - \mathbf{E}_O\boldsymbol{\iota}_N - \mathbf{E}_D\boldsymbol{\iota}_N + \boldsymbol{\iota}_n = \mathbf{0},$$

with $\bar{\xi}_t = N^{-1}\boldsymbol{\iota}'_N\boldsymbol{\xi}_t$. Since $\mathbf{Q}$ is the same in every period, it commutes with the lag, and applying it term by term to the matrix form of the model gives the transformed model:

$$\begin{aligned}
\tilde{\mathbf{y}}_t = \mathbf{Q}\mathbf{y}_t &= \rho\,\mathbf{Q}\mathbf{y}_{t-1} + \mathbf{Q}\mathbf{X}_t\boldsymbol{\beta} + \mathbf{Q}\boldsymbol{\mu} + \mathbf{Q}\mathbf{E}_O\boldsymbol{\lambda}_t + \mathbf{Q}\mathbf{E}_D\boldsymbol{\xi}_t + \mathbf{Q}\boldsymbol{\varepsilon}_t \\
&= \rho\,\tilde{\mathbf{y}}_{t-1} + \tilde{\mathbf{X}}_t\boldsymbol{\beta} + \tilde{\boldsymbol{\mu}} + \mathbf{r}_t + \tilde{\boldsymbol{\varepsilon}}_t,
\end{aligned}$$

in which the remainder collects the two expressions derived above,

$$\mathbf{r}_t = \frac{\mathbf{E}_D\boldsymbol{\lambda}_t + \mathbf{E}_O\boldsymbol{\xi}_t - \big(\bar{\lambda}_t + \bar{\xi}_t\big)\,\boldsymbol{\iota}_n}{N-1},$$

where $\tilde{\mathbf{X}}_t = \mathbf{Q}\mathbf{X}_t$, $\tilde{\boldsymbol{\mu}} = \mathbf{Q}\boldsymbol{\mu}$ and $\tilde{\boldsymbol{\varepsilon}}_t = \mathbf{Q}\boldsymbol{\varepsilon}_t$, or, for a single pair, since the row of $\mathbf{E}_D\boldsymbol{\lambda}_t$ for pair (i,j) is λ_{jt} and that of $\mathbf{E}_O\boldsymbol{\xi}_t$ is ξ_{it},

$$\tilde{y}_{ijt} = \rho\,\tilde{y}_{ij,t-1} + \boldsymbol{\beta}'\tilde{\mathbf{x}}_{ijt} + \tilde{\mu}_{ij} + r_{ijt} + \tilde{\varepsilon}_{ijt}, \qquad r_{ijt} = \frac{\lambda_{jt} + \xi_{it} - \bar{\lambda}_t - \bar{\xi}_t}{N-1}.$$

The transformation removes the origin-time effect of the exporter and the destination-time effect of the importer exactly. What remains of the two sets of effects is r_{ijt}, the destination-time effect of the exporting country and the origin-time effect of the importing country deflated by $N-1$, which arises only because the diagonal pairs $i = j$ are absent from the cross-section. It is $O_p(N^{-1})$ for every pair. In a complete cross-section the Online Supplement shows that the scaled sample moment of the remainder is of order N^{-1} against an order one sampling error, so it is negligible at the rate at which the estimator converges. This result covers complete cross-sections only; the application is unbalanced, and the Online Supplement reports a numerical check for that case rather than a proof.

The least-squares projection on $(\mathbf{E}_O, \mathbf{E}_D)$ would remove both sets of effects without a remainder (Lu et al., 2021); the simple averages in $\mathbf{Q}$ are retained because they define the estimator. This is the only step in the estimator that has no precedent in the two-dimensional

dynamic panel literature: it is a within-period two-way demeaning of the cross-section, distinct from the time-dimension transformations introduced next, and the two are combined explicitly in the composed transformation. The moment conditions of Yang and Zhang (2023), built from products over four dyads, are free of the same exporter-time and importer-time effects exactly in finite samples whereas the cross-sectional demeaning removes them up to a remainder that vanishes as the number of countries grows. Because the remainder falls with N, a larger cross-section works in favour of the transformation.

The construction shares a methodological family with the orthogonal forward-differencing transformation of Kuersteiner and Prucha (2020), in that both are explicit linear operators designed to annihilate a specific unobserved component while preserving the orthogonality of the resulting moment conditions. The two transformations are not interchangeable. Theirs removes a single individual factor loading on a common time factor within a standard two-dimensional panel and is built so that the transformed disturbances are serially uncorrelated. In contrast, $\mathbf{Q}$ removes two cross-sectional fixed effects simultaneously within a given period. The resulting instrument set relies on the demeaned series retaining, rather than losing, its autocovariance structure over time, which underlies the rank condition for identification.

Transforming the time dimension and limiting instrument count

For each pair (i,j), stack the transformed series over the observed periods into the $(T+1)\times 1$ vector $\tilde{\mathbf{y}}_{ij} = (\tilde{y}_{ij0}, \dots, \tilde{y}_{ijT})'$, its lag into $\tilde{\mathbf{y}}_{ij,-1} = (0, \tilde{y}_{ij0}, \dots, \tilde{y}_{ij,T-1})'$, whose first entry is never used, and the regressors into the $(T+1)\times K$ matrix $\widetilde{\mathbf{X}}_{ij}$ with rows $\tilde{\mathbf{x}}'_{ijt}$. The equations are written for $t = 2, \dots, T$, the periods for which both a first difference and an instrument dated $t-2$ exist. The first-difference matrix $\mathbf{D}_T$ and the level-selection matrix $\mathbf{L}_T$, both of dimension $(T-1)\times(T+1)$, are:

$$\mathbf{D}_T = \begin{bmatrix} 0 & -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & -1 & 1 \end{bmatrix}, \qquad \mathbf{L}_T = (\mathbf{0}_{T-1},\ \mathbf{0}_{T-1},\ \mathbf{I}_{T-1}).$$

Applying the two matrices gives $\Delta\tilde{\mathbf{y}}_{ij} = \mathbf{D}_T\tilde{\mathbf{y}}_{ij} = (\Delta\tilde{y}_{ij2}, \dots, \Delta\tilde{y}_{ijT})'$, free of $\tilde{\mu}_{ij}$, and $\mathbf{L}_T\tilde{\mathbf{y}}_{ij} = (\tilde{y}_{ij2}, \dots, \tilde{y}_{ijT})'$, the demeaned levels of the level equation. Since $\mathbf{D}_T$ and $\mathbf{L}_T$ act only on the time index, they are unchanged from the corresponding transformations in two-dimensional dynamic panel GMM (Arellano & Bond, 1991); the dyadic structure enters only through $\mathbf{Q}$.

Stacking the transformed model of pair (i,j) over time gives $\tilde{\mathbf{y}}_{ij} = \rho\,\tilde{\mathbf{y}}_{ij,-1} + \widetilde{\mathbf{X}}_{ij}\boldsymbol{\beta} + \tilde{\mu}_{ij}\boldsymbol{\iota}_{T+1} + \tilde{\mathbf{u}}_{ij}$, where $\tilde{\mathbf{u}}_{ij} = (\tilde{u}_{ij0}, \dots, \tilde{u}_{ijT})'$ and $\tilde{u}_{ijt} = r_{ijt} + \tilde{\varepsilon}_{ijt}$. Because $\mathbf{D}_T\boldsymbol{\iota}_{T+1} = \mathbf{0}$ and $\mathbf{L}_T\boldsymbol{\iota}_{T+1} = \boldsymbol{\iota}_{T-1}$, premultiplying by the two matrices gives the differenced and level equations:

$$\mathbf{D}_T\tilde{\mathbf{y}}_{ij} = \rho\,\mathbf{D}_T\tilde{\mathbf{y}}_{ij,-1} + \mathbf{D}_T\widetilde{\mathbf{X}}_{ij}\boldsymbol{\beta} + \mathbf{D}_T\tilde{\mathbf{u}}_{ij},$$
$$\mathbf{L}_T\tilde{\mathbf{y}}_{ij} = \rho\,\mathbf{L}_T\tilde{\mathbf{y}}_{ij,-1} + \mathbf{L}_T\widetilde{\mathbf{X}}_{ij}\boldsymbol{\beta} + \tilde{\mu}_{ij}\boldsymbol{\iota}_{T-1} + \mathbf{L}_T\tilde{\mathbf{u}}_{ij},$$

whose rows for period t read:

$$\Delta\tilde{y}_{ijt} = \rho\,\Delta\tilde{y}_{ij,t-1} + \boldsymbol{\beta}'\Delta\tilde{\mathbf{x}}_{ijt} + \Delta r_{ijt} + \Delta\tilde{\varepsilon}_{ijt},$$
$$\tilde{y}_{ijt} = \rho\,\tilde{y}_{ij,t-1} + \boldsymbol{\beta}'\tilde{\mathbf{x}}_{ijt} + \tilde{\mu}_{ij} + r_{ijt} + \tilde{\varepsilon}_{ijt}, \qquad t = 2, \dots, T.$$

To limit the number of instruments, the estimator follows the collapsed instrument strategy of Roodman (2009), stacking each lag into a single column across periods rather than using the full triangular instrument set. The differenced equation uses the transformed outcome and regressors at lags $s = 2,3,4$, and the level equation uses their first differences at lags $s = 1,2,3$, with an entry set to zero where the lag falls before the first observed period. For the differenced equation the collapsed instrument matrix, of dimension $(T-1)\times 3(K+1)$, is:

$$\mathbf{Z}^{D}_{ij,\text{coll}} = \begin{bmatrix} \tilde{y}_{ij0} & \tilde{\mathbf{x}}'_{ij0} & 0 & \mathbf{0} & 0 & \mathbf{0} \\ \tilde{y}_{ij1} & \tilde{\mathbf{x}}'_{ij1} & \tilde{y}_{ij0} & \tilde{\mathbf{x}}'_{ij0} & 0 & \mathbf{0} \\ \tilde{y}_{ij2} & \tilde{\mathbf{x}}'_{ij2} & \tilde{y}_{ij1} & \tilde{\mathbf{x}}'_{ij1} & \tilde{y}_{ij0} & \tilde{\mathbf{x}}'_{ij0} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{y}_{ij,T-2} & \tilde{\mathbf{x}}'_{ij,T-2} & \tilde{y}_{ij,T-3} & \tilde{\mathbf{x}}'_{ij,T-3} & \tilde{y}_{ij,T-4} & \tilde{\mathbf{x}}'_{ij,T-4} \end{bmatrix},$$

and for the level equation it is:

$$\mathbf{Z}^{L}_{ij,\text{coll}} = \begin{bmatrix} \Delta\tilde{y}_{ij1} & \Delta\tilde{\mathbf{x}}'_{ij1} & 0 & \mathbf{0} & 0 & \mathbf{0} \\ \Delta\tilde{y}_{ij2} & \Delta\tilde{\mathbf{x}}'_{ij2} & \Delta\tilde{y}_{ij1} & \Delta\tilde{\mathbf{x}}'_{ij1} & 0 & \mathbf{0} \\ \Delta\tilde{y}_{ij3} & \Delta\tilde{\mathbf{x}}'_{ij3} & \Delta\tilde{y}_{ij2} & \Delta\tilde{\mathbf{x}}'_{ij2} & \Delta\tilde{y}_{ij1} & \Delta\tilde{\mathbf{x}}'_{ij1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Delta\tilde{y}_{ij,T-1} & \Delta\tilde{\mathbf{x}}'_{ij,T-1} & \Delta\tilde{y}_{ij,T-2} & \Delta\tilde{\mathbf{x}}'_{ij,T-2} & \Delta\tilde{y}_{ij,T-3} & \Delta\tilde{\mathbf{x}}'_{ij,T-3} \end{bmatrix},$$

also of dimension $(T-1) \times 3(K+1)$. Each column holds one lag of the transformed outcome or of a regressor across all periods, which collapses what would otherwise be a triangular array growing quadratically in T into a matrix with three columns per variable. This avoids the instrument proliferation that weakens the Hansen test of overidentifying restrictions (Roodman, 2009). In these matrices the regressors enter through their lags, which treats them as predetermined, and this is the form used in the Monte Carlo experiments. In the application the regressors are treated as strictly exogenous and enter the instrument set as standard instruments for themselves so that only the lagged outcome is instrumented in collapsed form.

The validity of the level-equation moment conditions additionally requires an initial-conditions restriction analogous to that of Blundell and Bond (1998): the deviation of the initial bilateral trade flow from its pair-specific long-run mean must be uncorrelated with the pair fixed effect. This condition, standard in the system GMM literature, is maintained by assumption throughout.

Combining the two transformations into one instrument set

The full instrument construction first applies the cross-sectional demeaning within each period and then the time-dimension transformation across periods. Let $\mathbf{y} = (\mathbf{y}'_0, \dots, \mathbf{y}'_T)'$ stack all periods and let $\mathbf{e}_{ij}$ be the $n \times 1$ unit vector of pair (i,j) so that $\mathbf{e}'_{ij}\mathbf{Q}$ is the row of the demeaning operator that belongs to that pair. Then the demeaned series of the pair and its difference and level transformations are:

$$\tilde{\mathbf{y}}_{ij} = \left(\mathbf{I}_{T+1} \otimes \mathbf{e}'_{ij}\mathbf{Q}\right)\mathbf{y}, \qquad \Delta\tilde{\mathbf{y}}_{ij} = \mathbf{D}_T\left(\mathbf{I}_{T+1} \otimes \mathbf{e}'_{ij}\mathbf{Q}\right)\mathbf{y}, \qquad \mathbf{L}_T\tilde{\mathbf{y}}_{ij} = \mathbf{L}_T\left(\mathbf{I}_{T+1} \otimes \mathbf{e}'_{ij}\mathbf{Q}\right)\mathbf{y}.$$

This is the single construction in which the two transformations act together. The row $\mathbf{e}'_{ij}\mathbf{Q}$ involves every pair in the period, so the demeaning must be applied to the whole cross-section before the pair series are formed; it removes λ_{it} and ξ_{jt}, up to r_{ijt}, before $\mathbf{D}_T$ or $\mathbf{L}_T$ acts on the resulting time series. Since y_{ijs} for $s \le t-2$ is a function of past shocks, past regressors and the time-invariant components only, the transformed lagged levels $\tilde{y}_{ij,s}$, $s \le t-2$, are uncorrelated with $\Delta\tilde{\varepsilon}_{ijt}$ and correlated with $\Delta\tilde{y}_{ij,t-1}$, so they can be used as instruments. Letting z denote the outcome or any regressor, the moment conditions of the differenced and level equations, for $t = 2, \dots, T$, decompose as:

$$\mathbb{E}\left(\tilde{z}_{ij,t-s}\,\Delta\tilde{u}_{ijt}\right) = \mathbb{E}\left(\tilde{z}_{ij,t-s}\,\Delta\tilde{\varepsilon}_{ijt}\right) + \mathbb{E}\left(\tilde{z}_{ij,t-s}\,\Delta r_{ijt}\right) = 0 + O(N^{-2}), s = 2,3,4,$$

$$\mathbb{E}\left[\Delta\tilde{z}_{ij,t-s}\left(\tilde{\mu}_{ij} + \tilde{u}_{ijt}\right)\right] = \mathbb{E}\left(\Delta\tilde{z}_{ij,t-s}\,\tilde{\mu}_{ij}\right) + \mathbb{E}\left(\Delta\tilde{z}_{ij,t-s}\,\tilde{\varepsilon}_{ijt}\right) + \mathbb{E}\left(\Delta\tilde{z}_{ij,t-s}\,r_{ijt}\right) = 0 + 0 + O(N^{-2}), s = 1,2,3.$$

The error terms vanish because the instruments are dated $t-1$ or earlier, the pair-effect term vanishes under the initial-conditions restriction stated above and the remainder terms are of order N^{-2}, as the Online Supplement shows for complete cross-sections, which is negligible at the rate at which the estimator converges. In matrix form the conditions read $\mathbb{E}\left(\mathbf{Z}^{D\prime}_{ij,\text{coll}}\mathbf{D}_T\tilde{\mathbf{u}}_{ij}\right) = \mathbf{0}$ and $\mathbb{E}\left[\mathbf{Z}^{L\prime}_{ij,\text{coll}}\left(\tilde{\mu}_{ij}\boldsymbol{\iota}_{T-1} + \mathbf{L}_T\tilde{\mathbf{u}}_{ij}\right)\right] = \mathbf{0}$ up to the same order. The full

collapsed instrument matrix for pair (i,j), of dimension $2(T-1)\times 6(K+1)$, stacks both blocks block-diagonally:

$$\mathbf{Z}_{ij}^{\text{sys}} = \begin{bmatrix} \mathbf{Z}_{ij,\text{coll}}^{D} & \mathbf{0} \\ \mathbf{0} & \mathbf{Z}_{ij,\text{coll}}^{L} \end{bmatrix}.$$

The estimators compared in this paper

This paper applies six estimators of $\boldsymbol{\theta} = (\rho, \boldsymbol{\beta}')'$ throughout, each defined by a different choice of cross-sectional transformation, time-dimension transformation and instrument matrix. For the proposed estimator, stack the differenced and level equations of pair (i,j) into a single system:

$$\underset{2(T-1)\times 1}{\mathbf{q}_{ij}} = \begin{bmatrix} \mathbf{D}_T \tilde{\mathbf{y}}_{ij} \\ \mathbf{L}_T \tilde{\mathbf{y}}_{ij} \end{bmatrix}, \qquad \underset{2(T-1)\times(K+1)}{\mathbf{W}_{ij}} = \begin{bmatrix} \mathbf{D}_T \tilde{\mathbf{y}}_{ij,-1} & \mathbf{D}_T \tilde{\mathbf{X}}_{ij} \\ \mathbf{L}_T \tilde{\mathbf{y}}_{ij,-1} & \mathbf{L}_T \tilde{\mathbf{X}}_{ij} \end{bmatrix},$$

so that $\mathbf{q}_{ij} = \mathbf{W}_{ij}\boldsymbol{\theta} + \tilde{\mathbf{u}}_{ij}^{\text{sys}}$ with $\tilde{\mathbf{u}}_{ij}^{\text{sys}} = \left(\left(\mathbf{D}_T \tilde{\mathbf{u}}_{ij}\right)', \left(\tilde{\mu}_{ij}\boldsymbol{\iota}_{T-1} + \mathbf{L}_T \tilde{\mathbf{u}}_{ij}\right)' \right)'$. Summing over pairs defines the $6(K+1)\times(K+1)$ matrix $\mathbf{A}$ and the $6(K+1)\times 1$ vector $\mathbf{b}$,

$$\mathbf{A} = \sum_{i=1}^{N}\sum_{j\neq i} \mathbf{Z}_{ij}^{\text{sys}\prime}\,\mathbf{W}_{ij}, \qquad \mathbf{b} = \sum_{i=1}^{N}\sum_{j\neq i} \mathbf{Z}_{ij}^{\text{sys}\prime}\,\mathbf{q}_{ij},$$

so that the sample moments are $\mathbf{b} - \mathbf{A}\boldsymbol{\theta} = \sum_{i=1}^{N}\sum_{j\neq i} \mathbf{Z}_{ij}^{\text{sys}\prime}\left(\mathbf{q}_{ij} - \mathbf{W}_{ij}\boldsymbol{\theta}\right)$. The one-step 3D-SysGMM estimator minimises the quadratic form of these moments and setting the derivative to zero gives its closed form:

$$\begin{aligned} \widehat{\boldsymbol{\theta}}_{(1)}^{\text{3D-Sys}} &= \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\ (\mathbf{b} - \mathbf{A}\boldsymbol{\theta})'\boldsymbol{\Psi}_1(\mathbf{b} - \mathbf{A}\boldsymbol{\theta}), \\ \mathbf{0} &= -2\,\mathbf{A}'\boldsymbol{\Psi}_1\left(\mathbf{b} - \mathbf{A}\widehat{\boldsymbol{\theta}}_{(1)}^{\text{3D-Sys}}\right), \\ \widehat{\boldsymbol{\theta}}_{(1)}^{\text{3D-Sys}} &= (\mathbf{A}'\boldsymbol{\Psi}_1\mathbf{A})^{-1}\mathbf{A}'\boldsymbol{\Psi}_1\mathbf{b}, \end{aligned}$$

with the one-step weighting matrix

$$\boldsymbol{\Psi}_1 = \left(\sum_{i=1}^{N}\sum_{j\neq i} \mathbf{Z}_{ij}^{\text{sys}\prime}\,\mathbf{H}\,\mathbf{Z}_{ij}^{\text{sys}}\right)^{-1},$$

where $\mathbf{H}$ is a known positive definite matrix of dimension $2(T-1)$, the identity in the Monte Carlo experiments.

The two-dimensional estimators replace the within-period two-way demeaning with period demeaning, $\ddot{\mathbf{y}}_t = \mathbf{P}\mathbf{y}_t$ with $\mathbf{P} = \mathbf{I}_n - n^{-1}\boldsymbol{\iota}_n\boldsymbol{\iota}'_n$, which removes common period effects only. The Difference GMM estimator of Arellano and Bond (1991) uses the differenced block alone:

$$\widehat{\boldsymbol{\theta}}^{\text{Diff}} = (\mathbf{A}^{D\prime}\boldsymbol{\Psi}_1^{D}\mathbf{A}^{D})^{-1}\mathbf{A}^{D\prime}\boldsymbol{\Psi}_1^{D}\mathbf{b}^{D},$$

with

$$\mathbf{A}^{D} = \sum_{i=1}^{N}\sum_{j\neq i} \ddot{\mathbf{Z}}_{ij}^{D\prime}\left(\mathbf{D}_T\ddot{\mathbf{y}}_{ij,-1},\ \mathbf{D}_T\ddot{\mathbf{X}}_{ij}\right), \qquad \mathbf{b}^{D} = \sum_{i=1}^{N}\sum_{j\neq i} \ddot{\mathbf{Z}}_{ij}^{D\prime}\,\mathbf{D}_T\ddot{\mathbf{y}}_{ij},$$

where $\ddot{\mathbf{Z}}_{ij}^{D}$ is the collapsed matrix of the differenced equation above built from the period-demeaned series and $\boldsymbol{\Psi}_1^{D} = \left(\sum_{i=1}^{N}\sum_{j\neq i} \ddot{\mathbf{Z}}_{ij}^{D\prime}\,\mathbf{H}_D\ddot{\mathbf{Z}}_{ij}^{D}\right)^{-1}$ for a known positive definite $\mathbf{H}_D$. The standard system GMM estimator of Blundell and Bond (1998) is the one-step estimator above with $\ddot{\mathbf{y}}$ and $\ddot{\mathbf{X}}$ in place of $\tilde{\mathbf{y}}$ and $\tilde{\mathbf{X}}$ throughout. The forward-orthogonal-deviations estimator of Hayakawa and Qi (2020) replaces first differences with the forward orthogonal deviations of Arellano and Bover (1995),

$$y_{ijt}^{*} = c_t\left(\ddot{y}_{ijt} - \tfrac{1}{T-t}\textstyle\sum_{s=t+1}^{T}\ddot{y}_{ijs}\right), \qquad c_t = \left(\tfrac{T-t}{T-t+1}\right)^{1/2}, \qquad t = 1,\ldots,T-1,$$

which remove the pair effect without introducing the serial correlation that first differencing creates in the transformed errors. In matrix form $\mathbf{y}^{*}_{ij} = \mathbf{F}_T \ddot{\mathbf{y}}_{ij}$, where the $(T-1)\times(T+1)$ matrix is given by:

$$\mathbf{F}_T = \begin{bmatrix} 0 & c_1 & -\frac{c_1}{T-1} & -\frac{c_1}{T-1} & \cdots & -\frac{c_1}{T-1} \\ 0 & 0 & c_2 & -\frac{c_2}{T-2} & \cdots & -\frac{c_2}{T-2} \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & c_{T-1} & -c_{T-1} \end{bmatrix}$$

This matrix satisfies $\mathbf{F}_T \boldsymbol{\iota}_{T+1} = \mathbf{0}$ and $\mathbf{F}_T \mathbf{F}'_T = \mathbf{I}_{T-1}$ so that it removes the pair effect and maps serially uncorrelated homoscedastic errors into serially uncorrelated homoscedastic errors (Arellano & Bover, 1995). Stacking $\mathbf{y}^{*}_{ij} = \left(y^{*}_{ij1}, \ldots, y^{*}_{ij,T-1}\right)'$, forming $\mathbf{y}^{*}_{ij,-1}$ and $\mathbf{X}^{*}_{ij}$ in the same way from the lagged outcome and the regressors and using the period-demeaned levels at lags 1 to 3 as instruments,

$$\mathbf{Z}^{F}_{ij,\text{coll}} = \begin{bmatrix} \ddot{y}_{ij0} & \ddot{\mathbf{x}}'_{ij0} & 0 & \mathbf{0} & 0 & \mathbf{0} \\ \ddot{y}_{ij1} & \ddot{\mathbf{x}}'_{ij1} & \ddot{y}_{ij0} & \ddot{\mathbf{x}}'_{ij0} & 0 & \mathbf{0} \\ \ddot{y}_{ij2} & \ddot{\mathbf{x}}'_{ij2} & \ddot{y}_{ij1} & \ddot{\mathbf{x}}'_{ij1} & \ddot{y}_{ij0} & \ddot{\mathbf{x}}'_{ij0} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \ddot{y}_{ij,T-2} & \ddot{\mathbf{x}}'_{ij,T-2} & \ddot{y}_{ij,T-3} & \ddot{\mathbf{x}}'_{ij,T-3} & \ddot{y}_{ij,T-4} & \ddot{\mathbf{x}}'_{ij,T-4} \end{bmatrix},$$

the estimator is:

$$\widehat{\boldsymbol{\theta}}^{\text{FOD}} = (\mathbf{A}^{F\prime}\boldsymbol{\Psi}^{F}_{1}\mathbf{A}^{F})^{-1}\mathbf{A}^{F\prime}\boldsymbol{\Psi}^{F}_{1}\mathbf{b}^{F},$$

with

$$\mathbf{A}^{F} = \textstyle\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}^{F\prime}_{ij,\text{coll}}\left(\mathbf{y}^{*}_{ij,-1},\, \mathbf{X}^{*}_{ij}\right), \qquad \mathbf{b}^{F} = \textstyle\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}^{F\prime}_{ij,\text{coll}}\,\mathbf{y}^{*}_{ij},$$

$$\text{and } \boldsymbol{\Psi}^{F}_{1} = \left(\textstyle\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}^{F\prime}_{ij,\text{coll}}\,\mathbf{Z}^{F}_{ij,\text{coll}}\right)^{-1}.$$

The remaining two estimators are least-squares estimators. The bias-corrected least-squares dummy variable estimator applies the split-panel jackknife principle of Dhaene and Jochmans (2015), adapted to the linear dynamic panel following the half-panel jackknife of Chudik et al. (2018), to the within estimator. With a dot denoting the deviation of a period-demeaned variable from its pair mean over the estimation periods and $\mathbf{w}_{ijt} = \left(\ddot{y}_{ij,t-1},\, \ddot{\mathbf{x}}'_{ijt}\right)'$,

$$\widehat{\boldsymbol{\theta}}^{\text{W}} = \left(\textstyle\sum_{i=1}^{N}\sum_{j\neq i}\sum_{t=1}^{T}\dot{\mathbf{w}}_{ijt}\,\dot{\mathbf{w}}'_{ijt}\right)^{-1}\sum_{i=1}^{N}\sum_{j\neq i}\sum_{t=1}^{T}\dot{\mathbf{w}}_{ijt}\,\dot{y}_{ijt}, \qquad \widehat{\boldsymbol{\theta}}^{\text{BC}} = 2\,\widehat{\boldsymbol{\theta}}^{\text{W}} - \tfrac{1}{2}\left(\widehat{\boldsymbol{\theta}}^{\text{W}}_{a} + \widehat{\boldsymbol{\theta}}^{\text{W}}_{b}\right),$$

where $\widehat{\boldsymbol{\theta}}^{\text{W}}_{a}$ and $\widehat{\boldsymbol{\theta}}^{\text{W}}_{b}$ are the within estimates from the first and second halves of the estimation periods. When the halves have different lengths T_a and T_b, the weights 2 and $1/2$ become $1+2\omega$ and ω with $\omega = [T(1/T_a + 1/T_b) - 2]^{-1}$. The three-way fixed-effects estimator follows the generalised design of Baltagi et al. (2003) and absorbs the pair, origin-year and destination-year effects of the static model with $\rho = 0$. Stacking all periods into $\mathbf{y} = (\mathbf{y}'_1, \ldots, \mathbf{y}'_T)'$ and $\mathbf{X} = (\mathbf{X}'_1, \ldots, \mathbf{X}'_T)'$, the three sets of effects enter through the indicator matrix $\mathbf{C} = (\boldsymbol{\iota}_T \otimes \mathbf{I}_n,\ \mathbf{I}_T \otimes \mathbf{E}_O,\ \mathbf{I}_T \otimes \mathbf{E}_D)$, and

$$\widehat{\boldsymbol{\beta}}^{\text{3FE}} = (\mathbf{X}'\mathbf{M}_{\mathbf{C}}\mathbf{X})^{-1}\mathbf{X}'\mathbf{M}_{\mathbf{C}}\mathbf{y}, \qquad \mathbf{M}_{\mathbf{C}} = \mathbf{I}_{nT} - \mathbf{C}(\mathbf{C}'\mathbf{C})^{-}\mathbf{C}',$$

where $(\cdot)^{-}$ denotes a generalised inverse, needed because the three sets of indicators are collinear. Because the static specification omits the lagged dependent variable, this estimator cannot recover the persistence parameter, its central limitation for this application.

Of the six estimators derived in this subsection, three are carried into the main empirical results in Table 1 alongside a two-way fixed-effects benchmark and the two static PPML specifications introduced above: the proposed 3D-SysGMM, standard system GMM and difference GMM. The three-way fixed-effects estimator is not estimated separately in linear

form since the three-way PPML column already demonstrates the same absorption result: origin-time and destination-time fixed effects absorb every regressor that varies only by origin or only by destination, which is why the gross domestic product (GDP) and GDP per capita of the origin and of the destination are dropped from that column automatically in Table 1. Forward-orthogonal-deviations and the bias-corrected least-squares dummy variable estimator are derived here for completeness and are compared with the other estimators in the Monte Carlo experiments of the Online Supplement; neither is validated for the present unbalanced panel and 3D fixed-effect structure, and both remain candidates for future robustness work.

Efficient two-step estimation and standard errors

The estimators above are one-step estimators. The two-step estimator used throughout the empirical section replaces $\boldsymbol{\Psi}_1$ with the inverse of the pair-clustered covariance of the moments evaluated at the one-step residuals $\widehat{\mathbf{u}}_{ij(1)} = \mathbf{q}_{ij} - \mathbf{W}_{ij}\widehat{\boldsymbol{\theta}}_{(1)}$:

$$\widehat{\boldsymbol{\theta}} = \left(\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\mathbf{A}\right)^{-1}\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\mathbf{b}, \qquad \widehat{\boldsymbol{\Psi}}_2 = \left(\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\,\widehat{\mathbf{u}}_{ij(1)}\widehat{\mathbf{u}}'_{ij(1)}\mathbf{Z}_{ij}^{\text{sys}}\right)^{-1}.$$

Its conventional variance estimate $\widehat{\mathbf{V}}_2 = \left(\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\mathbf{A}\right)^{-1}$ ignores the estimation of the weighting matrix, so standard errors use the finite-sample correction of Windmeijer (2005) throughout the paper:

$$\widehat{\text{Var}}\left(\widehat{\boldsymbol{\theta}}\right) = \widehat{\mathbf{V}}_2 + \widehat{\mathbf{F}}\widehat{\mathbf{V}}_2 + \widehat{\mathbf{V}}_2\widehat{\mathbf{F}}' + \widehat{\mathbf{F}}\widehat{\mathbf{V}}_1\widehat{\mathbf{F}}',$$

where $\widehat{\mathbf{V}}_1 = \mathbf{B}_1\mathbf{A}'\boldsymbol{\Psi}_1\widehat{\boldsymbol{\Psi}}_2^{-1}\boldsymbol{\Psi}_1\mathbf{A}\mathbf{B}_1$, with $\mathbf{B}_1 = (\mathbf{A}'\boldsymbol{\Psi}_1\mathbf{A})^{-1}$, is the robust variance of the one-step estimator and the kth column of $\widehat{\mathbf{F}}$ is:

$$\widehat{\mathbf{F}}_k = \widehat{\mathbf{V}}_2\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\left[\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\left(\mathbf{w}_{ij,k}\widehat{\mathbf{u}}'_{ij(1)} + \widehat{\mathbf{u}}_{ij(1)}\mathbf{w}'_{ij,k}\right)\mathbf{Z}_{ij}^{\text{sys}}\right]\widehat{\boldsymbol{\Psi}}_2\,\widehat{\mathbf{g}},$$
$$\widehat{\mathbf{g}} = \sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\left(\mathbf{q}_{ij} - \mathbf{W}_{ij}\widehat{\boldsymbol{\theta}}\right),$$

with $\mathbf{w}_{ij,k}$ the kth column of $\mathbf{W}_{ij}$. The Hansen statistic is $\widehat{\mathbf{g}}'\widehat{\boldsymbol{\Psi}}_2\widehat{\mathbf{g}}$, with degrees of freedom equal to the number of instruments minus $K+1$. Substituting $\mathbf{q}_{ij} = \mathbf{W}_{ij}\boldsymbol{\theta}_0 + \tilde{\mathbf{u}}_{ij}^{\text{sys}}$ into the two-step estimator gives the expansion:

$$\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0 = \left(\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\mathbf{A}\right)^{-1}\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2(\mathbf{b} - \mathbf{A}\boldsymbol{\theta}_0) = \left(\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\mathbf{A}\right)^{-1}\mathbf{A}'\widehat{\boldsymbol{\Psi}}_2\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\,\tilde{\mathbf{u}}_{ij}^{\text{sys}},$$
$$\sqrt{n}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) = \left[\frac{1}{n}\mathbf{A}'\left(n\widehat{\boldsymbol{\Psi}}_2\right)\frac{1}{n}\mathbf{A}\right]^{-1}\left[\frac{1}{n}\mathbf{A}'\left(n\widehat{\boldsymbol{\Psi}}_2\right)\right]\frac{1}{\sqrt{n}}\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\,\tilde{\mathbf{u}}_{ij}^{\text{sys}},$$

in which the matrices in square brackets converge to $\mathbf{G}'\boldsymbol{\Omega}^{-1}\mathbf{G}$ and $\mathbf{G}'\boldsymbol{\Omega}^{-1}$. The Online Supplement makes the conditions stated below the dynamic panel model precise and shows that the scaled moment sum is asymptotically normal with variance $\boldsymbol{\Omega}$ so that, as $N\to\infty$ with T fixed, where the number of pairs n grows at the rate N^2,

$$\sqrt{n}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) \xrightarrow{d} \mathcal{N}\left(\mathbf{0},\ (\mathbf{G}'\boldsymbol{\Omega}^{-1}\mathbf{G})^{-1}\right), \qquad \mathbf{G} = \text{plim}\,\frac{1}{n}\mathbf{A},$$
$$\boldsymbol{\Omega} = \text{plim}\,\frac{1}{n}\sum_{i=1}^{N}\sum_{j\neq i}\mathbf{Z}_{ij}^{\text{sys}\prime}\,\tilde{\mathbf{u}}_{ij}^{\text{sys}}\tilde{\mathbf{u}}_{ij}^{\text{sys}\prime}\mathbf{Z}_{ij}^{\text{sys}},$$

with $\mathbf{G}$ of full column rank, using the central limit theorem of Kuersteiner and Prucha (2013) for panels with cross-sectional dependence and sequentially exogenous regressors. The estimator draws on several established strands of method. Its moment conditions extend those of Blundell and Bond (1998) to a three-index structure, in the spirit of the forward-orthogonal-deviations refinement of Hayakawa and Qi (2020). The cross-sectional demeaning adapts the common correlated effects tradition (Pesaran, 2006) to a moment-condition setting, and, unlike the bias-corrected fixed-effects estimator of Kao et al. (2021), the estimator needs no bias correction when T is fixed. The comparison between the dynamic estimates and a Hausman-Taylor specification for the time-invariant gravity terms follows Egger and Pfaffermayr (2004) and Kripfganz and Schwarz (2019), who show that static and dynamic

models can disagree sharply on the distance effect once dynamics and time-invariant identification are handled jointly.

Finite-sample performance

Monte Carlo experiments reported in the Online Supplement compare the six estimators in designs that reproduce the dimensions of the application. The data are generated from the dynamic panel model above with one regressor for 10 to 35 countries observed over 15 to 26 periods, with persistence between 0.3 and 0.9, two error variances and two ratios of fixed-effect to error variance, giving 128 cells with 1,000 replications each. In the first regime the origin-time and destination-time effects are serially independent and unrelated to the regressor; in the second they are persistent and the regressor loads on them, which is the case the transformation is designed for.

When the origin-time and destination-time effects are serially independent, the two-dimensional estimators remain consistent, but their pair-clustered standard errors ignore the correlation between pairs that share a country. The rejection frequencies of their t-tests therefore rise with the number of countries and reach between 0.10 and 0.64 for the persistence parameter at the empirical scale, and their tests of overidentifying restrictions and of second-order serial correlation over-reject in the same way. When the effects are persistent and correlated with the regressor, the two-dimensional estimators are inconsistent and their bias does not shrink as the number of countries grows. In both regimes the proposed estimator has an absolute bias below 0.01 at the empirical scale, rejection frequencies between 0.05 and 0.13 for the persistence parameter and between 0.05 and 0.08 for the slope, and specification tests that reject with frequencies close to the nominal level. The supplement also derives the exact remainder left by the transformation and the limiting distribution of the two-step estimator.

3. Results and discussion

3.1 Data

The sample covers bilateral clean energy trade among 35 countries over 1995-2020, giving 1,190 country pairs and 28,920 pair-year observations with positive recorded trade, out of 30,940 possible pair-years, so the panel is unbalanced. The dependent variable is the natural logarithm of bilateral clean energy trade in the Harmonized System 1992 (HS92) classification (Gaulier & Zignago, 2010). Pairs that record no trade in any sample year are excluded.

The regressors are the logged GDP and logged GDP per capita of each partner, logged bilateral distance, indicators for a common border, common language, colonial ties and joint World Trade Organization (WTO) membership, and a bilateral EPS divergence index. Three period indicators mark the post-Paris years, the global financial crisis and the COVID-19 shock. Each period indicator is constant within a year, so it is absorbed by the time structure of the dynamic estimators and by the year effect of the static estimator and does not enter the reported coefficients.

Figure 1 shows that trade rises for all nine exporters shown and that differences between destinations persist across years, with destination effects alone accounting for 39% to 81% of the variation in ln trade of an exporter, which motivates the dynamic specification. The lower-income exporters are China, Turkey and Russia; the middle-income exporters are Italy, Canada and New Zealand; and the higher-income exporters are Germany, Sweden and Australia. Each panel has its own scale, set between the 2nd and 98th percentiles of the exporter, with values outside this range set to its limits. Descriptive statistics (Table A2), preliminary panel diagnostics (Table A3), which indicate strong cross-sectional dependence and slope heterogeneity, and the list of countries (Table A4) are reported in the Appendix, together with the analytical flow of the paper (Table A5) and the construction of the proposed estimator (Table A6).

The EPS divergence index used in Tables 1 to 4 is the signed difference between the exporter and importer EPS scores. A signed difference is the sum of an exporter-year term and an importer-year term, so the exporter-time and importer-time effects absorb it exactly. The three-way PPML and 3D-SysGMM estimators therefore cannot identify its coefficient, and the same applies to GDP and GDP per capita, which are also country-time variables. Tables 5 to 7 re-estimate every specification with the absolute EPS divergence, the absolute value of the same difference, which is not additive in the two country-time terms and is therefore identified by the corrected estimator. Tables 1 to 4 are retained because the two-dimensional estimators identify the signed measure, which also records which partner is the stricter one. Figure 2 (c) shows, for North and South exporters as defined in the income-pair splits below, that mean stringency rises in both groups and that the mean absolute EPS divergence stays between 1.1 and 1.2 after 2011. Panels (a) and (b) of Figure 2 cover 1995 to 2016, panel (c) covers 1995 to 2020 and the dotted line marks the Paris Agreement.

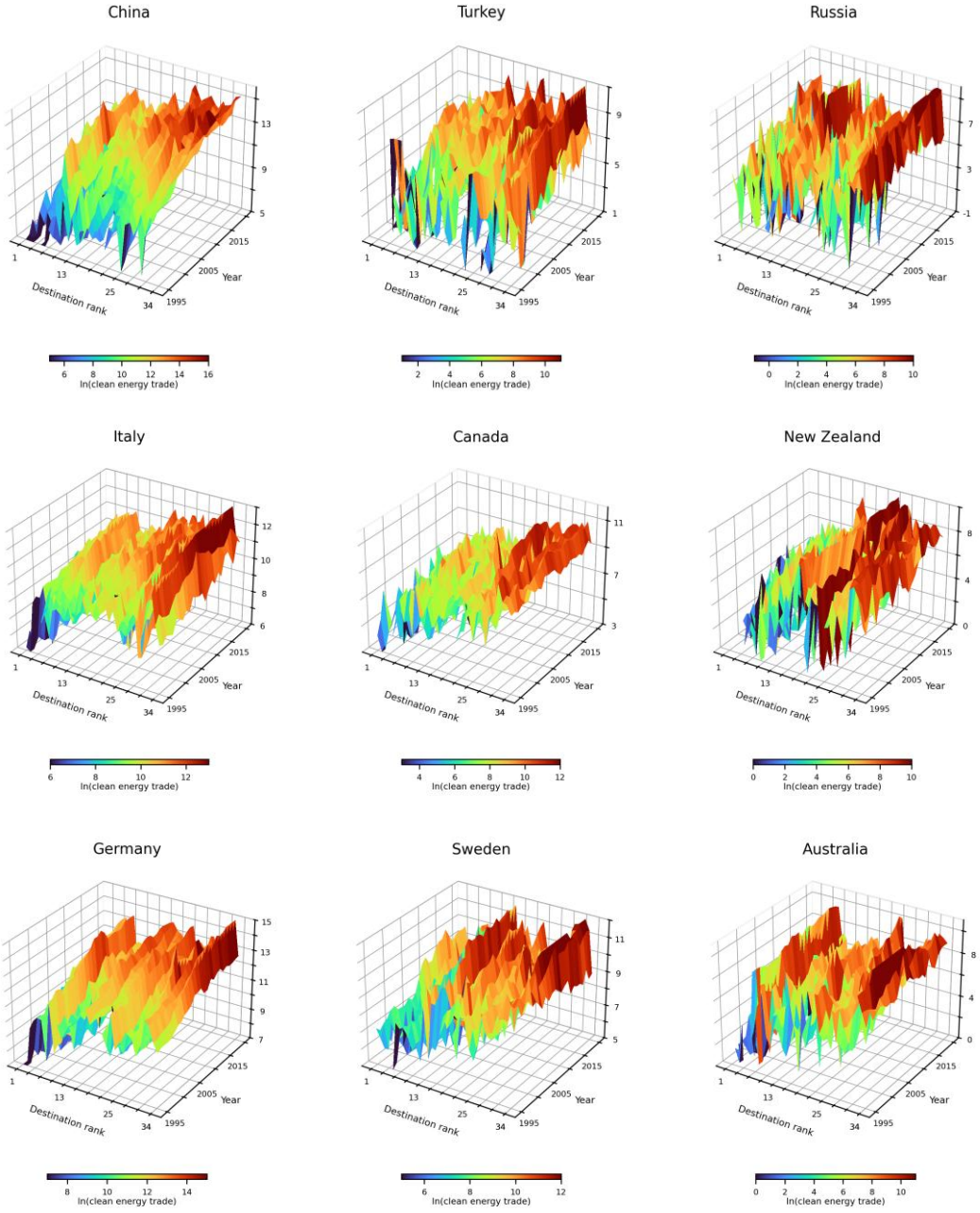


Figure 1. Clean energy trade by exporter income group. (a) Lower income. (b) Middle income. (c) Higher income.

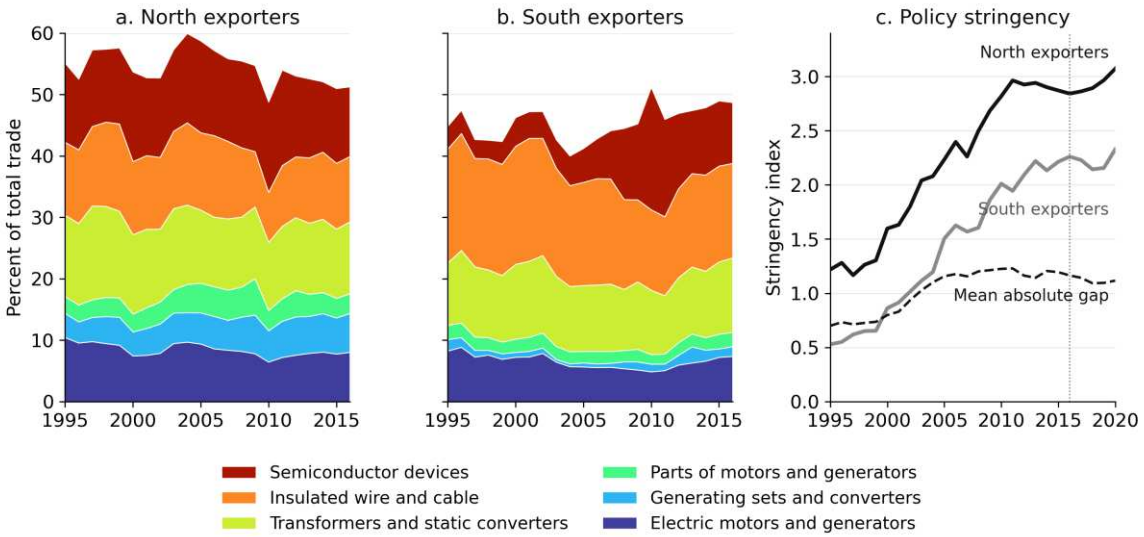


Figure 2. Product composition of clean energy trade and environmental policy stringency by income group. (a) North exporters. (b) South exporters. (c) Policy stringency.

3.2 Estimation results

Table 1 reports eight specifications in total: two static PPML columns (columns 1 and 2), three further static columns that vary the fixed-effect structure or the estimation sample (columns 3 to 5: pair-and-year within fixed effects, a sample excluding the 2008-2009 financial crisis and a balanced panel), and three dynamic columns with a lagged dependent variable (columns 6 to 8: standard system GMM, difference GMM and the corrected 3D-SysGMM).

Economic size, not policy, dominates the determinants of bilateral clean energy trade. The exporter output elasticity is large, positive and precisely estimated, and the importer output elasticity is positive and significant, consistent with the central role of manufacturing scale in clean energy supply, where a small number of large economies account for most exports. Columns 1 and 2 of Table 1 apply the PPML gravity estimator of Santos Silva and Tenreyro (2006) with year and pair fixed effects and its three-way extension by Weidner and Zylkin (2021) with origin-time and destination-time fixed effects.

Bilateral distance is absorbed by the pair effects and is not interpreted (see the notes to Table 1). Figure 3 shows instead the descriptive gradient for the 1995-2020 pair means, with marker area proportional to the share of each pair in total clean energy trade and a negative slope, which pools exporters and importers of different sizes and is not an estimate of the effect of distance. The WTO membership indicator is imprecisely estimated in the two-way PPML column. Columns 6 and 7 apply the system and difference GMM estimators of Blundell and Bond (1998) and Arellano and Bond (1991); column 8 applies the corrected 3D-SysGMM estimator developed above. Persistence and the EPS association from these three dynamic columns are examined next.

Table 5 repeats the eight columns with the absolute EPS divergence. Persistence under the corrected 3D-SysGMM is little changed from Table 1 and remains close to the standard system GMM estimate. The EPS coefficient is positive in the PPML columns and negative in the fixed-effects column and under the system and corrected estimators, with the corrected estimate less than half the size of the standard system GMM estimate, a comparison of point estimates that this paper does not test formally. This is consistent with a two-dimensional estimator attributing part of the exporter-time and importer-time heterogeneity to the policy measure although the opposite signs in the PPML and GMM columns indicate that functional form and dynamics also matter for the sign, a difference that this paper does not reconcile.

Panel B of Table 5 shows that the positive static association remains under the variance weighting of Kwon et al. (2026), that the estimated variance exponent differs from the Gamma-

PML assumption of 2 under which the association disappears and that the dynamic estimate moves toward zero once the common factors of Ye and Wu (2014) or the exporter-time and importer-time effects are removed.

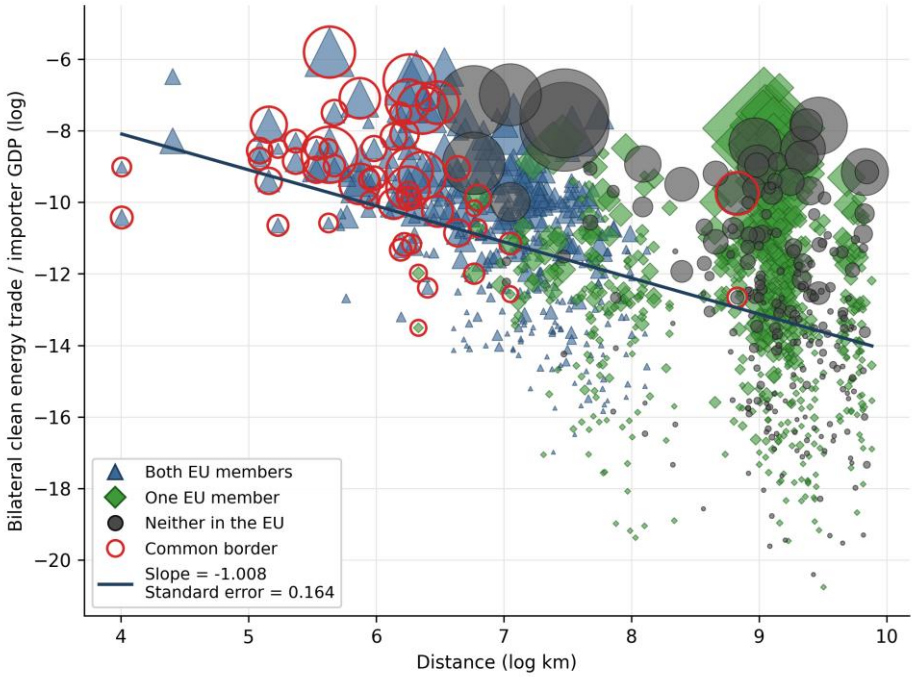


Figure 3. Distance and clean energy trade relative to importer GDP.

3.3 Robustness

Two identification threats motivate the checks in Table 2. If the Paris Agreement shifted how policy stringency maps into trade, pooling pre- and post-2016 observations would blend two distinct regimes into one misleading average effect. If a single large exporter drove the full-sample estimates, the corrected estimator would be describing the trade pattern of one country rather than a general one. Splitting the sample by period tests the first threat and excluding China and the three largest exporters in turn tests the second.

Persistence is stable across the two sub-periods and both leave-one-out cuts, close to the full-sample estimate in Table 1, indicating the corrected estimator is not merely fitting a single period or a single dominant trader. The signed EPS coefficient in Table 2 is markedly larger after the Paris Agreement, consistent with EPS divergence becoming a stronger trade signal once binding commitments took effect though the post-Paris sub-period has only five years and the improved second-order serial correlation (AR(2)) and Hansen diagnostics there likely reflect reduced power rather than a better-specified model. The main visible change under leave-one-out is that the exporter GDP per capita elasticity roughly doubles once China is excluded, consistent with the rapid growth of per-capita income in China over the sample period alongside its trade volume, so its inclusion partly flattens the estimated per-capita income gradient.

The same temporal and leave-one-out design as in Table 2 is applied to the absolute EPS divergence in Table 6. Persistence is again stable in all four columns. The EPS coefficient is negative in every column and larger in size after the Paris Agreement, so the change in magnitude across periods does not depend on the measure of divergence although the sign does.

The specification tests of the dynamic columns are the remaining concern. In the corrected 3D-SysGMM column of Table 1, both the second-order serial correlation test and the Hansen test of overidentifying restrictions reject their null hypotheses while the Monte Carlo evidence

above reports rejection frequencies close to the nominal level. A natural explanation is that the baseline instrument set, lagged demeaned trade from two periods back, is invalid if the differenced idiosyncratic error follows a first-order moving-average process.

Re-estimating the same specification with instruments dated three periods back and earlier, which remain valid under that alternative, leaves the persistence estimate and the EPS coefficient close to their baseline values and leaves both tests still rejecting. The third-order serial correlation test does not reject under either instrument set, so the rejection does not propagate to higher orders. The persistence and policy estimates are therefore not an artefact of the specific instrument lag chosen, and the source of the second-order rejection remains an open question for this application, consistent with the finite-sample over-rejection documented for related two-dimensional estimators in the Monte Carlo evidence above.

Treating the absolute EPS divergence as predetermined rather than strictly exogenous, and instrumenting it with its own lags dated two to four periods back as in the Monte Carlo design, leaves the persistence estimate and the sign and size of the EPS coefficient close to the baseline but doubles its standard error, so the coefficient is no longer significant at conventional levels; instrumenting every regressor by its own lags gives the same result. The results of these checks are available from the authors on request.

A pooled EPS coefficient could mask offsetting effects across heterogeneous trading partners and products, so Table 3 splits the sample along both dimensions. The EPS coefficient is positive and statistically significant only for South-South pairs and negative and imprecisely estimated for North-North and North-South pairs. This pattern is consistent with EPS divergence redirecting clean energy trade primarily among developing-country partners, where regulatory gaps are wider and trade patterns more responsive to a shifting cost or competitiveness signal while among high-income partners and across the North-South divide the effect is not distinguishable from zero.

The output elasticities also vary by group, with GDP destination entering significantly positive at the 5% level only for South-South pairs and GDP origin entering significantly positive only for North-South pairs, indicating the gravity relationship itself is heterogeneous across income groups rather than uniform across the full sample.

The product sub-basket columns of the same table show a parallel difference by product type: the EPS coefficient is negative and significant only for the solar and semiconductor basket and is close to zero elsewhere. This means that, under the signed measure, the aggregate EPS coefficient in Table 1 is not a uniform policy effect but one driven almost entirely by a single product segment, a distinction any policy instrument targeting clean energy trade broadly would miss. The GDP origin elasticity is also larger for the solar and semiconductor basket than for the other two, consistent with photovoltaic manufacturing being more geographically concentrated than motors, converters or cable. Figure 2 (a) and (b) split the three baskets of Table 3 (headings 8501 to 8504, 8544 and 8541) into six headings: semiconductor devices are the largest heading for North exporters (13% of trade) and insulated cable for South exporters (17%).

The income-pair and product splits of Table 3 are repeated with the absolute EPS divergence in Table 7. The coefficient is negative and significant for South-South and North-South pairs and close to zero for North-North pairs, so the positive South-South coefficient in Table 3 does not carry over to the absolute measure. In the product models the coefficient is positive and significant for generation and conversion machinery and for grid and cable equipment and positive but imprecisely estimated for the solar and semiconductor basket, so the association for that basket in Table 3 is specific to the signed measure.

A further threat to the main results is that clustering choice, rather than the underlying relationship, could be driving which coefficients appear precisely estimated. Table 4 re-estimates the primary PPML specification under three clustering choices; the point estimates are identical across all three columns by construction since only the standard errors change

with the clustering choice. If the significance pattern in Table 1 were an artefact of the clustering choice, the standard errors would shift enough to overturn it; they do not. GDP origin, GDP destination and EPS divergence remain precisely estimated under all three choices, confirming the main gravity and policy findings are not sensitive to how standard errors are computed.

The WTO membership indicator is the coefficient that changes: it becomes significant under exporter-level clustering, likely reflecting the smaller effective number of clusters since exporter-level clustering collapses the cross-sectional dimension from 1,190 pairs to 35 exporters, rather than a more correct standard error. Distance also changes significance under pair-by-year clustering but is not interpreted for the reason given in the notes to Table 1. The one-way pair-clustered standard errors reported as the primary specification in Table 1 are the most conservative of the three and are retained throughout the paper.

A related concern is inference in the PPML columns. Pfaffermayr (2026) reports Monte Carlo evidence that country-pair clustered standard errors of fixed-effects PPML estimators in gravity panels with autocorrelated disturbances are biased downward, so the significance of the PPML coefficients may be overstated; the bias-corrected standard errors of that study are not computed here.

3.4 Discussion

The findings relate to three literatures: structural gravity estimation, the econometrics of multi-way panel models and the role of environmental policy in shaping trade composition. On the gravity side, economic size dominates: the exporter and importer output elasticities under the primary PPML specification are large, positive and precisely estimated, mirroring the magnitudes in Santos Silva and Tenreyro (2006) and the broader structural gravity literature surveyed in Anderson and van Wincoop (2003), consistent with a small number of large manufacturing economies accounting for most clean energy supply. On persistence, the moderate estimate under standard system GMM, little changed under the corrected three-dimensional specification, lies well below 1, indicating that bilateral clean energy trade adjusts toward its long-run level over several years rather than instantaneously.

The persistence result qualifies rather than confirms the general concern, raised in the multi-way panel literature, that two-dimensional estimators misstate genuine state dependence when higher-dimensional heterogeneity is present. Origin-time and destination-time heterogeneity in this application correlates only weakly with lagged trade, so removing it barely moves the persistence estimate. The methodological contribution is therefore not a revised persistence figure but an indication of how much three-dimensional heterogeneity can distort it in a setting of this kind, complementing rather than overturning the static finding of Egger and Pfaffermayr (2003) that bilateral interaction effects account for most of the variation in trade flows.

Correcting for three-dimensional heterogeneity has its largest effect on the policy channel. The signed EPS divergence used in Tables 1 to 3 cannot be identified by the corrected estimator, so the comparison across estimators rests on the absolute measure in Table 5. Tables 6 and 7 show that the association is negative and precisely estimated in South-South and North-South pairs and absent in North-North pairs and that it is positive in the PPML specification for generation and conversion machinery and for grid and cable equipment. The association for the solar and semiconductor basket under the signed measure (Table 3) is not reproduced by the absolute measure. Neither the compliance-cost nor the Porter-style channel is therefore supported uniformly since the negative GMM association is in line with the former whereas the positive PPML association for generation and grid equipment is in line with the latter. These interpretations of the channels are conditional on strict exogeneity of the divergence measure.

Three further interpretations follow. The negative association under the system and corrected estimators is consistent with regulatory distance acting as a pair-specific entry cost (Kox &

Lejour, 2005), and Ghodsi (2024) shows for information and communication technology goods that bilateral regulatory convergence is identified under country-product-time fixed effects whereas unilateral measures are absorbed, the same identification logic as in the three-dimensional design here. This interpretation is symmetric whereas a compliance cost falls on one partner; the design cannot separate the two because signed and direction-specific gaps are absorbed by the exporter-time and importer-time effects.

Evidence on regulatory differences between partners points in a similar direction in standards-heavy sectors, with some dependence on direction. Winchester et al. (2012) find that agri-food trade falls when importing countries set stricter maximum residue limits for plant products than exporting countries, and Engemann et al. (2025) find that dissimilarity in such limits reduces the stability of trade relationships. Bao and Qiu (2012) find that technical barriers to trade lower the probability of exporting but raise export volumes, and Crivelli and Gröschl (2016) find that sanitary and phytosanitary measures hinder trade overall but are associated with higher flows conditional on market entry. These studies use sector-specific standards and not a composite stringency index, so they motivate the regulatory-distance interpretation without establishing its sign for clean energy trade.

A moderate lagged coefficient under the corrected estimator indicates partial adjustment and lies well below unit persistence. This is compatible with the entry-cost argument made in the Introduction although the studies cited there concern firm-level export status and the interpretation is suggestive only. The absolute EPS divergence may also partly proxy dissimilarity in green capabilities because countries with higher green complexity have more stringent policies even after controlling for income per capita (Mealy & Teytelboym, 2022), and although country-level capability measures are absorbed by the exporter-time and importer-time effects, the absolute dissimilarity between two partners is a pair-level quantity that these effects do not absorb.

Finally, the contrasts of Baltagi et al. (2003) between trade theories cannot be examined on the same footing because the income and size variables on which they rest are country-time variables that the exporter-time and importer-time effects largely absorb, in line with the view of Serlenga and Shin (2007) and Larch et al. (2025) that gravity estimates alone cannot discriminate between trade theories.

Two further interpretations come from related studies of environmental policy and trade, and neither is a result of this paper. Resource dependence theory, as applied by Shao and Li (2025), holds that exporters respond to higher external trade costs by shifting sales across partners and importers by raising domestic innovation, so a pair that becomes costlier to serve loses trade relative to the other pairs of the same exporter. If a larger stringency gap raised the cost of serving a partner, the same logic would imply less bilateral trade, which the pair-level variation in the absolute EPS divergence could register. Shao and Li (2025) derive this logic for geopolitical risk and not for regulatory differences, and this paper has no measure of geopolitical risk, so the interpretation is not tested here.

The substitution effect reported by Cantore and Cheng (2018) concerns the importer level since a higher environment-related tax revenue of the importing country is associated with lower imports of environmental goods, which they read as import substitution. The importer level is absorbed by the importer-time effects, so this channel is not tested here although it could be reflected in a bilateral gap in which the importer is the stricter partner if the displacement of imports by domestic production differs across exporters.

This sensitivity to the measure of divergence, to the estimator and to sample splitting limits how far the policy channel can be interpreted. The sign of the policy association is not stable across specifications, and the policy findings carry less weight than the gravity fundamentals and the persistence result.

For policy design, the sign of the association depends on the estimator and on whether the measure records which partner is the stricter one, and the heterogeneity across income-pair

types and product baskets is larger than the aggregate suggests. A single aggregate EPS coefficient is therefore a weak basis for calibrating instruments such as carbon border adjustments or renewable-energy trade agreements.

The sample has a strong European dimension. Nineteen of the 35 economies are current member states of the European Union (EU), and 950 of the 1,190 directed pairs involve at least one member state (342 are intra-EU pairs). The income-pair results therefore describe trade in which European exporters and importers figure prominently and bear on the design of European clean technology trade instruments although the EPS association is not estimated separately for EU pairs here.

4. Conclusion

The estimates indicate that the trade consequences of environmental policy divergence are sensitive to how ordinary bilateral heterogeneity, such as long-standing trading relationships or shared institutions, is treated. Once that heterogeneity is removed, persistence changes little but the association between the absolute EPS divergence and trade is markedly smaller in point estimates than under standard system GMM. Its sign and its distribution across partner types and products depend on the measure used.

The signed measure is significant only for the solar and semiconductor basket, and the absolute measure is negative under system GMM and the corrected estimator and positive for generation and grid equipment under PPML. Instruments calibrated to an average effect may therefore misjudge the response in specific product segments. These findings rest on a corrected estimator that removes bilateral, exporter-year and importer-year heterogeneity jointly, so it identifies only variables that vary within exporter-year and importer-year cells.

The paper has six limitations. First, the clean energy series covers a small set of product categories on the Asia-Pacific Economic Cooperation environmental goods list, and wind-specific generating sets are separately identifiable only from 2002, so wind trade is understated before then. Second, the sample covers major trading economies over 1995 to 2020 and may not extend to smaller or developing economies, and a small share of the possible pair-years is unobserved, a case that the bound on the transformation remainder, derived for complete cross-sections, does not cover. Third, the EPS index is a composite that does not separate subsidies, standards and carbon pricing.

Fourth, GDP and the EPS divergence enter as exogenous regressors and the significance of the corrected absolute coefficient depends on this treatment. GDP is not instrumented in the PPML columns and the Hansen and second-order serial correlation tests reject for both system estimators. Fifth, the direction of divergence and country-level controls such as GDP are not identified in the corrected column, so the signed measure is retained in Tables 1 to 3 for the estimators that can identify it. Sixth, the absolute EPS divergence pools two regimes. Demand pull gives a positive role to importers with demand-side policy support (Groba & Cao, 2015), innovation and technology gaps give one to stringent exporters (Fabrizi et al., 2024) and importer regulation may respond to access to foreign technology (Lovely & Popp, 2011), which would make the gap depend on lagged trade. Separating these parts requires a design that does not absorb the signed difference.

Four extensions follow. A fuller product panel beyond the six-category definition would test whether the product patterns hold more widely, and the same estimator applied to smaller and developing exporters would test generality. Decomposing the EPS index into component instruments would show which type of policy drives the association. Instrumenting GDP with further lags in the collapsed-instrument framework, or treating bilateral trade capacity as an accumulated stock, would test whether the findings survive relaxing exogenous GDP.

Table 1. Determinants of bilateral clean energy trade: static and dynamic specifications.

	Static specifications					Dynamic specifications		
Variable	**PPML 2-way**	**PPML 3-way**	**FE (within)**	**Drop crisis**	**Balanced sample**	**System GMM**	**Diff. GMM**	**3D-SysGMM (corrected)**
CE trade (lag)	-	-	-	-	-	0.3923***	0.3170***	0.3328***
						(0.0229)	(0.0246)	(0.0154)
GDP origin	0.8585***	-	1.2817***	0.8759***	0.8517***	0.5613***	0.4530***	1.4453***
	(0.0846)		(0.0988)	(0.0820)	(0.0883)	(0.0354)	(0.1498)	(0.1654)
GDP dest.	0.4820***	-	1.0410***	0.4835***	0.4673***	0.4984***	1.0819***	0.9132***
	(0.1593)		(0.1134)	(0.1551)	(0.1619)	(0.0320)	(0.1437)	(0.1879)
GDPpc origin	-0.0900**	-	-0.3245***	-0.0988***	-0.0851**	0.1512***	-0.0932	-0.0394
	(0.0355)		(0.0440)	(0.0343)	(0.0384)	(0.0476)	(0.0726)	(0.2159)
GDPpc dest.	-0.0816	-	-0.0659	-0.0643	-0.0818	0.0782**	-0.3132***	-0.0017
	(0.0530)		(0.0461)	(0.0479)	(0.0545)	(0.0366)	(0.0817)	(0.2875)
Distance	1.7550	-	-5.0515***	-	-	-	-	-
	(3.2449)		(1.9306)					
WTO membership	-0.1335	-0.1356*	0.1927**	-0.0956	-0.1430	-	-	-
	(0.1290)	(0.0819)	(0.0750)	(0.1293)	(0.1328)			
EPS divergence	-0.1286**	-	0.0225	-0.1180**	-0.1312**	0.1182***	-0.0072	0.7748***
	(0.0524)		(0.0254)	(0.0511)	(0.0546)	(0.0199)	(0.0237)	(0.2608)
Diagnostics								
Observations	28,919	28,919	28,919	25,394	20,072	28,920	28,920	28,920
Pairs	1,190	1,190	1,190	1,190	772	1,190	1,190	1,190
Pseudo R^2	0.949	0.977	0.066	0.951	0.946	-	-	-
AR(2) p-value	-	-	-	-	-	0.002	0.005	0.006
Hansen p-value	-	-	-	-	-	0.000	0.000	0.000

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors (SE) in parentheses, clustered by pair for the PPML and fixed-effects (FE) columns and Windmeijer (2005)-corrected for the GMM columns. CE trade is bilateral clean energy trade, GDPpc is GDP per capita, dest. is destination, Diff. GMM is difference GMM and the FE column includes pair and year effects. The full-sample static columns use 28,919 observations because one pair is observed in a single year and its observation is absorbed by the pair effect. Distance is constant over time up to rounding so its coefficients are not interpreted. GDP, GDP per capita and the signed EPS divergence are absorbed by the exporter-time and importer-time effects, so they are dropped from the PPML 3-way column and their 3D-SysGMM estimates are not interpreted. Table 5 re-estimates the table with the absolute EPS divergence.

Table 2. Persistence and gravity determinants: temporal split and leave-one-out sensitivity.

	Temporal split		Leave-one-out	
Variable	**Pre-Paris (1995-2015)**	**Post-Paris (2016-2020)**	**Exclude China**	**Exclude top-3 exporters (CHN, DEU, JPN)**
CE trade (lag)	0.3796***	0.4433***	0.3817***	0.3632***
	(0.0241)	(0.0714)	(0.0234)	(0.0238)
GDP origin	0.5876***	0.4984***	0.4917***	0.4416***
	(0.0367)	(0.0724)	(0.0367)	(0.0404)
GDP dest.	0.5099***	0.4621***	0.4983***	0.5135***
	(0.0327)	(0.0697)	(0.0339)	(0.0368)
GDPpc origin	0.1474***	0.2349***	0.3162***	0.3240***
	(0.0478)	(0.0664)	(0.0595)	(0.0618)
GDPpc dest.	0.0676*	0.2509***	0.0903**	0.0913**
	(0.0360)	(0.0599)	(0.0410)	(0.0433)
EPS divergence	0.1172***	0.2048***	0.1250***	0.1259***
	(0.0208)	(0.0331)	(0.0207)	(0.0222)
Diagnostics				
Observations	23,018	5,902	27,197	23,882
Pairs	1,190	1,188	1,122	992
AR(2) p-value	0.006	0.418	0.003	0.003
Hansen p-value	0.000	0.056	0.000	0.000

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. SE in parentheses, Windmeijer (2005)-corrected. System GMM estimator of Blundell and Bond (1998). The Exclude China and Exclude top-3 exporters columns drop all pairs involving China and the three largest exporters by total clean energy trade value (China, Germany and Japan), respectively.

Table 3. Gravity determinants by income-pair type and product sub-basket.

	Income-pair type	Product sub-basket

Variable	North-North	North-South	South-South	Solar/ semiconductor	Generation/ conversion	Grid/ cable
GDP origin	-0.7889	1.0382***	-0.3921	1.5336***	0.6091***	0.9594***
	(0.6947)	(0.1338)	(0.7786)	(0.1707)	(0.1298)	(0.1186)
GDP dest.	0.5997	0.2471*	1.8642***	0.6244***	0.6103***	0.6161***
	(0.6487)	(0.1294)	(0.6088)	(0.1907)	(0.1435)	(0.1329)
GDPpc origin	1.2900*	-0.3259***	1.0427	-0.2101***	-0.1134***	-0.2697***
	(0.7705)	(0.0598)	(0.7928)	(0.0478)	(0.0255)	(0.0454)
GDPpc dest.	0.3179	0.0769	-0.7518	-0.2413***	-0.0443	-0.0614
	(0.7223)	(0.0525)	(0.5829)	(0.0709)	(0.0557)	(0.0573)
EPS divergence	-0.0582	-0.0277	0.1247**	-0.2026**	0.0232	0.0018
	(0.0370)	(0.0295)	(0.0600)	(0.0958)	(0.0281)	(0.0407)
WTO membership	-	-	-	-0.0235	0.0060	0.1027
				(0.1614)	(0.0991)	(0.0670)
Diagnostics						
Observations	7,339	14,278	7,303	22,099	23,964	23,413
Pairs	570	1,015	631	-	-	-
Within R^2	0.023	0.025	0.045	-	-	-
Pseudo R^2	-	-	-	0.928	0.953	0.956

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. SE in parentheses, clustered by pair. The income-pair columns use the static two-way (pair and year) fixed-effects estimator of Egger and Pfaffermayr (2003), with North (South) denoting log GDP per capita above (below) the sample median. The product columns use the PPML estimator of Santos Silva and Tenreyro (2006) on disaggregated BACI HS92 data (Gaulier & Zignago, 2010) restricted to 1995-2016. Distance and WTO membership are not included in the income-pair columns.

Table 4. Sensitivity to standard error clustering: PPML gravity.

Variable	Cluster: pair	Cluster: pair x year	Cluster: exporter
GDP origin	0.8585***	0.8585***	0.8585***
	(0.0846)	(0.1037)	(0.1361)
GDP dest.	0.4820***	0.4820***	0.4820***
	(0.1593)	(0.1616)	(0.1415)
GDPpc origin	-0.0900**	-0.0900*	-0.0900
	(0.0355)	(0.0477)	(0.0768)
GDPpc dest.	-0.0816	-0.0816	-0.0816
	(0.0530)	(0.0700)	(0.0823)
EPS divergence	-0.1286**	-0.1286**	-0.1286**
	(0.0524)	(0.0539)	(0.0568)
Distance	1.7550	1.7550**	1.7550
	(3.2449)	(0.8396)	(3.4111)
WTO membership	-0.1335	-0.1335	-0.1335***
	(0.1290)	(0.1327)	(0.0434)

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. SE in parentheses. PPML estimator of Santos Silva and Tenreyro (2006) with year and pair fixed effects. Coefficients are identical across columns by construction and only the standard errors vary with the clustering choice. Distance is constant over time up to rounding and is not interpreted.

Table 5. Determinants with the absolute EPS divergence.

Panel A: Baseline estimators

	Static specifications					Dynamic specifications		
Variable	**PPML 2-way**	**PPML 3-way**	**FE (within)**	**Drop crisis**	**Balanced sample**	**System GMM**	**Diff. GMM**	**3D-SysGMM (corrected)**
CE trade (lag)	-	-	-	-	-	0.4110***	0.3165***	0.3369***
						(0.0232)	(0.0246)	(0.0155)
GDP origin	0.7863***	-	1.3181***	0.8148***	0.7782***	0.5584***	0.4462***	n.i.
	(0.0791)		(0.0986)	(0.0731)	(0.0825)	(0.0357)	(0.1499)	
GDP dest.	0.6308***	-	1.0738***	0.6016***	0.6180***	0.4774***	1.0796***	n.i.
	(0.1599)		(0.1135)	(0.1557)	(0.1625)	(0.0326)	(0.1439)	
GDPpc origin	-0.0741*	-	-0.3400***	-0.0847**	-0.0718*	0.2003***	-0.0914	n.i.
	(0.0388)		(0.0439)	(0.0370)	(0.0414)	(0.0461)	(0.0727)	
GDPpc dest.	-0.0570	-	-0.0860*	-0.0408	-0.0600	-0.0029	-0.3120***	n.i.
	(0.0498)		(0.0456)	(0.0480)	(0.0514)	(0.0341)	(0.0819)	
Distance	1.3872	-	-4.8713**	-	-	-	-	-
	(3.0925)		(1.9215)					
WTO membership	-0.1312	-0.1433*	0.2038***	-0.0952	-0.1440	-	-	-
	(0.1269)	(0.0753)	(0.0748)	(0.1290)	(0.1305)			
Abs. EPS divergence	0.1321**	0.1232***	-0.1246***	0.1227**	0.1266**	-0.1736***	0.0177	-0.0750***
	(0.0525)	(0.0252)	(0.0292)	(0.0509)	(0.0545)	(0.0264)	(0.0280)	(0.0248)

Diagnostics								
Observations	28,919	28,919	28,919	25,394	20,072	28,920	28,920	28,920
Pairs	1,190	1,190	1,190	1,190	772	1,190	1,190	1,190
Pseudo R^2	0.949	0.978	0.069	0.951	0.946	-	-	-
AR(2) p-value	-	-	-	-	-	0.001	0.005	0.004
Hansen p-value	-	-	-	-	-	0.000	0.000	0.000
Panel B: Alternative estimators								
Variable	**PPML 3-way**	**G-PPML 3-way**	**Gamma-PML 3-way**	**Diff. GMM (balanced)**	**Ye and Wu (r = 1)**	**Ye and Wu (r = 2)**	**Ye and Wu (r = 3)**	**3D-SysGMM (balanced)**
CE trade (lag)	-	-	-	0.4385*** (0.0322)	0.4588*** (0.0270)	0.3584*** (0.0210)	0.2659*** (0.0172)	0.4436*** (0.0198)
Abs. EPS divergence	0.1232*** (0.0252)	0.1022*** (0.0243)	-0.0065 (0.0248)	0.2559*** (0.0741)	0.0494 (0.0601)	0.0484 (0.0502)	-0.0168 (0.0452)	-0.0125 (0.0465)
Variance exponent	1 (fixed)	1.226 (0.064)	2 (fixed)	-	-	-	-	-
Observations	28,919	28,919	28,919	20,072	20,072	20,072	20,072	20,072
Pairs	1,190	1,190	1,190	772	772	772	772	772
Hansen p-value	-	-	-	0.000	0.002	0.042	0.189	0.001

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. SE in parentheses as in Table 1. EPS divergence is the absolute difference between the exporter and importer EPS scores. n.i. = not identified. G-PPML (Kwon et al., 2026) estimates the variance exponent and Gamma-PML fixes it at 2. Panel B uses the balanced subset of 772 pairs and predetermined regressors in the Diff. GMM, Ye and Wu (2014) and 3D-SysGMM columns, against exogenous regressors in Panel A. The SE of Ye and Wu (2014) ignore the estimation of the factors.

Table 6. Persistence and gravity determinants: absolute EPS divergence.

	Temporal split		**Leave-one-out**	
Variable	**Pre-Paris (1995-2015)**	**Post-Paris (2016-2020)**	**Exclude China**	**Exclude top-3 exporters (CHN, DEU, JPN)**
CE trade (lag)	0.3969*** (0.0245)	0.5586*** (0.0685)	0.4026*** (0.0237)	0.3816*** (0.0240)
GDP origin	0.5814*** (0.0368)	0.4171*** (0.0739)	0.4883*** (0.0368)	0.4348*** (0.0409)
GDP dest.	0.4899*** (0.0331)	0.3370*** (0.0666)	0.4722*** (0.0346)	0.4928*** (0.0377)
GDPpc origin	0.1912*** (0.0458)	0.2812*** (0.0711)	0.3651*** (0.0564)	0.3811*** (0.0589)
GDPpc dest.	-0.0086 (0.0333)	0.0952* (0.0555)	-0.0019 (0.0374)	0.0047 (0.0400)
Abs. EPS divergence	-0.1712*** (0.0271)	-0.2309*** (0.0477)	-0.2019*** (0.0279)	-0.1867*** (0.0305)
Diagnostics				
Observations	23,018	5,902	27,197	23,882
Pairs	1,190	1,188	1,122	992
AR(2) p-value	0.004	0.290	0.002	0.002
Hansen p-value	0.000	0.000	0.000	0.000

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Same specifications as Table 2, with EPS divergence defined as the absolute value of the difference between the exporter and importer EPS scores. SE in parentheses, Windmeijer (2005)-corrected. System GMM estimator of Blundell and Bond (1998).

Table 7. Gravity determinants by income pair and product: absolute EPS divergence.

	Income-pair type			**Product sub-basket**		
Variable	**North-North**	**North-South**	**South-South**	**Solar/ semiconductor**	**Generation/ conversion**	**Grid/ cable**
GDP origin	-0.8281 (0.6952)	1.0514*** (0.1337)	-0.3741 (0.7661)	1.3992*** (0.1689)	0.6415*** (0.1164)	1.0043*** (0.1070)
GDP dest.	0.6086 (0.6472)	0.2554** (0.1289)	2.2004*** (0.6172)	0.7621*** (0.2080)	0.6162*** (0.1312)	0.6122*** (0.1262)
GDPpc origin	1.3260* (0.7709)	-0.3459*** (0.0596)	1.1052 (0.7718)	-0.1989*** (0.0438)	-0.1011*** (0.0240)	-0.2578*** (0.0494)
GDPpc dest.	0.3146 (0.7199)	0.0678 (0.0519)	-1.1007* (0.5866)	-0.1859*** (0.0665)	-0.0316 (0.0516)	-0.0358 (0.0555)

Abs. EPS divergence	0.0062 (0.0449)	-0.0994*** (0.0342)	-0.2093*** (0.0617)	0.1485 (0.0991)	0.1057*** (0.0280)	0.1323*** (0.0316)
WTO membership	-	-	-	-0.0336 (0.1300)	0.0020 (0.0961)	0.1036* (0.0626)
Diagnostics						
Observations	7,339	14,278	7,303	22,099	23,964	23,413
Pairs	570	1,015	631	-	-	-
Within R^2	0.022	0.027	0.048	-	-	-
Pseudo R^2	-	-	-	0.928	0.954	0.957

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Same specifications as Table 3, with EPS divergence defined as the absolute value of the difference between the exporter and importer EPS scores. SE in parentheses, clustered by pair. The income-pair columns use the static two-way (pair and year) fixed-effects estimator and the product columns use PPML with pair and year effects.

Declaration Statement

Data Availability

All data are from open, publicly accessible sources, and no proprietary or restricted data were used: BACI and GeoDist of CEPII, the OECD Environmental Policy Stringency database, the World Bank World Development Indicators and the WTO Regional Trade Agreements Database. The processed panel dataset and the complete replication code supporting the findings of this study are available at https://doi.org/10.5281/zenodo.23402581

Declaration of Generative AI

During the preparation of this work the authors used a large language model assistant in order to support language editing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Funding statement

This research received no external funding.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.

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Appendix

Table A1. Summary of related studies.

Study	Method(s)	DV	IV(s)	Panel/Period	Key finding
Panel A: Clean energy trade					
Costantini & Crespi (2008)	Gravity, panel FE	Energy-tech exports	Env. regulation stringency, GDP, distance	Industrialised countries	Stringent env. regulation raises energy-tech export competitiveness
Cantore & Cheng (2018)	Gravity, panel FE, Hausman-Taylor	Environmental-goods trade	Importer env. tax, GDP	71 countries, 1999-2014	Importer env. tax associated with lower environmental-goods imports
Zhang et al. (2022)	Gravity, random effects	PV/wind trade	Trade agreement	ASEAN+CJK, 2012-2019	Agreements and market size raise RE-goods trade
Goswami et al. (2025)	Augmented gravity, PPML	Clean-energy product exports	GDP, distance, population, FTA	Emerging Asian econ., 2000-2020	Exporter GDP growth raises CEP exports in most countries
Shao & Li (2025)	Gravity, pair FE, PPML, 2SLS	Renewable energy technology exports	GPR, env. taxes, env. expenditure	42 economies, 1998-2020	GPR lowers exports; taxes strengthen, expenditure weakens the effect
Panel B: Policy and related outcomes					
Jug & Mirza (2005)	Gravity, GMM	Bilateral trade	Env. regulation stringency	European exporters	Negative association for European exporters, strengthened by GMM
Brandi et al. (2020)	Gravity, panel FE	Dirty/green export shares	Environmental provisions in PTAs	Worldwide, 1984-2016	Env. provisions can reduce dirty and raise green exports of developing countries
Hassan & Rousselière (2022)	System GMM (two-step)	Environmental innovation	EPS	27 OECD, 1990-2015	EPS accelerates environmental innovation
Kim & Lin (2022)	Dynamic panel GMM + quantile	EPS (as DV)	Trade openness	Panel, 1990-2015	Trade with South raises EPS, trade with North eases it
Hassan et al. (2024)	System GMM, FOD-GMM	RE consumption	EPS	32 OECD, 1990-2019	EPS raises renewable energy consumption
Alper et al. (2026)	Panel cointegration, causality	Fossil energy trade	EPS	27 OECD, 1994-2020	EPS reduces fossil-energy trade
Panel C: Three-dimensional panel applications					
Harris et al. (2002)	3W-FE	Bilateral trade flows	Env. regulation stringency	OECD, 1990-1996	Stringency effect becomes insignificant once exporter and importer effects enter
Costantini & Mazzanti (2012)	3W-SysGMM	Exports, incl. green goods	Energy and env. taxes, env. patents	14 EU exporters, 145 importers, 1996-2007	Energy and env. taxes raise high-tech and green exports
Aichele & Felbermayr (2015)	3W-FE	Embodied carbon in imports	Kyoto targets	40 countries, 12 sectors, 1995-2007	Kyoto raised embodied-carbon imports by about 8%
Larch et al. (2019)	3W-PPML	Bilateral trade flows	Currency unions, Euro	200+ countries, 65 years	Currency union and Euro effects small and insignificant
Kapetanios et al. (2021)	3D-CCE	Bilateral exports	EMU, CEE status	15 and 19 EU+ countries, 1970-2013	FE overstates the EMU and CEE effects relative to 3D-CCE

Weidner & Zylkin (2021)	3W-PPML, bias correction	Bilateral trade flows	FTA	169 countries, 1995-2015	Three-way PPML point estimates stay consistent, fixed T, but inference is biased
Yang & Zhang (2023)	3D-GMM	Exports	Currency unions, lagged trade	210 countries, 1948-2013	Moment conditions free of all three effects; EMU effects mostly insignificant
Jin et al. (2025)	3D-IFE	Bilateral trade	Lagged trade	28 countries, 641 pairs, 1956-2006	Mean persistence 0.36 (SD 0.24)
Kwon et al. (2026)	G-PPML	Bilateral trade flows by sector	Gravity covariates	105 manufacturing sectors, 2010-2019	Estimated variance exponents below 2 (0.52 to 1.67); standard errors about 20% lower than PPML
Sulaj (2026)	3W-PPML	Exports	EPS gaps	32 countries, 56 industries, 2000-2014	Market-based EPS gaps reduce intermediate exports in polluting industries

Notes: DV = dependent variable, IV(s) = independent variable(s), FOD-GMM = forward orthogonal deviations GMM, PTA(s) = preferential trade agreement(s), PV = photovoltaic, CJK = China, Japan, Korea, ASEAN = Association of Southeast Asian Nations, APEC = Asia-Pacific Economic Cooperation, CEP = clean energy product, HT = Hausman-Taylor, 2SLS = two-stage least squares, PCA = principal component analysis. FTA = free trade agreement, EPS = environmental policy stringency, 3W-FE = three-way (exporter, importer, time) fixed effects, 3W-PPML = three-way Poisson pseudo-maximum likelihood, 3W-SysGMM = three-way system GMM, 3D-CCE = three-dimensional common correlated effects, 3D-IFE = three-dimensional interactive fixed effects, 3D-GMM = three-dimensional GMM with moment conditions free of the effects, G-PPML = generalised PPML with an estimated variance exponent. EMU = European monetary union, CEE = European Community membership, RE = renewable energy, GPR = geopolitical risk.

Table A2. Descriptive statistics.

Variable	Mean	SD	Min	Max
CE trade	7.49	3.01	-6.21	16.06
GDP origin	26.65	1.45	22.20	30.32
GDP dest.	26.63	1.47	22.20	30.32
GDPpc origin	2.98	1.01	-0.50	8.87
GDPpc dest.	2.98	1.01	-0.50	8.87
EPS divergence	0.02	1.34	-4.06	4.06
Distance	8.26	1.15	4.01	9.88

Notes: N = 28,920 pair-year observations from 1,190 pairs and 35 countries over 1995-2020. SD = standard deviation. Trade, GDP, GDP per capita and distance are in natural logarithms. EPS divergence is the signed origin-minus-destination EPS difference and Tables 5 to 7 use its absolute value.

Table A3. Preliminary tests.

Panel A: CSD tests				
	CD	**BP-LM**	**SLM**	**BFK-SLM**
Stat.	14.71***	2,208,732***	1,264.20***	1,240.40***
Panel B: Serial correlation				
		BG/W	**W(1)**	
Stat.		6,553.91***	2,304.60***	
Panel C: Heteroscedasticity				
		BP	**SBP**	
Stat.		731.20***	724.69***	
Panel D: Poolability and unit root				
	F-test	**IPS**	**LLC**	**MW**
Stat.	73.98***	-16.98***	-22.45***	10,657***
Panel E: Unit root tests				
	Variable		**IPS stat.**	**LLC stat.**
	CE trade (DV)		-16.98***	-22.45***
	GDP origin		5.61	-23.89***
	GDP dest.		4.24	-21.63***
	GDPpc origin		3.47	-13.88***
	GDPpc dest.		2.03	-10.59***

EPS divergence	-8.96***	-13.05***

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. CSD = cross-sectional dependence, CD = Pesaran (2021) CD test, BP-LM = Breusch-Pagan LM test, SLM = Pesaran scaled LM test, BFK-SLM = Baltagi-Feng-Kao bias-corrected scaled LM test, BG/W = Breusch-Godfrey/Wooldridge test (panel LM form), W(1) = Wooldridge (2002) test for AR(1) in FE panels, BP = Breusch-Pagan test, SBP = studentised Breusch-Pagan test, IPS = Im-Pesaran-Shin (balanced subset of 772 pairs), LLC = Levin-Lin-Chu, MW = Maddala-Wu (Fisher-type).

Table A4. List of countries included in the sample.

Australia (AUS)	Chile (CHL)	Spain (ESP)	Hungary (HUN)	Italy (ITA)	Netherlands (NLD)	Slovakia (SVK)
Austria (AUT)	China (CHN)	Estonia (EST)	Indonesia (IDN)	Japan (JPN)	New Zealand (NZL)	Slovenia (SVN)
Belgium (BEL)	Czechia (CZE)	Finland (FIN)	Ireland (IRL)	South Korea (KOR)	Poland (POL)	Sweden (SWE)
Brazil (BRA)	Germany (DEU)	United Kingdom (GBR)	Iceland (ISL)	Luxembourg (LUX)	Portugal (PRT)	Turkey (TUR)
Canada (CAN)	Denmark (DNK)	Greece (GRC)	Israel (ISR)	Mexico (MEX)	Russia (RUS)	South Africa (ZAF)

Notes: ISO3 codes in parentheses, each country appears as both an origin and a destination in the pair-year panel, giving 35 x 34 = 1,190 directed pairs. The variable is constructed from BACI HS92 bilateral trade values (Gaulier & Zignago, 2010) for six clean energy product codes: 8501 (electric motors and generators), 8502 (electric generating sets and rotary converters), 8503 (parts for machines of heading 8501/8502), 8504 (electrical transformers, static converters and inductors), 8541 (diodes, transistors and semiconductor devices, including photovoltaic cells) and 8544 (insulated wire and cable). Pairs with zero recorded trade in every sample year are excluded.

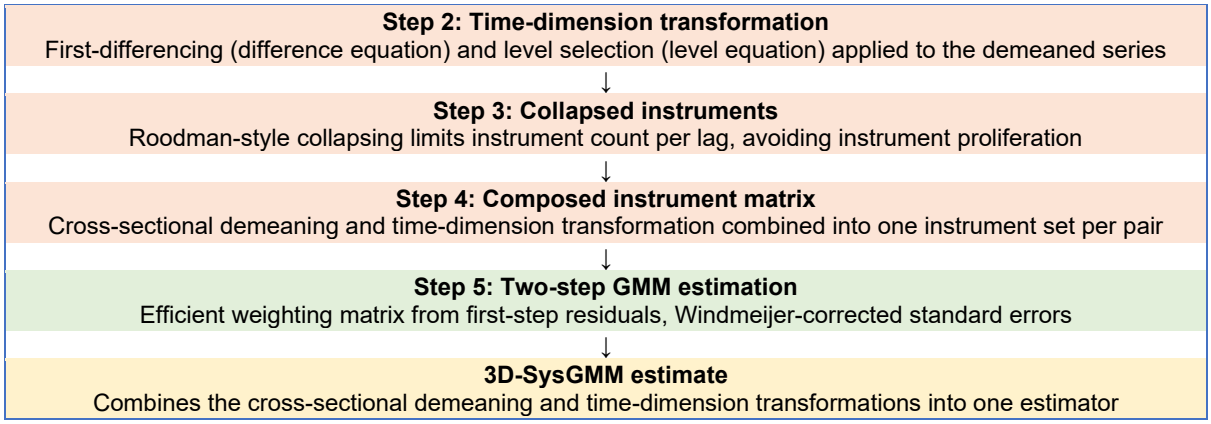
Table A5. Analytical flow.

Data BACI HS92 bilateral trade, 35 countries, 1995-2020, six clean energy product codes
↓
Preliminary panel diagnostics Cross-sectional dependence, serial correlation, heteroscedasticity, poolability, panel unit root
↓
Model specification Three-dimensional dynamic panel: pair, origin-time, destination-time fixed effects (model above)
↓
Static and dynamic estimators PPML (two-way, three-way), FE, System GMM, Difference GMM, corrected 3D-SysGMM
↓
Robustness and sensitivity Time period, income-pair heterogeneity, leave-one-out, clustering, product composition
↓
Discussion Interpretation against the multi-way panel methods literature and policy implications
↓
Conclusion

Notes: BACI = Base pour l'Analyse du Commerce International, HS92 = Harmonized System 1992, PPML = Poisson pseudo-maximum likelihood, FE = fixed effects, GMM = generalised method of moments, 3D-SysGMM = three-dimensional system GMM.

Table A6. Construction of the 3D-SysGMM estimator.

Raw dyadic panel y_{ijt} observed for origin i, destination j, time t, with pair, origin-time, destination-time effects
↓
Step 1: Cross-sectional demeaning Within-period demeaning removes origin-time and destination-time heterogeneity, leaving the pair effect (model above)
↓



Notes: GMM = generalised method of moments, 3D-SysGMM = three-dimensional system GMM.

Supplementary Files

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