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Material Heterogeneity and Waste-Trade Networks in EU-27 Circular-Economy Convergence

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ABSTRACT

EU monitoring summarizes circular-economy progress with aggregate indicators, although material-specific adjustment and cross-border secondary-resource links may follow different paths. This study examines convergence across the EU-27, heterogeneity among biomass, metal ores, non-metallic minerals, and fossil-energy materials, and network-conditional spatial associations. We assemble country-year and material-country-year panels for 2010–2024 (405 and 1620 observations) from Eurostat, bilateral waste-trade data, strategy-adoption dates, and socioeconomic controls. Sigma, cross-sectional and panel beta, and Phillips–Sul tests characterize convergence; two-way fixed-effects SAR, SEM, and SDM specifications use a fixed 2010–2012 total-waste matrix, and a Eurostat Comext mineral-recyclables matrix supports the MF3 analysis. Cross-sectional beta convergence in DMC per capita is detected for metal ores ($\beta = -0.0181$, $p = 0.037$; implied speed 2.08% per year) and fossil-energy materials ($\beta = -0.0206$, $p < 0.001$; 2.44%), but not for biomass or non-metallic minerals. Under the total-waste matrix, aggregate SDM outcome dependence is small ($\rho = 0.084$, $p = 0.368$), while the spatial lag of renewable-energy share is negative (-0.0673 , $p < 0.001$). For MF3, BIC selects SAR ($\rho = 0.352$, $p < 0.001$), while an SDM is retained as an incremental-fit sensitivity. Aggregate SDiD is not treated as causal because only three donors are available and the placebo p -value is 0.33; the treated-count-weighted pre-period slope is -0.0034 ($p = 0.308$). Material-level CR2 estimates show a conditional post-adoption association concentrated in MF3 (-0.1007 , $p = 0.020$). The findings support material-specific and network-aware monitoring and identify small-sample, network-selection, and policy-identification constraints.

JEL Classification: Q56, Q58, F18, R11, C23

1 | Introduction

The circular economy has become a central issue in EU resource security, climate governance, and industrial transformation (Blackburn et al. 2026; Ferrante et al. 2025). Since the first Circular Economy Action Plan was launched in 2015 (European Commission 2015), the EU has increasingly embedded circularity in environmental action programmes, industrial policy,

and the European Green Deal (Calisto Friant et al. 2021). The circular material use rate (CMUR) has become a key indicator for monitoring the transition from a linear to a circular economy (European Commission 2020; European Environment Agency 2024). Policy narratives often assume that the common market, environmental regulation, and technological diffusion will gradually lead Member States toward more similar circular performance (Arbolino et al. 2024; Claudio-Quiroga and

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Poza 2024). Empirically, however, progress has been slow and highly uneven. In 2024, the CMUR of the EU-27 was about 12.2%, only moderately higher than in 2010 (European Environment Agency 2025; Eurostat 2025). At the same time, cross-country level differences remained large, with order-of-magnitude gaps between leading and lagging countries (Castillo-Díaz et al. 2024).

Existing research provides an important basis for addressing these questions. The circular-economy measurement literature emphasizes that aggregate indicators can summarize broad trends but often hide technological, trade, and policy differences across materials (Linder et al. 2017; Moraga et al. 2019; Saidani et al. 2019). Convergence studies have found that EU resource efficiency and waste management may display multi-speed patterns, but most analyses remain at the aggregate-indicator level (Islam and Afolabi 2025; Marin et al. 2018; Presno et al. 2021). The spatial econometrics literature commonly uses distance matrices to study spillovers in environmental policy and green transition (Anselin 1988; Elhorst 2014; LeSage and Pace 2009), whereas the key media of the circular economy are waste, secondary materials, and cross-border supply chains rather than distance alone. The policy evaluation literature further cautions that, under staggered adoption and heterogeneous treatment effects, conventional two-way fixed effects and simple before-after comparisons can be misleading (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021).

This study addresses these issues within a unified framework. We construct a balanced EU-27 panel for 2010–2024 and compile material-flow accounts for biomass, metal ores, non-metallic minerals, and fossil-energy materials. Spatial proximity is represented by inverse distance, fixed early-period total-waste trade, sectoral similarity, and paper-, metal-, mineral-, and plastic-recyclables trade matrices. The mineral matrix is constructed from Eurostat Comext bilateral flows using the official mineral product basket and mirror reconciliation. Strategy adoption is examined only as supplementary evidence through aggregate SDiD diagnostics, material-level two-way fixed-effects associations, and event-time estimates.

The study makes three contributions. First, it moves EU circular-economy convergence analysis from a single aggregate rate to material-specific transition paths and clubs. Second, it treats spatial structure as an empirical choice by comparing geography with fixed early-period and material-specific trade networks. Third, it separates descriptive convergence, network-conditional spatial association, and supplementary policy evidence. This separation identifies where material and network heterogeneity are empirically important without attributing aggregate convergence to strategy adoption.

2 | Literature Review and Research Positioning

2.1 | Circular Economy Measurement and Convergence

The core idea of the circular economy can be traced to natural resource economics and industrial ecology (Blackburn et al. 2026). It emphasizes reducing dependence on virgin

resources through reduction, reuse, repair, remanufacturing, and recycling (Pearce and Turner 1989). Measurement has accompanied the concept from the beginning. The circular economy can be understood as the degree of closure at the product, firm, sector, or national level, or as a broader process involving resource productivity, waste recovery, recycled-material use, and declining environmental pressure (Linder et al. 2017; Moraga et al. 2019; Saidani et al. 2019). The CMUR used in the EU statistical system is attractive for policy because it directly measures the share of recycled materials in total domestic material use (Eurostat, cei_srm030). It also has limitations: by aggregating different materials into a single total, it cannot distinguish differences in recyclability, transportability, and policy tractability among metals, construction materials, biomass, and fossil energy materials (European Environment Agency 2024).

The convergence literature asks whether countries are moving toward a common steady state. Conventional sigma and beta convergence can identify declining dispersion and faster growth among initially low-level units, but they cannot characterize multi-club structures (Barro 1992; Phillips and Sul 2007). The Phillips–Sul method uses relative transition paths to identify common factors and individual time-varying loadings, making it suitable for testing club convergence (Phillips and Sul 2007, 2009). Studies of EU resource productivity, greenhouse-gas emissions, and waste management have already documented multi-speed Europe patterns, but they usually focus on aggregate indicators (Apergis and Payne 2017; Islam and Afolabi 2025; Lehmann et al. 2023; Marin et al. 2018; Presno et al. 2021). Policy-diffusion research also shows that international mechanisms and domestic institutional conditions jointly affect circular-economy policy adoption (Arbolino et al. 2024). This study extends the literature by applying club-convergence tests to four material flows, thereby identifying how the same country can occupy different positions across materials.

2.2 | Spatial Spillovers and Circular Economy Networks

Spatial econometric models allow outcomes in one country to be associated with outcomes and covariates in connected countries (Anselin 1988; LeSage and Pace 2009). SAR models capture dependence in the outcome, SEM models capture spatially correlated disturbances, and SDM models additionally include spatially lagged covariates (Elhorst 2014). Recent empirical work shows that waste and secondary-material trade forms multilayer and policy-sensitive networks (Poon et al. 2024), while EU studies link recycled-material trade to investment, recovery infrastructure, R&D, and circular-economy performance (Burinskienė et al. 2025; Lukács et al. 2026).

Accordingly, the analysis represents spatial structure through geographic distance, fixed early-period total-waste trade, sectoral similarity, and material-specific recyclable-trade matrices. These matrices correspond to different economic channels. Geographic proximity is most relevant where low value-to-weight ratios and transport costs localize adjustment, especially for construction minerals. Trade-based proximity captures linkages created by cross-border secondary-material markets. Recent EU evidence on recycled-material trade and construction and

excavation recovery supports analysing these channels separately (Burinskienė et al. 2025; Cristóbal et al. 2024).

2.3 | National Circular Economy Strategies as Supplementary Policy Evidence

EU Member States have adopted national circular economy strategies at different times, but adoption is not random (Arbolino et al. 2024; Mazur-Wierzbicka 2021). Early adopters may already have stronger administrative capacity, greener preferences, or more mature recycling markets, while late adopters may have responded formally to EU policy pressure (Arbolino et al. 2024; European Court of Auditors 2023). Simple before-after comparisons or average differences between adopting and non-adopting countries are therefore insufficient for identifying policy effects.

Policy evaluation under staggered adoption must address heterogeneous adoption timing, heterogeneous treatment effects, and donor-pool quality. Conventional *TWFE* may contain “bad comparisons”, whereas group-time average treatment effects, corrected event studies, design-based analysis, and robust DiD estimators provide more appropriate tools for staggered settings (Athey and Imbens 2022; Callaway and Sant’Anna 2021; de Chaisemartin and D’Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). Synthetic difference-in-differences combines unit weights from synthetic control with time weights from difference-in-differences and can partly mitigate deviations from parallel trends (Arkhangelsky et al. 2021; Arkhangelsky and Samkov 2025). At the same time, pre-trend tests and event-study estimates require cautious interpretation (Borusyak et al. 2024; Roth 2022). When the number of never-treated countries is small and their outcome paths are unusual, synthetic counterfactuals can still be distorted (Abadie 2021; Abadie et al. 2010). With only a few never-treated countries, donor composition and donor trajectories become central design constraints. Aggregate policy estimates should therefore be evaluated against donor weights, pre-treatment fit, placebo overlap, and cohort support. The identification and robustness presentation follows recent empirical practice on policy uncertainty and renewable-energy projects (Bettarelli et al. 2026; Cary and Ortez 2026).

3 | Materials and Methods

3.1 | Sample and Main Variables

The sample covers the EU-27 from 2010 to 2024, yielding 405 country-year observations. The core outcome is the circular material use rate, obtained from Eurostat’s *cei_srm030* circular-economy monitoring dataset. The indicator is defined as the share of recycled material input in total domestic material use and captures the extent to which economic activity relies on secondary materials (European Environment Agency 2025).

Material-level data come from Eurostat material flow accounts (*env_ac_mfa*). The analysis focuses on four major material categories: *MF1* biomass, *MF2* metal ores, *MF3* non-metallic minerals, and *MF4* fossil energy materials. For each material, we compile domestic material consumption, domestic

material input, imports, exports, and physical trade balance, and construct *DMC* per capita, material consumption per unit of *GDP*, and import share. The material panel contains 27 countries, 15 years, and four material categories, for a total of 1620 country-year-material observations.

Control variables include GDP per capita, manufacturing value-added share, R&D intensity, renewable-energy share, energy productivity, the share of the population aged 15–64 with ISCED 3–8 attainment, population density, and governance indicators, mainly from Eurostat, the World Bank WGI database, and CEPII GeoDist. The education series is Eurostat *edat_lfse_03* (annual frequency, both sexes, ages 15–64, unit: percent, ISCED 3–8) and therefore measures upper-secondary through tertiary attainment rather than tertiary education alone. The policy variable is the adoption year of a national circular-economy strategy, following the EEA Circularity Metrics Lab classification. Twenty-four countries adopted between 2016 and 2023; Croatia, Hungary, and Slovakia are coded as non-adopters during the sample. Tables A8 and A9 report descriptive statistics for the country-year panel and the material-country-year panel.

3.2 | Waste Trade and Spatial Weight Matrices

Bilateral waste-trade data for total waste, paper, metals, and plastics are taken from UN Comtrade. Reporter exports and partner imports are reconciled using mirror statistics, and each bilateral flow is averaged over the relevant construction window before row standardization. For non-metallic minerals, we additionally use Eurostat Comext DS-045409 and the official *env_wastrdmp* mineral product basket. The downloaded bilateral mineral data cover the EU-27 over 2010–2024; reporter totals were validated against the official Eurostat aggregate series (correlation = 0.999998). The mineral basket is dominated by slags and ashes and is used as a proxy for traded mineral recyclable materials.

Seven spatial matrices are examined. $\mathbf{W}_1$ is inverse great-circle distance. $\mathbf{W}_2$ is total waste trade, with the 2010–2012 average fixed for the baseline and the 2010–2024 average used only for sensitivity analysis. $\mathbf{W}_3$ is cosine similarity in 11-sector value-added shares. $\mathbf{W}_{2,MF1}$, $\mathbf{W}_{2,MF2}$, $\mathbf{W}_{2,MF3}$, and $\mathbf{W}_{2,MF4}$ represent paper, metal, mineral-recyclables, and plastic trade, respectively. $\mathbf{W}_{2,MF3}$ uses 2010–2012 Eurostat Comext flows and the maximum of reported exports and mirror imports; mean-mirror, symmetric, and full-period variants are sensitivity cases. All diagonal entries are zero and all estimable matrices are row-standardized. Table A12 records the construction rule, source, window, directionality, and use of every matrix.

The baseline $\mathbf{W}_2$ and $\mathbf{W}_{2,MF3}$ matrices are fixed from 2010 to 2012, before the 2015 and 2020 EU action plans and most national strategy adoptions. This ordering reduces mechanical feedback from later outcomes into the baseline network definition but does not remove endogenous network formation. Full-period trade matrices, alternative mirror reconciliation, symmetry, distance, lagged covariates, and a strict 2013–2024 outcome sample are reported as sensitivity checks. Spatial coefficients are interpreted as conditional associations within the specified network.

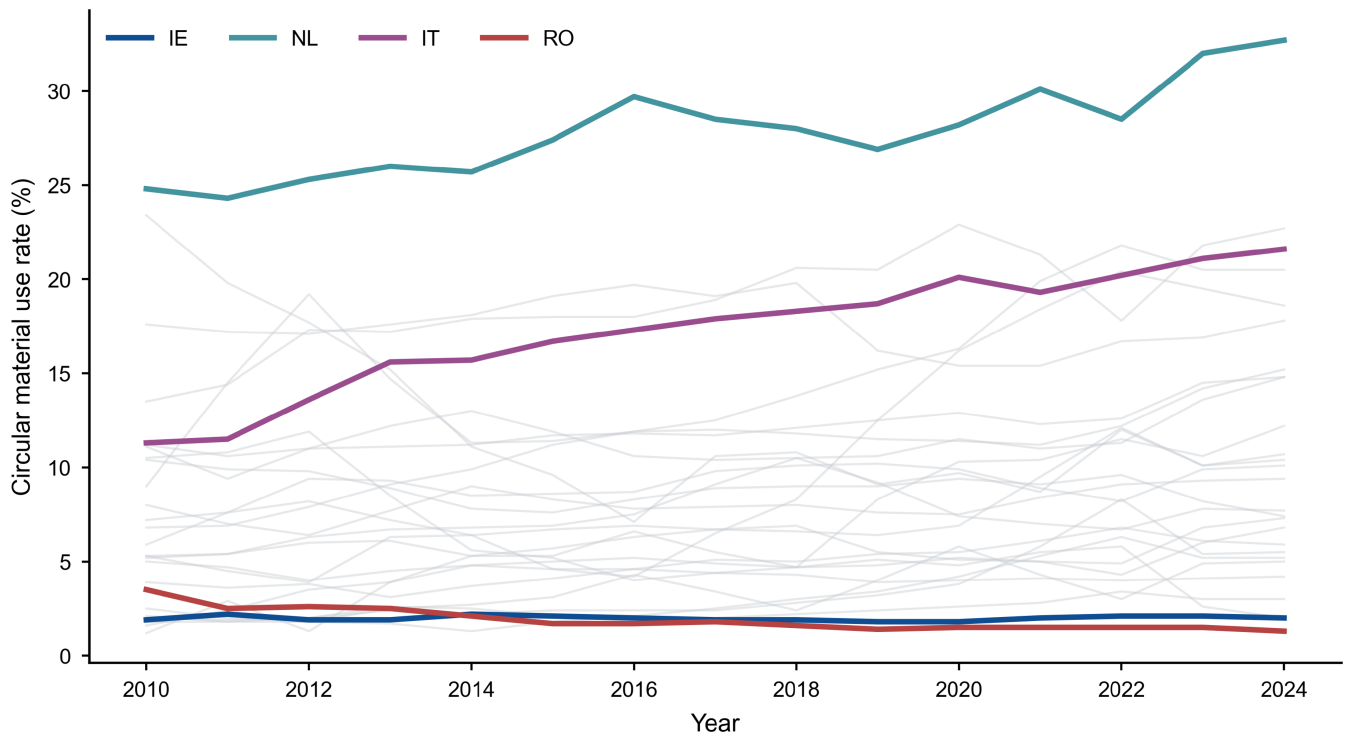


FIGURE 1 | Evolution of CMUR in the EU-27, 2010–2024. The figure shows annual CMUR trajectories for Member States and highlights substantial cross-country heterogeneity in circular-economy progress. Most countries do not rise along a common slope, indicating that subsequent convergence tests must distinguish common trends from country-specific dynamics.

Figure 1 presents EU-27 CMUR trajectories, Figure 2 shows the fixed early-period total-waste matrix, and Figure 3 compares the seven spatial matrices.

3.3 | Empirical Strategy

3.3.1 | Outcome Measurement and Convergence Tests

The empirical design proceeds in four stages: convergence measurement; spatial-model selection; network-timing and specification sensitivity; and supplementary policy diagnostics. Aggregate CMUR is analyzed as $\ln(\text{CMUR})$, which is defined for all 405 observations. Material outcomes are analyzed in logs only when strictly positive. The DMC-per-capita log samples therefore contain 405 observations for MF1 and MF3, 396 for MF2 (nine non-positive observations excluded), and 404 for MF4 (one excluded). Cross-sectional beta tests require positive observations in both 2010 and 2024 and a complete country path, yielding 27, 24, 27, and 26 countries for MF1–MF4. The asinh sensitivity uses $\text{asinh}(y/s_m)$, where s_m is the material-specific median of positive observations, retains all observations, and is interpreted in transformed units rather than as a percentage. No additive offset is used in the logarithmic specifications.

$$\text{CMUR}_{it}(\%) = \frac{U_{it}}{\text{DMC}_{it} + U_{it}} \times 100\% \quad (1)$$

In Equation (1), CMUR_{it} is the circular material use rate of country i in year t ; U_{it} is recycled material input; and DMC_{it} is domestic material consumption. The subscripts i and t index country and year, respectively.

Material consumption per capita is defined as:

$$\text{DMCpc}_{imt} = \frac{\text{DMC}_{imt}}{\text{POP}_{it}} \quad (2)$$

In Equation (2), DMCpc_{imt} is per capita domestic material consumption for country i , material m , and year t ; DMC_{imt} is total domestic material consumption for the corresponding material; POP_{it} is the population of country i in year t ; and m indexes the material category.

First, sigma dispersion, beta convergence, and Phillips–Sul club convergence are used to characterize convergence dynamics. The sigma test is interpreted as a test of whether cross-country dispersion declines over time. It is specified as:

$$\sigma_t = \text{SD}_i(z_{it}), \quad \sigma_t = \alpha_\sigma + \delta_\sigma t + e_t^\sigma \quad (3)$$

In Equation (3), σ_t is the cross-country standard deviation of the transformed outcome z_{it} in year t ; $\text{SD}_i(\cdot)$ denotes the standard deviation across countries; z_{it} is the transformed outcome defined above and therefore Equation (3) does not take a second logarithm of the raw indicator; α_σ is the intercept; δ_σ is the time-trend coefficient; and e_t^σ is the disturbance term in the sigma-dispersion regression. If $\delta_\sigma < 0$, cross-country dispersion declines; if $\delta_\sigma > 0$, dispersion increases.

Unconditional beta convergence relates average growth over the sample period to the initial level:

$$\frac{z_{i,T} - z_{i,0}}{T} = \alpha_{CS} + \beta_{CS} z_{i,0} + e_i^{CS} \quad (4)$$

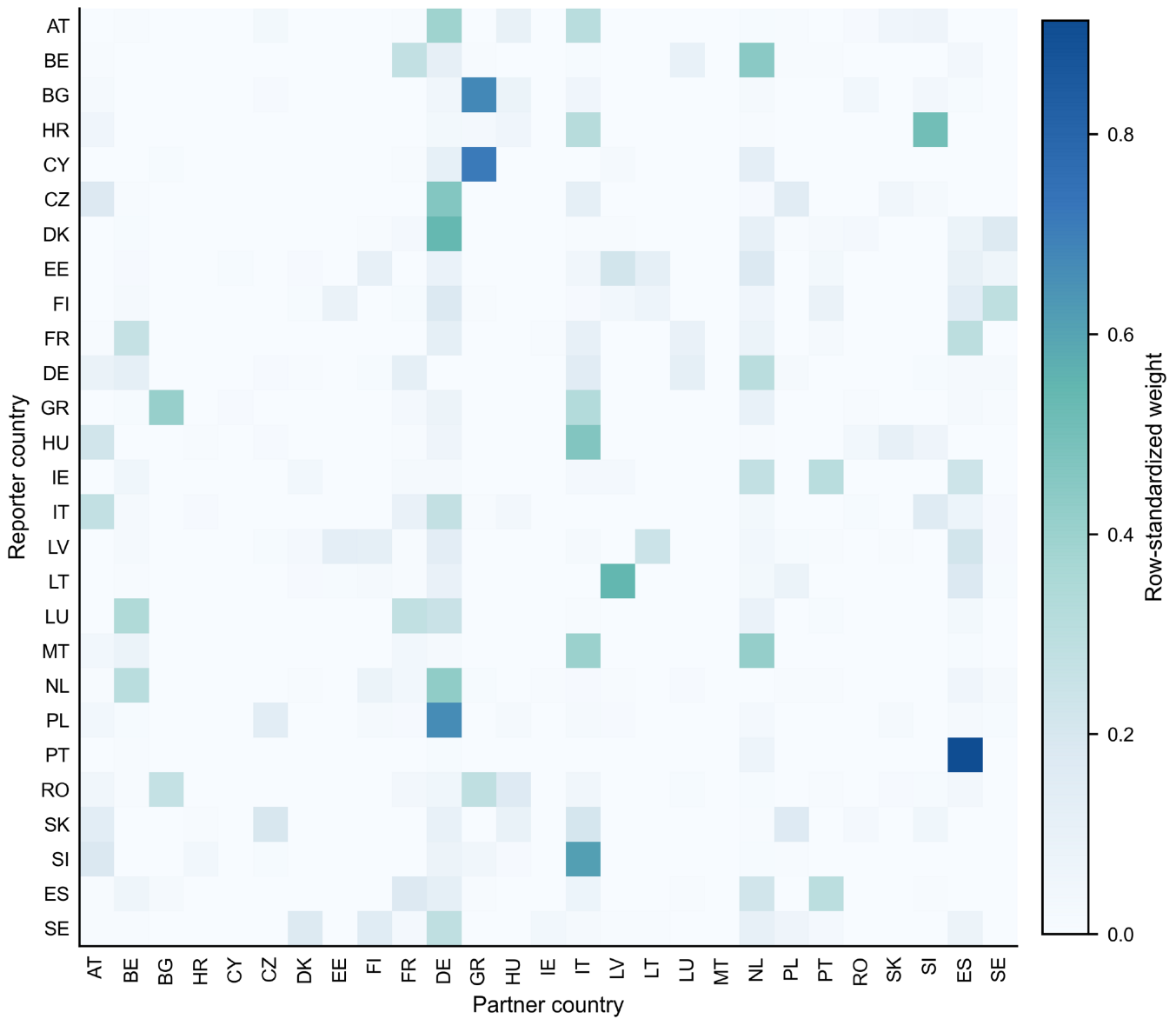


FIGURE 2 | Fixed early-period W_2 bilateral total-waste matrix. Weights average mirror-reconciled flows over 2010–2012; diagonal entries are zero and rows are standardized.

In Equation (4), T denotes 2024, 0 denotes 2010, and $\mathcal{T} = 14$ is the elapsed interval; $z_{i,T}$ and $z_{i,0}$ are the final- and initial-period transformed outcomes; α^{CS} is the intercept; β^{CS} is the unconditional beta coefficient; and e_i^{CS} is the disturbance. A negative β^{CS} indicates faster annualized growth among initially lower-level countries within the complete positive endpoint sample.

The implied annual convergence speed over the 14-year interval is:

$$\lambda^{CS} = -(1/\mathcal{T}) \ln(1 + \beta^{CS}\mathcal{T}) \quad (5)$$

In Equation (5), $\lambda^{CS} = -\ln(1 + 14\beta^{CS})/14$; it is reported only when $1 + 14\beta^{CS} > 0$.

Conditional beta convergence is further estimated using a two-way fixed-effects panel model:

$$\Delta z_{it} = \phi z_{i,t-1} + \mathbf{X}_{it}^T \boldsymbol{\gamma} + \mu_i + \tau_t + e_{it}^{FE} \quad (6)$$

In Equation (6), Δz_{it} is the annual change in the transformed outcome, $z_{i,t-1}$ is its lagged level, $\mathbf{X}_{it}$ is the covariate vector, $\boldsymbol{\gamma}$ is the associated coefficient vector, μ_i and τ_t are country and year fixed effects, and e_{it}^{FE} is the disturbance. The coefficient ϕ measures conditional within-country mean reversion. It differs from the cross-sectional β in Equations (4) and (5), which relates annualized long-run growth to the initial country level.

The Phillips–Sul method tests for a common convergence path and club structure (Phillips and Sul 2007, 2009). Unlike the beta-convergence regressions, it is implemented on positive level indicators or normalized transition indices, denoted q_{it} . For CMUR, q_{it} is the CMUR level; for material indicators, q_{it} is the positive level indicator or an index normalized to the initial year. This avoids negative relative transition parameters generated mechanically by logarithms of variables below one. Let q_{it} be represented as the product of a common factor and an individual time-varying loading:

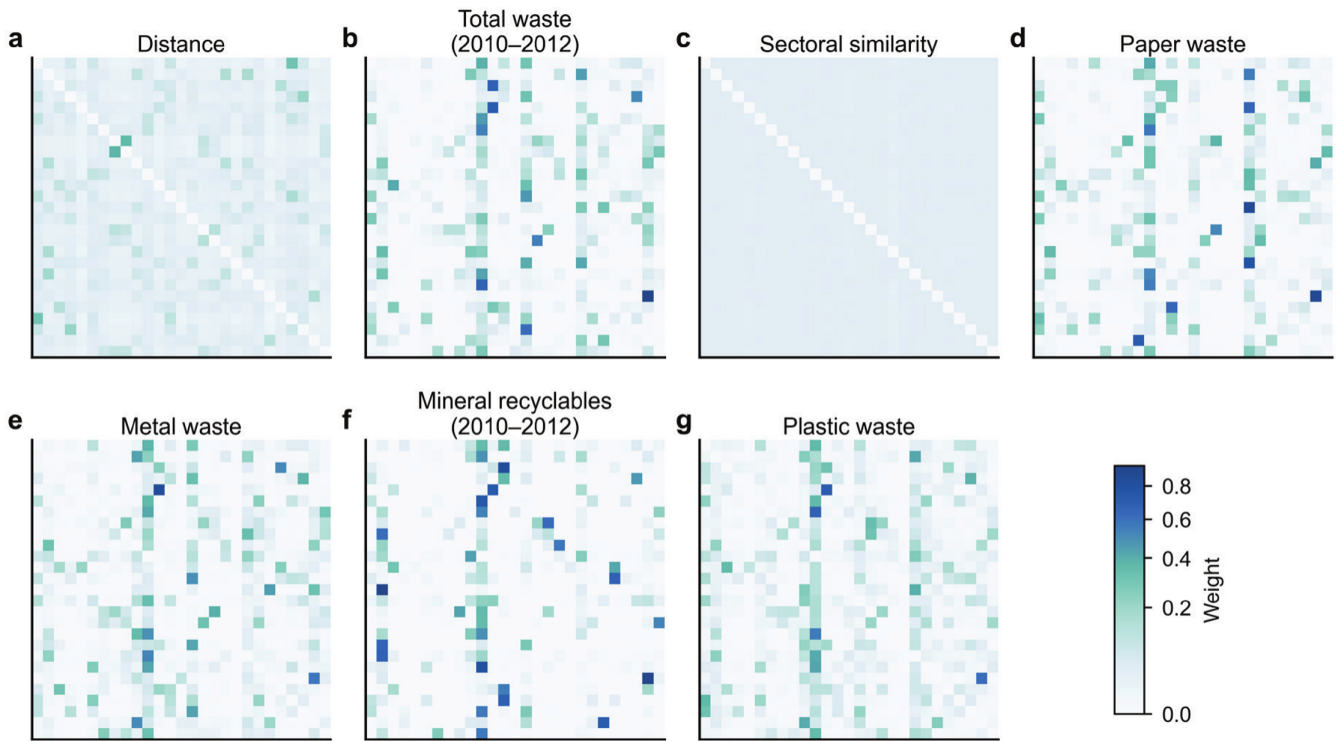


FIGURE 3 | Descriptive comparison of seven spatial matrices. W_3 represents sectoral similarity and is retained for network description. It is excluded from regression estimation because X and WX are nearly collinear; the remaining six matrices yield identified spatial specifications.

$$q_{it} = \delta_{it}\mu_t \quad (7)$$

In Equation (7), q_{it} is the positive level indicator or normalized transition index used in the Phillips–Sul test; μ_t is the common time-varying factor shared by all countries; and δ_{it} is the country-specific time-varying loading that captures how country i deviates from the common factor in year t .

The relative transition parameter is defined as:

$$h_{it} = \frac{q_{it}}{N^{-1} \sum_{j=1}^N q_{jt}} \quad (8)$$

In Equation (8), h_{it} is the relative transition parameter; N is the number of countries; and $N^{-1} \sum_{j=1}^N q_{jt}$ is the cross-sectional average of the positive level indicator or normalized transition index in year t . The summation index is written as j to distinguish the countries being averaged from the focal country i .

Its cross-sectional variance is:

$$H_t = N^{-1} \sum_{i=1}^N (h_{it} - 1)^2 \quad (9)$$

In Equation (9), H_t is the cross-sectional variance of the relative transition parameters in year t ; h_{it} is defined in Equation (8); and N is the number of countries. Here the summation index i ranges over all countries, so that H_t is computed as a within-year cross-sectional variance of the (already country-specific) transition parameters h_{it} .

The log- t regression is:

$$\ln\left(\frac{H_1}{H_t}\right) - 2 \ln L(t) = a + b \ln t + u_t \quad (10)$$

In Equation (10), H_1 and H_t are transition variances; $L(t) = \ln(t+1)$; a is the intercept; b is the convergence parameter; and u_t is the disturbance. The primary Phillips–Sul input is positive DMC per capita over the complete 2010–2024 country path with trim $r/T=0.3$. A one-sided t -statistic below -1.65 rejects single convergence. Club labels are ordered by descending terminal relative-transition level; Club 1 is the highest terminal-level club. Trim 0.2 and 0.4 and post-2015 samples are sensitivity checks. Club memberships are reported as descriptive convergence classifications.

3.3.2 | Spatial-Model Selection and Estimation

Moran's I summarizes late-period cross-sectional association. The panel model ladder estimates TWFE, SAR, SEM, and SDM specifications on a common country-year sample. BIC determines the primary specification, while the SDM–SAR likelihood-ratio test measures the incremental contribution of spatially lagged covariates. BIC selects SDM for aggregate CMUR and SAR for MF3 under the mineral-recyclables matrix. The MF3 SDM is reported as a sensitivity because the WX terms add statistically significant fit. All panel models include country and year fixed effects.

$$w_{ij} = \frac{\tilde{w}_{ij}}{\sum_{j \neq i} \tilde{w}_{ij}}, w_{ii} = 0 \quad (11)$$

In Equation (11), w_{ij} is the row-standardized spatial weight from country i to country j ; $\tilde{w}_{ij}$ is the unstandardized weight defined by inverse distance, bilateral waste-trade weight, or sectoral similarity; and $w_{ii} = 0$ excludes self-links.

Moran's I is defined as:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2}, S_0 = \sum_i \sum_j w_{ij} \quad (12)$$

In Equation (12), I is Moran's I ; N is the number of countries; S_0 is the sum of all spatial weights; w_{ij} is the spatial weight linking countries i and j ; y_i and y_j are the country-level cross-sectional values used as inputs to Moran's I ; and $\bar{y}$ is their cross-country mean. To keep the spatial notation conventional, y_i is used only in Equation (12) to denote the country-level average of the transformed outcome z_{it} over the late-period window 2018–2024. Formally, $y_i = T_S^{-1} \sum_{t \in S} z_{it}$, where $S = \{2018, \dots, 2024\}$ and $T_S = 7$. For aggregate CMUR, $z_{it} = \ln(\text{CMUR}_{it})$. This averaging smooths short-run annual fluctuations while preserving cross-country differences in circular performance. Time-varying shocks such as COVID-19 and the 2022 energy-price episode are not the object of the cross-sectional model. They are better addressed in specifications that retain the annual dimension, such as the panel SDM in Equation (14) and the event-study design in Equation (19), rather than in the averaged cross-sectional setting. The same construction defines the cross-sectional outcome vector Y in Equation (13). The cross-sectional specifications therefore describe average country-level differences over 2018–2024.

The cross-sectional SDM is specified as:

$$Y = \rho WY + X\beta^S + WX\theta^S + e^S \quad (13)$$

In Equation (13), Y is the cross-sectional vector of country-level averages of the transformed outcome z_{it} ; WY is the spatially lagged outcome; X is the matrix of covariates; WX is the matrix of spatially lagged covariates; ρ is the spatial autoregressive coefficient; β^S and θ^S are the direct and spatial-lag coefficient vectors in the cross-sectional model; and e^S is the cross-sectional disturbance vector.

The panel two-way fixed-effects SDM is specified as:

$$z_{it} = \rho \sum_{j \neq i} w_{ij} z_{jt} + X_{it}^T \beta^P + \sum_{j \neq i} w_{ij} X_{jt}^T \theta^P + \mu_i + \tau_t + e_{it}^P \quad (14)$$

In Equation (14), z_{it} is the transformed outcome for country i in year t ; $\sum_{j \neq i} w_{ij} z_{jt}$ is the spatially lagged transformed outcome in the same year t ; X_{it} is the domestic covariate vector; $\sum_{j \neq i} w_{ij} X_{jt}$ is the spatially weighted partner-country covariate vector in year t ; ρ captures spatial dependence in the outcome; β^P and θ^P are the domestic and spatial-spillover coefficient vectors in the panel model; μ_i and τ_t are country and year fixed effects; and e_{it}^P is the panel SDM disturbance. In the baseline specification, W is time-invariant and row-standardized; when a time-varying matrix is used, w_{ij} is replaced by $w_{ij,t}$. In estimation, z , Wz , X , and WX are demeaned by both country and year where applicable, and the spatial likelihood includes the $\ln|I - \rho W|$ Jacobian term.

The baseline W_2 is fixed from 2010 to 2012 while the outcome panel spans 2010–2024. A stricter sensitivity estimates the model on 2013–2024 so that every outcome observation follows the matrix-construction window. The 2010–2024 W_2 is used only as a full-period sensitivity. These timing choices cannot eliminate selection into trade links; ρ and WX coefficients remain network-conditional associations.

To interpret SDM coefficients, we use the LeSage-Pace impact decomposition (LeSage and Pace 2009):

$$\frac{\partial Y}{\partial X_k} = (I_N - \rho W)^{-1} (I_N \beta_k + W \theta_k) \quad (15)$$

In Equation (15), $\partial Y / \partial X_k$ is the impact matrix for covariate k ; I_N is the $N \times N$ identity matrix; W is the row-standardized spatial weight matrix; ρ is the spatial autoregressive coefficient; and β_k and θ_k are the domestic and spatial-lag coefficients. The mean diagonal element is the direct effect, the mean row sum of off-diagonal elements is the indirect effect, and their sum is the total effect.

3.3.3 | Network Timing and Sensitivity Analysis

Third, a backward-looking three-year rolling trade matrix describes how the observed network changes over time. The matrix for year t uses flows from $t-2$ through t , with the available preceding years used at the start of the sample. Frobenius distance from the 2010 matrix is reported as a descriptive measure of structural drift:

$$D_t = \|W_t - W_{2010}\|_F \quad (16)$$

In Equation (16), D_t is the Frobenius distance between the backward-looking matrix W_t and the 2010 benchmark. It is used only to document network change.

3.3.4 | Supplementary Policy Design and Diagnostics

Fourth, staggered-adoption SDiD and material event-time models provide supplementary evidence on national strategies. Aggregate SDiD has only three never-treated donors, so donor weights, pre-treatment RMSPE, a treated-count-weighted cohort-averaged pre-period path, and 300 random-adoption-year placebos are evaluated before the pooled ATT is described. Material models use log-positive DMC per capita, country and year fixed effects, and country-clustered CR2 inference with t and F reference distributions based on 26 denominator degrees of freedom. The early group includes 2016–2019 adopters (10 countries) and the late group includes 2020–2023 adopters (14 countries), so the 2019 cohort is not omitted. Event time -1 is the reference; bins are ≤ -5 , -4 , -3 , -2 , 0 , 1 , 2 , 3 , 4 , and ≥ 5 , and the four pre-period coefficients are tested jointly.

$$\hat{\tau}_g^{\text{SDiD}} = \Delta_g^{\text{treated}} - \Delta_g^{\text{donor}} \quad (17)$$

$$\Delta_g^{\text{treated}} = \bar{Y}_{G_g, \text{post}(g)} - \sum_{t < g} \hat{\lambda}_{tg} \bar{Y}_{G_g, t}$$

$$\Delta_g^{\text{donor}} = \sum_{j \in C} \hat{\omega}_{jg} \left[\bar{Y}_{j, \text{post}(g)} - \sum_{i < g} \hat{\lambda}_{ig} Y_{jt} \right]$$

$$\hat{\tau}^{\text{pool}} = \sum_g \pi_g \hat{\tau}_g^{\text{SDiD}}, \pi_g = \frac{N_g T_{\text{post},g}}{\sum_h N_h T_{\text{post},h}}$$

In Equation (17), the cohort estimate is the treated component minus the donor component. G_g is the cohort adopting in year g ; C is the never-treated donor pool; Y_{it} is $\ln(\text{CMUR})$ for country i in year t ; and the cohort mean at date s is the average of Y_{is} over treated countries i in G_g . The quantities λ_{ig} and ω_{jg} denote the estimated cohort-specific pre-treatment time and donor weights. Each set of weights is non-negative and normalized to one. Cohort estimates are pooled with π_g proportional to the number of treated countries N_g multiplied by the cohort-specific number of post-adoption periods $T_{\text{post},g}$. Random-adoption-year placebos and pre-period diagnostics are used to assess the credibility of this aggregate comparison.

At the material level, each material is estimated separately with country and year fixed effects:

$$z_{it}^m = \alpha_m + \kappa_m \text{CE}_{it} + \mu_i^m + \tau_t^m + v_{it}^m \quad (18)$$

In Equation (18), z_{itm} is the transformed outcome for country i , material m , and year t ; CE_{it} indicates that country i has adopted a national circular-economy strategy by year t ; α_m is the material-specific intercept; κ_m is the material-specific post-adoption coefficient; μ_{im} denotes country fixed effects within material m ; τ_{tm} denotes year fixed effects within material m ; and v_{itm} is the disturbance. The four material equations are estimated separately rather than as a stacked interaction regression.

The event-study model is written as:

$$z_{it}^m = \alpha_m + \sum_{k \neq -1} \delta_{mk} \mathbf{1}(t - G_i = k) + \mu_i^m + \tau_t^m + \xi_{it}^m \quad (19)$$

In Equation (19), G_i is the adoption year for country i ; $k = t - G_i$ is event time; $\mathbf{1}(t - G_i = k)$ is an indicator for event-time bin k ; $k = -1$ is the reference period; δ_{mk} is the material-specific event-time coefficient; μ_{im} and τ_{tm} are country and year fixed effects within material m ; and ξ_{itm} is the disturbance. Each material event study is estimated separately. The four pre-treatment coefficients are tested jointly, and country-clustered CR2 intervals account for leverage within the 27 country clusters.

3.3.5 | Implementation and Reproducibility

All analyses were conducted in Python 3.13.1 with NumPy 2.3.4, pandas 2.2.2, SciPy 1.17.0, statsmodels 0.14.6, matplotlib 3.10.8, and linearmodels 7.0. Spatial panel estimates use concentrated Gaussian maximum likelihood after two-way demeaning, an eigenvalue log-determinant, and a bounded scalar optimizer for ρ or λ on $(-0.98, 0.98)$, with $\text{xatol} = 10^{-11}$. Standard errors use a numerical-Hessian asymptotic approximation; no Lee–Yu small-sample correction is applied. LeSage–Pace impacts use 1500 multivariate-normal draws with seed 20,260,824. The

W -label placebo uses 500 simultaneous row/column permutations with seed 20,260,825. The SDiD placebo analysis uses 300 random-adoption-year draws. Material-policy inference uses a custom country-clustered CR2 implementation. The leverage adjustment is applied within each of 27 country clusters; coefficient tests use Student t reference distributions and joint pre-period tests use F reference distributions, both with 26 denominator degrees of freedom.

4 | Results

4.1 | Material Heterogeneity in EU Circular Economy Convergence

4.1.1 | Aggregate Convergence and Material Divergence

Cross-sectional beta results are selective. For DMC per capita, metal ores have $\beta = -0.0181$ ($p = 0.037$), implying 2.08% annual convergence over 2010–2024, and fossil-energy materials have $\beta = -0.0206$ ($p < 0.001$), implying 2.44%. Biomass ($\beta = -0.0007$, $p = 0.880$) and non-metallic minerals ($\beta = -0.0059$, $p = 0.587$) do not show statistically distinguishable cross-sectional convergence. The endpoint-complete samples contain 27, 24, 27, and 26 countries, respectively. Panel-FE mean-reversion coefficients are negative for all four materials, but these within-country associations answer a different question from the endpoint regressions.

Table 1 summarizes the main convergence results. Figure 4 presents sigma convergence across the four material categories; aggregate and additional material-level diagnostics are provided in Appendix Figures A1–A4.

Sigma convergence, however, reveals different directions across materials. Cross-country dispersion in biomass DMC per capita changes insignificantly. Dispersion in metal ores declines, but the statistical evidence is weak. Dispersion in fossil energy materials declines significantly, whereas the *sigma* slope for non-metallic minerals is positive and highly significant. This means that construction-related material consumption across EU Member States has not converged over time but has become more differentiated. Because aggregate CMUR combines multiple materials and recycled inputs, it can easily translate fossil-energy convergence and non-metallic-mineral divergence into a mild aggregate improvement.

4.1.2 | Club Convergence: No Single Path

Phillips–Sul tests reject a single transition path for all primary DMC-per-capita specifications. MF2 is the boundary case: its inference and resulting club structure are more sensitive to the trim choice and to the smaller complete positive sample. The trim-0.3, 2010–2024 DMC-per-capita specification is used as the primary definition; alternative trims and sample periods are reported as sensitivity analyses.

Club membership shows that the same country can occupy very different relative positions across materials. Nordic countries often appear in high-consumption clubs for biomass, metals, and

TABLE 1 | Convergence dynamics by material category and indicator in the EU-27, 2010–2024.

Material	Indicator	σ slope	β cross-section	φ panel FE	Phillips–Sul t
Biomass	DMC per capita	+0.0002	−0.0007	−0.5423***	−15.36
Biomass	Material intensity	−0.0067***	−0.0195***	−0.3391***	−3.42
Biomass	Import dependence	−0.0062***	−0.0141**	−0.3845***	−17.23
Metal ores	DMC per capita	−0.0178	−0.0181**	−0.7223	−32.82
Metal ores	Material intensity	−0.0216**	−0.0193**	−0.7106	−18.18
Metal ores	Import dependence	−0.0051**	−0.0089	−0.0701***	−17.14
Non-metallic minerals	DMC per capita	+0.0059***	−0.0059	−0.3297***	−12.57
Non-metallic minerals	Material intensity	+0.0053***	+0.0058	−0.3987***	−14.16
Non-metallic minerals	Import dependence	−0.0015	−0.0032	−0.3363***	−20.00
Fossil-energy materials	DMC per capita	−0.0098***	−0.0206***	−0.4729***	−3.65
Fossil-energy materials	Material intensity	−0.0129***	−0.0185***	−0.4089***	−2.88
Fossil-energy materials	Import dependence	−0.0135***	−0.0236***	−0.1529***	−5.95

Note: All entries use the analysis sample and the log-positive-only rule. Sigma slopes are trends in the cross-country standard deviation of the logged indicator. Cross-sectional beta uses 2010 and 2024 over a 14-year interval and requires a complete positive path; DMC-per-capita N is 27, 24, 27, and 26 for MF1–MF4. Panel FE includes country and year effects with country-clustered covariance. Phillips–Sul tests use positive levels, trim $r/T = 0.3$, and complete paths; $t < -1.65$ rejects single convergence. *** and ** denote two-sided $p < 0.01$ and 0.05 for sigma and beta estimates.

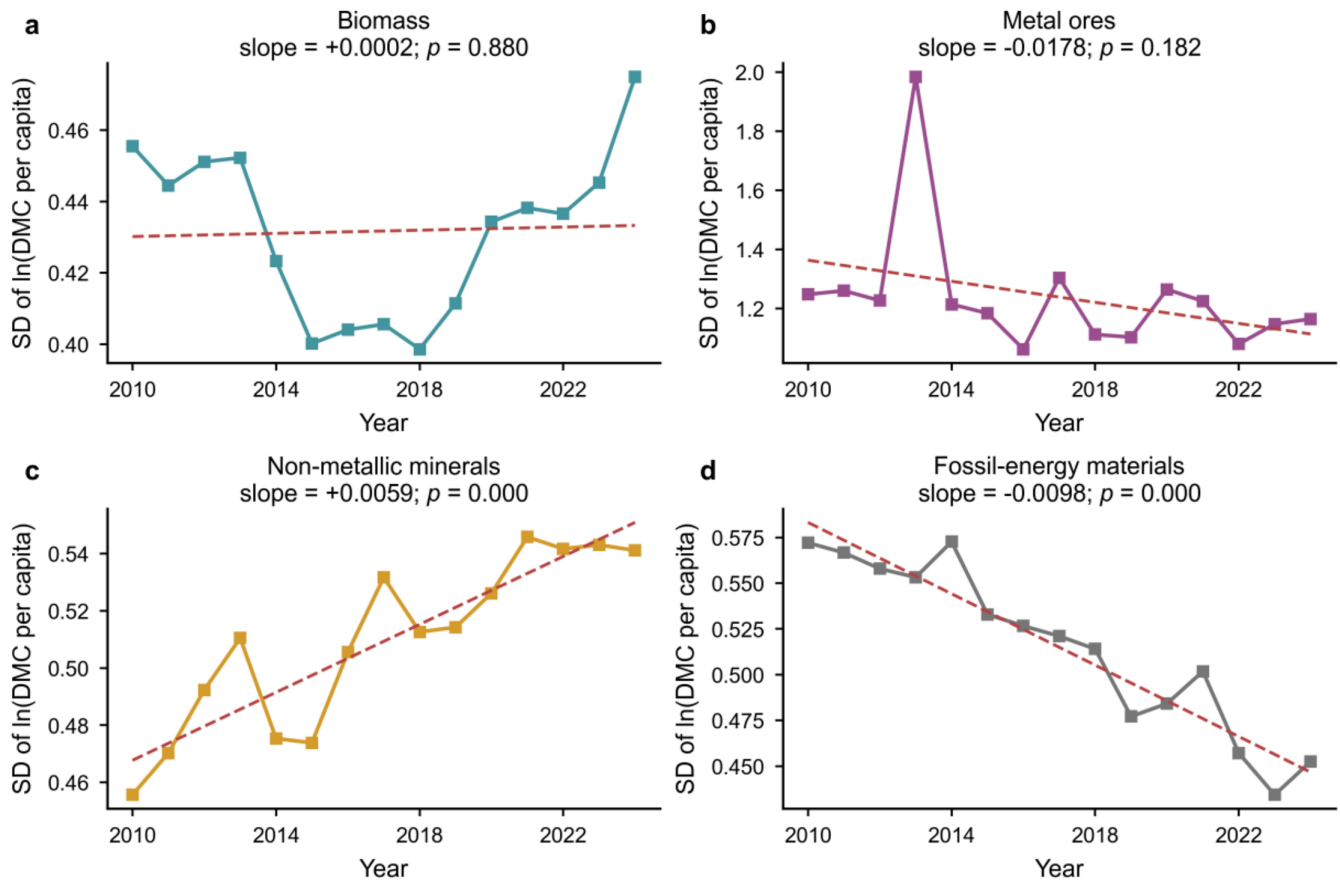


FIGURE 4 | Sigma convergence by material category. The figure compares changes over time in cross-country dispersion of DMC per capita for the four material categories. Fossil energy materials exhibit a clearer decline in dispersion, while non-metallic minerals show an upward trend, providing core evidence for material divergence.

fossil energy materials, but they do not form a unified group for non-metallic minerals. Some Southern and Central-Eastern European countries remain in low-consumption clubs across

several material dimensions. More importantly, the post-2015 sample displays a larger number of clubs: CMUR expands from two to three clubs, biomass from four to five, and non-metallic

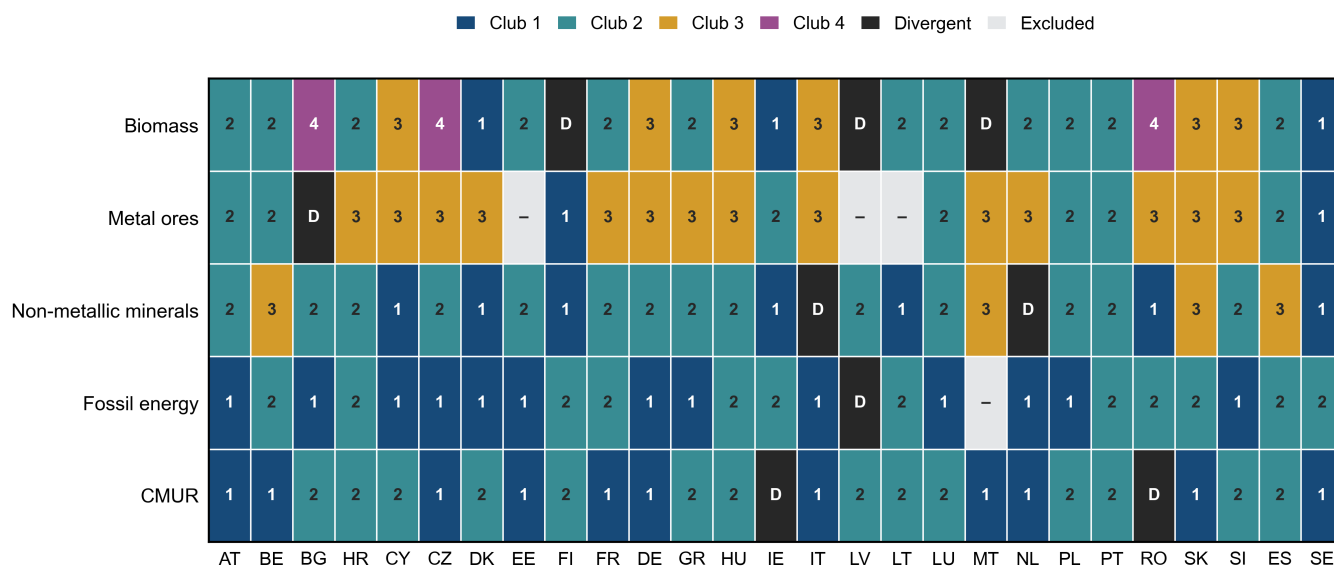


FIGURE 5 | Phillips–Sul club membership for four material-specific DMC per capita indicators and aggregate CMUR over 2010–2024 sample with trim $r/T = 0.3$. Within each indicator, club labels are ordered by descending terminal relative-transition level; Club 1 is the highest terminal-level club. Material DMC classifications use complete positive country paths.

minerals from three to four. This indicates that the EU circular transition is not simply moving toward a common steady state but is becoming more differentiated in the later period.

Figure 5 compresses country-material club membership into a heat map and visually shows that the same country can belong to different clubs across materials. The full country-by-material membership table and Phillips–Sul relative transition paths are reported in Appendix Table A1 and Appendix Figure A5. If policymakers rely only on aggregate CMUR targets, they may incorrectly infer that Member States are merely moving at different speeds along the same transition path. The material-level results indicate that different materials face distinct industrial, technological, and policy constraints, requiring differentiated governance.

4.2 | Spatial Propagation Through Waste-Trade Networks

4.2.1 | Evidence From Moran's I

Late-period Moran's I is 0.310 under the fixed early-period total-waste matrix and 0.333 under the metal-waste matrix, compared with 0.025 under distance. These descriptive results indicate that countries connected through selected secondary-resource networks have more similar CMUR levels. The panel estimates provide a different result: aggregate outcome dependence is negative under distance ($\rho = -0.478$, $p = 0.009$) but small and imprecise under the fixed early-period total-waste matrix ($\rho = 0.084$, $p = 0.368$). The contrast shows that level clustering and within-country outcome dependence are distinct empirical objects.

Figure 6 compares late-period Moran statistics and full-panel outcome dependence across distance and trade matrices. Trade-network Moran statistics are positive, but the

corresponding aggregate panel ρ estimates are generally imprecise. Positive trade-network Moran statistics therefore coexist with generally imprecise panel ρ estimates; subsequent interpretation focuses on the selected model and the spatially lagged covariates.

4.2.2 | Cross-Sectional and Panel Spatial Durbin Models

Cross-sectional models are descriptive late-period-average diagnostics ($N = 27$) and are not used for causal or dynamic inference. The aggregate panel uses 405 country-year observations and the fixed 2010–2012 W_2 . The common-sample ladder compares TWFE, SAR, SEM, and SDM. BIC is lowest for SDM (66.14 vs. 80.83 for TWFE, 85.41 for SAR, and 81.99 for SEM), and SDM also improves on SAR by LR = 43.28 ($p < 0.001$). SDM is retained for aggregate CMUR because it has the lowest BIC and improves on SAR in the LR test. Inference is based on the 27-country panel with asymptotic spatial standard errors. Appendix Tables A2 and A3 provide the underlying cross-sectional diagnostics and panel fit comparisons, while Appendix Figures A6 and A7 visualize the coefficient comparison.

The aggregate spatial autoregressive parameter remains imprecise in the selected SDM ($\rho = 0.0836$, $p = 0.368$). Model improvement therefore comes from partner-country covariates rather than direct CMUR dependence. The domestic coefficients for $\ln(\text{GDP per capita})$, R&D intensity, and renewable-energy share are 0.603 ($p = 0.005$), 0.384 ($p < 0.001$), and 0.0413 ($p < 0.001$), respectively. Spatially lagged manufacturing share is positive (0.186, $p < 0.001$), while spatially lagged renewable-energy share is negative (-0.0673 , $p < 0.001$). These are conditional associations, and Table 2 reports the full coefficient vector.

The LeSage–Pace decomposition distinguishes average direct, indirect, and total associations. R&D intensity has a positive

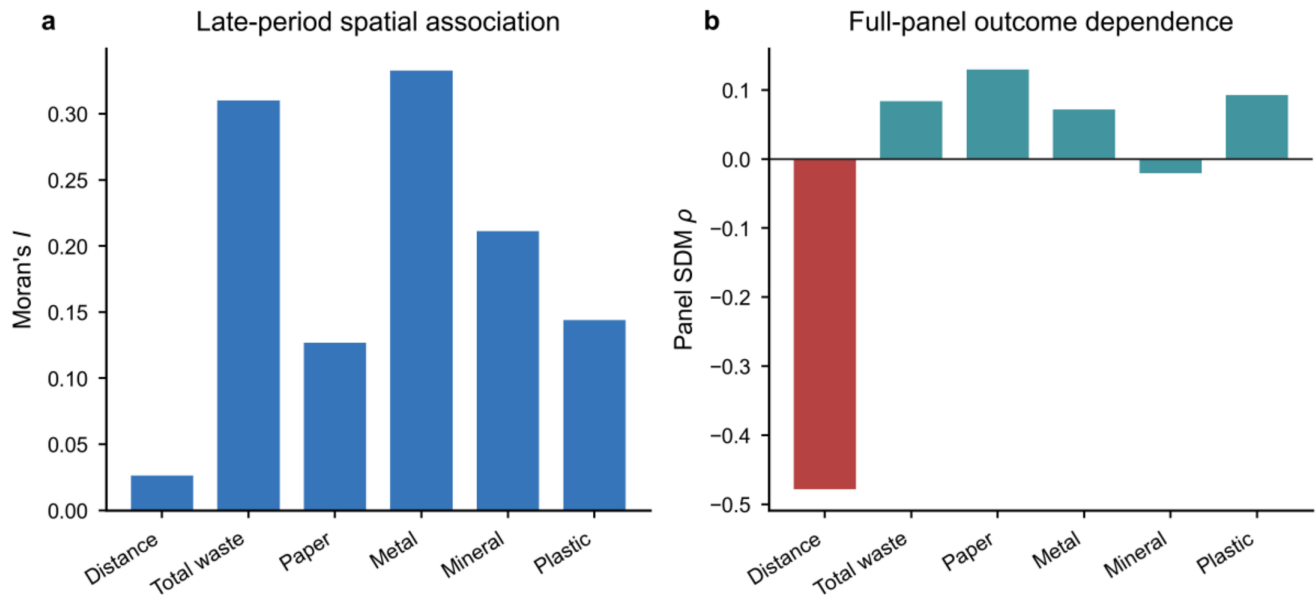


FIGURE 6 | Late-period Moran's I and full-panel SDM outcome dependence across geographic and trade matrices. Red denotes $p < 0.05$ for panel ρ . Positive late-period clustering coexists with generally imprecise full-panel ρ estimates.

TABLE 2 | Aggregate two-way fixed-effects SDM under fixed 2010–2012 W_2 total-waste trade.

Variables	Coefficient	SE
$\ln(\text{GDP per capita})$	+0.6032***	(0.2129)
Manufacturing share	−0.0021	(0.0082)
R&D intensity	+0.3838***	(0.0733)
Renewable share	+0.0413***	(0.0077)
$W \cdot \ln(\text{GDP per capita})$	−0.4144	(0.6396)
$W \cdot \text{Manufacturing share}$	+0.1860***	(0.0395)
$W \cdot \text{R\&D intensity}$	−0.2783	(0.2031)
$W \cdot \text{Renewable share}$	−0.0673***	(0.0163)
$Wy(\rho)$	+0.0836	(0.0929)

Note: Outcome: $\ln(\text{CMUR})$. Sample: EU-27, 2010–2024, $N = 405$. W : fixed 2010–2012 row-standardized bilateral total-waste matrix with zero diagonal. Country and year fixed effects are included. Standard errors are numerical-Hessian asymptotic approximations. Coefficients are network-conditional associations. *** denotes $p < 0.01$.

direct association of 0.381, while its indirect association is imprecise. Renewable-energy share has a positive direct association of 0.0406 and a negative indirect association of −0.0690; its total association is −0.0284 with a 95% simulation interval spanning zero. $\ln(\text{GDP per capita})$ has a positive direct association, but the indirect and total estimates are imprecise. Figure 7 reports estimates with 95% simulation intervals.

Using the 2010–2024 W_2 as a sensitivity produces renewable-energy and W -renewable coefficients of 0.0394 and −0.0653, with $\rho = 0.0884$. More stringently, estimating outcomes only in 2013–2024 under the fixed 2010–2012 matrix yields $\rho = 0.1617$ ($p = 0.098$), renewable-energy share = 0.0325 ($p < 0.001$), and W -renewable share = −0.0464 ($p = 0.0035$; $N = 324$). The signs of the renewable terms persist when every outcome observation follows the matrix window.

4.2.3 | Network Evolution and Full-Sample Robustness

The observed waste-trade network changed over 2010–2024: relative to 2010, the Frobenius distance of the backward-looking matrix reached about 1.15 in 2024 and its off-diagonal correlation with the 2010 matrix declined to about 0.89. These statistics document network restructuring but are not used to define separate estimation samples.

Appendix Figures A8 and A9 describe network drift and early-versus-late heat maps. Network evolution is assessed descriptively, while spatial models are estimated on the full panel.

Under the fixed early-period matrix, SDM remains preferred to SAR by LR and BIC. Lagging all covariates by one and 2 years preserves the positive domestic renewable association (0.0489 and 0.0587) and the negative spatial-lag association (−0.0826 and −0.0892). The lagged-covariate results are consistent with the full-sample network-conditional associations.

4.2.4 | Material-Specific Spatial Dependence

Material-level estimates depend on the network and the selected model. Metal ores have the largest positive SDM outcome dependence under the metal-waste matrix ($\rho = 0.582$, $p < 0.001$), while biomass dependence under paper trade is smaller ($\rho = 0.222$, $p = 0.010$). For MF3, the 2010–2012 mineral-recyclables ladder gives BIC values of −519.60 (TWFE), −560.62 (SAR), −545.87 (SEM), and −548.48 (SDM), so SAR is the primary specification ($\rho = 0.352$, $p < 0.001$). The SDM is retained as a sensitivity because it improves on SAR by LR = 11.87 ($p = 0.018$). Under distance, MF3 SDM dependence is negative ($\rho = -0.448$, $p = 0.018$). Table 3 summarizes the material-specific model comparison, and Appendix Table A11 reports the MF3 model ladder.

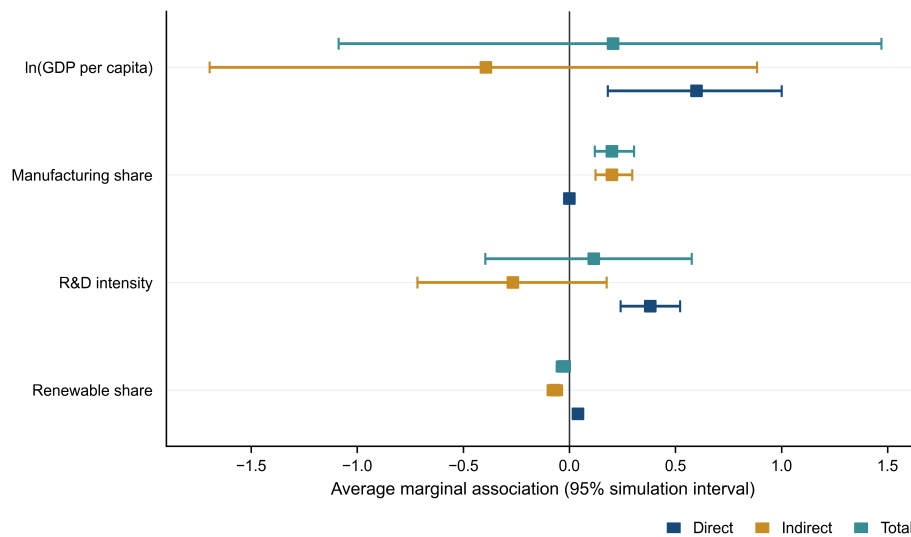


FIGURE 7 | LeSage–Pace direct, indirect, and total associations under fixed 2010–2012 W_2 . Intervals are based on 1500 multivariate-normal draws (seed 20,260,824).

TABLE 3 | Material-specific panel spatial-model comparison.

Material	Weight matrix	$\rho (W \cdot y)$	Log-lik SDM	Log-lik SAR	LR test
Biomass	Paper-specific	+0.222**	394.67	375.44	+38.45***
Biomass	Total trade	+0.154*	389.03	373.35	+31.36***
Metal ores	Metals-specific	+0.582***	−310.29	−388.94	+157.29***
Metal ores	Total trade	+0.630***	−302.18	−384.23	+164.10***
Non-metallic minerals	Mineral recyclables (SAR)	+0.352***	—	298.32	—
Non-metallic minerals	Mineral recyclables (SDM)	+0.271***	304.26	298.32	+11.87**
Non-metallic minerals	Total trade	+0.178**	286.38	281.80	+9.16*
Non-metallic minerals	Distance	−0.448**	292.44	274.82	+35.23***
Fossil energy	Plastics-specific	−0.002	−252.42	−271.55	+38.25***
Fossil energy	Total trade	+0.019	−252.39	−271.55	+38.33***

Note: Outcome: log-positive DMC per capita. MF3 mineral models use the fixed 2010–2012 Eurostat Comext directed matrix and the official analysis panel. BIC is the primary selection rule and favors SAR; LR reports the incremental SDM fit. All models include country and year fixed effects. ***, **, and * denote $p < 0.01$, 0.05, and 0.10.

The MF3 comparison distinguishes two network concepts. Positive dependence under mineral-recyclables trade describes cross-border co-movement in traded slags, ashes, and related secondary materials. Negative dependence under distance is consistent with local construction cycles, low value-to-weight ratios, transport costs, and regional specialization. The mineral-recyclables matrix represents cross-border flows of slags, ashes, and related products; construction-and-demolition flows are only partially captured.

4.3 | Supplementary Policy Evidence

4.3.1 | Aggregate CMUR: Donor Support and Placebo Evidence

The aggregate SDiD donor pool contains only Croatia, Hungary, and Slovakia. Cohort-specific donor weights and pre-treatment RMSPEs are reported in Table A5. A treated-count-weighted cohort-averaged pre-period path has slope -0.0034 ($SE = 0.0032$,

$p = 0.308$) across 13 event times. This test does not reject a linear pre-period slope, but it does not resolve the limited-donor problem. In 300 random-adoption-year placebos, 33% of estimates are at least as negative as the pooled descriptive estimate, and the placebo mean is close to that estimate. Appendix Figures A10 and A11 show the cohort paths and cohort-specific effects.

The cohort-weighted aggregate estimate is approximately -0.175 , but it is reported only as a descriptive sensitivity. Near-universal adoption leaves little untreated support for late cohorts, cohort pre-fit varies (RMSPE 0.033–0.187 in $\ln(\text{CMUR})$), and donor-pool jackknifing has only three units. The pooled coefficient is therefore reported descriptively, with emphasis on cohort-specific fit, donor weights, and placebo overlap.

Donor support is the binding design limitation: the synthetic paths rely on different combinations of HR, HU, and SK, and later cohorts have shorter post-adoption windows. These

diagnostics show that the pooled estimate depends strongly on the three-country donor structure.

4.3.2 | Material-Level Associations Are Concentrated in Non-Metallic Minerals

Material-level estimates use the log-positive samples and country-clustered CR2 inference. The pooled MF3 coefficient is -0.1007 (CR2 SE = 0.0407, $p = 0.020$), corresponding to an approximate 9.58% lower post-adoption outcome conditional on country and year effects. Biomass ($p = 0.721$), metal ores ($p = 0.634$), and fossil-energy materials ($p = 0.475$) are imprecise. The early MF3 coefficient is -0.1570 ($p = 0.012$; 10 countries, 2016–2019), while the late coefficient is -0.0327 ($p = 0.480$; 14 countries, 2020–2023). Table 4 reports the pooled and early- and late-adopter estimates.

Event-time estimates use -1 as the reference and country-clustered CR2 intervals. Joint tests of the four pre-period bins do not reject for MF1 ($p = 0.478$), MF2 ($p = 0.402$), MF3 ($p = 0.208$),

or MF4 ($p = 0.945$), although the MF3 coefficient at event time -2 is individually positive ($p = 0.037$). MF3 coefficients become negative after adoption and are individually distinguishable from zero from event time 1 onward in several bins, but support declines from 24 countries near adoption to 10 countries in the ≥ 5 bin. Taken together, the MF3 event-time pattern is consistent with a post-adoption decline, while the significant -2 lead and declining cohort support indicate that the path also reflects pre-adoption differences and changing sample composition. Figure 8 and Table A10 report estimates and support.

The comparison of material-level post-adoption associations between early and late adopters is reported in Appendix Figure A12.

4.4 | Robustness and Supplementary Diagnostics

Robustness checks distinguish coefficient stability from identification. The aggregate ladder selects SDM; the 2013–2024

TABLE 4 | Material-level post-adoption associations with country-clustered CR2 inference.

Material	Pooled assoc. (log)	CR2 SE	Approx. %	Early 2016–2019	Late 2020–2023
Biomass	-0.0092	0.0256	-0.92%	$+0.0184$	-0.0425
Metal ores	-0.0465	0.0966	-4.54%	-0.0212	-0.0764
Non-metallic minerals	-0.1007^{**}	0.0407	-9.58%	-0.1570^{**}	-0.0327
Fossil-energy materials	-0.0273	0.0377	-2.69%	-0.0558	$+0.0071$

Note: Outcome: $\ln(\text{DMC per capita})$ restricted to positive observations; MF1/MF3 $N = 405$, MF2 $N = 396$, MF4 $N = 404$. The model includes country and year fixed effects. CR2 standard errors are clustered by country and use 26 denominator degrees of freedom. Early adopters are 2016–2019 (10 countries); late adopters are 2020–2023 (14 countries). Percentage values are $100[\exp(b)-1]$. ** denotes $p < 0.05$.

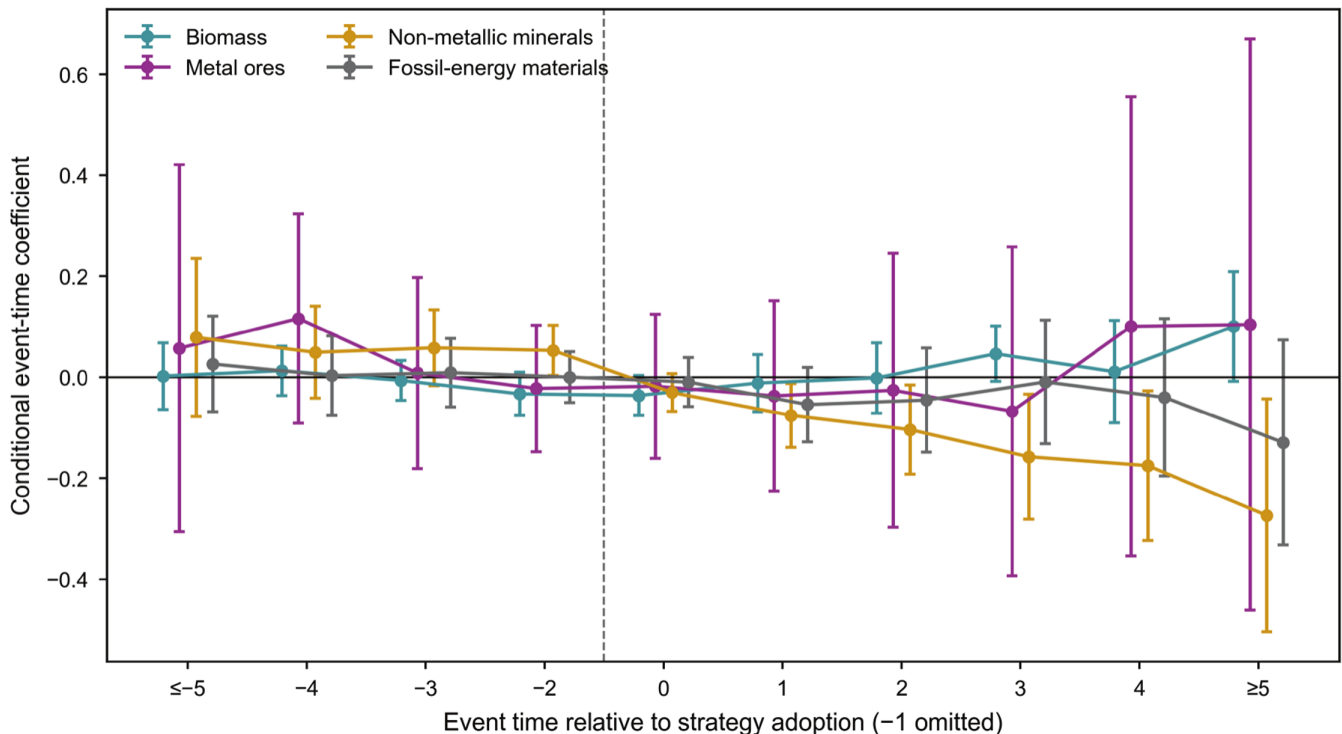


FIGURE 8 | Material-specific event-time associations with country-clustered CR2 95% intervals. Event time -1 is omitted; tails are binned at ≤ -5 and ≥ 5 . Joint pre-period tests and support are reported in Table A10.

TABLE 5 | Summary of robustness checks and supplementary diagnostics.

Test	Quantity	Result	Interpretation
Aggregate ladder	SDM vs. SAR	BIC 66.14 vs. 85.41; LR 43.28, $p < 0.001$	SDM selected
Strict timing	2013–2024 outcomes	$\rho = 0.162$ ($p = 0.098$); $\mathbf{W}$ -renew. = -0.046 ($p = 0.004$)	Signs persist; $N = 324$
Stepwise controls	M4–M6	$\mathbf{W}$ -renew. -0.067 to -0.054 ; all $p \leq 0.0014$	Robust to education controls
Leave one country out	$\mathbf{W}$ -renew.	Range -0.104 to -0.038 ; 27/27 $p < 0.05$	Stable across leave-one-out estimates
$\mathbf{W}$ permutation	$\rho/\mathbf{W}$ -renew.	$p = 0.740/p = 0.092$ (500; seed 20,260,825)	Limited network specificity
MF3 ladder	SAR vs. SDM	BIC -560.62 vs. -548.48 ; LR 11.87, $p = 0.018$	SAR primary; SDM sensitivity
$\mathbf{W}_3$ diagnostic	Sectoral matrix	cond. = 844,651; max $ \text{corr}(X, \mathbf{W}X) = 0.990$; boundary	Excluded because of near-collinearity
SDiD pre-period	Weighted path slope	-0.0034 (SE = 0.0032), $p = 0.308$	Linear slope not rejected
SDiD placebo	300 random-year draws	Baseline ≈ -0.175 ; $p = 0.33$	No support for causal interpretation
Material policy	MF3 pooled	-0.1007 (CR2 SE = 0.0407), $p = 0.020$	Conditional association

Note: Outcome, sample, matrix, transformation, inference, draw count, and seed are stated in the corresponding rows or appendix tables.

strict timing sample preserves the renewable and $\mathbf{W}$ -renewable signs; stepwise controls and leave-one-country-out estimates retain the negative $\mathbf{W}$ -renewable coefficient. The 500-draw label-permutation p -values are 0.740 for ρ and 0.092 for $\mathbf{W}$ -renewable. The permutation evidence limits attribution to the exact observed network. MF3 results follow the BIC/LR rule, $\mathbf{W}_3$ is reported as not estimable, and policy evidence is bounded by CR2 and donor diagnostics. Table 5 summarizes these checks.

Scaled-asinh sensitivity retains all 405 observations per material and remains concentrated in MF3 (coefficient = -0.0739 , CR2 $p = 0.010$); MF2 (-0.0191 , $p = 0.705$) and MF4 (-0.0257 , $p = 0.438$) remain imprecise (Table A13). Across directed max-mirror, mean-mirror, symmetric, and full-period MF3 matrices, BIC selects SAR and ρ remains positive (0.303–0.352; all $p < 0.001$; Table A14).

Layered-control, leave-one-country-out, and $\mathbf{W}$ -permutation results are reported in Appendix Figures A13–A15. $\mathbf{W}$ -renewable remains negative and statistically distinguishable from zero after governance and education controls and in every leave-one-country-out estimate; the permutation distribution provides a more conservative test of network specificity.

The aggregate SDiD results are summarized descriptively because placebo estimates overlap the baseline and the donor pool contains three countries. At the material level, MF3 is the only pooled CR2 coefficient distinguishable from zero; the significant -2 lead and declining support define the interpretation of its event-time pattern.

SDiD pre-trend, random-treatment-year placebo, and Phillips–Sul sensitivity figures are reported in Appendix Figures A16–A18.

4.5 | Temporal-Ordering and Specification Sensitivity

The fixed 2010–2012 $\mathbf{W}_2$ provides early-period ordering, and Table A6 compares lagged covariates, full-period $\mathbf{W}_2$, distance, and the strict 2013–2024 outcome sample. The implications of endogenous network formation are discussed in Section 5.5.

First, all covariates are lagged by 1 and 2 years. The domestic renewable coefficient rises from 0.0413 to 0.0489 and 0.0587, while the spatial-lag coefficient changes from -0.0673 to -0.0826 and -0.0892 . The signs remain stable and both coefficients remain statistically distinguishable from zero.

Second, $\mathbf{W}_2$ is fixed from 2010 to 2012 in the baseline and the 2010–2024 matrix is a sensitivity. The latter produces renewable and $\mathbf{W}$ -renewable coefficients of 0.0394 and -0.0653 , close to the baseline, with small imprecise ρ in both cases.

A stricter temporal-ordering sample excludes 2010–2012 outcomes. Over 2013–2024, $\rho = 0.1617$ ($p = 0.098$), renewable-energy share = 0.0325 ($p < 0.001$), and $\mathbf{W}$ -renewable share = -0.0464 ($p = 0.0035$; $N = 324$).

Third, the distance matrix produces a positive domestic renewable coefficient (0.0381, $p < 0.001$), a negative spatial-lag coefficient (-0.2143 , $p < 0.001$), and negative outcome dependence ($\rho = -0.478$, $p = 0.009$). The different magnitude and ρ sign show that geographic and trade networks encode distinct structures.

Fourth, the Hausman test comparing fixed and random effects gives $H = 7.246$ ($p = 0.124$; Table A7). FE is retained because persistent country characteristics, including geography, institutional history, and industrial structure, are likely to correlate with the explanatory variables (Wooldridge 2010). The Hausman result is reported as a specification diagnostic rather than as the model-selection rule.

Timing and specification checks preserve the signs of the domestic and network-weighted renewable terms. Their interpretation remains network-conditional, with uncertainty arising from the 27-country sample, asymptotic spatial inference, endogenous network formation, and the permutation results.

5 | Discussion

5.1 | Material-Specific Convergence and Aggregate Monitoring

The convergence results show that EU circular-economy adjustment is material-specific. Metal ores and fossil-energy materials exhibit endpoint beta convergence, whereas biomass and

non-metallic minerals do not, and cross-country dispersion in non-metallic-mineral DMC rises. The Phillips–Sul tests add a second layer: most materials follow multiple transition paths, and the same Member State can occupy different clubs across materials. This extends earlier evidence of multi-speed convergence in EU waste management and resource productivity (Islam and Afolabi 2025; Lehmann et al. 2023; Marin et al. 2018). Those studies identify persistent country groups; the present results show that group membership also depends on the physical material being monitored.

Material properties provide a plausible explanation for this pattern. Fossil-energy material use is exposed to common EU decarbonization rules, fuel substitution, and energy-efficiency improvements, which can compress cross-country differences. Metal ores have high unit values and established international markets, so technology diffusion and cross-border sourcing can also support catch-up. Biomass remains tied to land endowments, agricultural and forestry structures, and national bioeconomy profiles. Non-metallic minerals are dominated by construction materials whose demand follows housing, infrastructure, and public-investment cycles. Aggregate CMUR can therefore improve while these underlying material systems move in different directions.

This distinction also affects how convergence should be interpreted. DMC per capita measures material throughput, not circularity itself. A lower value may reflect material efficiency and substitution, but it may also follow a construction slowdown, industrial restructuring, or a shift in embodied material use through trade. The MF3 post-adoption coefficient should therefore be read together with material intensity, import dependence, recycled-content use, and construction activity. This is consistent with the broader indicator literature, which recommends complementary measures rather than a single aggregate circularity metric (Linder et al. 2017; Moraga et al. 2019; Saidani et al. 2019).

5.2 | Waste-Trade Networks and Spatial Transmission

The spatial estimates further show that the definition of proximity changes the empirical picture. Late-period CMUR is more strongly clustered under total- and metal-waste trade matrices than under geographic distance. In the panel models, however, aggregate trade-network ρ is small, while spatially lagged partner characteristics materially improve model fit. This separates two processes: trade-connected countries can occupy similar circularity levels, yet annual adjustment is associated more with the characteristics of connected partners than with direct copying of their CMUR. The result aligns with studies that describe waste trade as a multilayer network shaped by recovery capacity, regulation, and market specialization (Burinskienė et al. 2025; Lukács et al. 2026; Poon et al. 2024).

The positive domestic renewable-energy coefficient and negative network-weighted renewable coefficient point to a possible specialization channel. Domestic renewable deployment may complement recycling through lower-carbon energy, investment capacity, and industrial modernization. A country connected to renewable-intensive partners may instead rely more heavily

on imported secondary materials or external recovery capacity, reducing the correspondence between partner renewable shares and domestic CMUR. The coefficient pattern is also compatible with omitted differences in industrial composition and network position. The W-label permutation distribution overlaps the observed coefficient, so product-level trade, treatment-capacity, and price data are needed to evaluate the specialization explanation directly.

5.3 | Dual Spatial Mechanisms in Non-Metallic Minerals

MF3 provides the clearest evidence that one material can operate through more than one spatial mechanism. Under the dedicated mineral-recyclables matrix, the preferred SAR model yields positive dependence. The matrix is dominated by slags, ashes, and related secondary mineral products that can be shipped to specialized processors or industrial users across borders. Positive ρ therefore reflects co-movement within a traded secondary-material segment. This is consistent with evidence that cross-border waste shipments connect treatment capacity and downstream resource use across the EU (de Lange 2024; European Environment Agency 2021).

The distance matrix produces the opposite sign because bulk non-metallic-mineral DMC is governed mainly by local construction systems. Sand, gravel, stone, concrete, excavated soil, and demolition materials have low value-to-weight ratios. Transport costs limit long-distance movement, while national building cycles, quarry resources, infrastructure programmes, procurement rules, and recycled-aggregate standards determine demand. Neighboring countries may therefore experience asynchronous construction cycles or compete for regional processing capacity, generating negative geographic dependence. Cristóbal et al. (2024) similarly show that the management of excavation and construction waste depends on specific local treatment and reuse pathways.

The positive trade-network coefficient and negative distance coefficient are complementary. The trade matrix captures the smaller, more tradable mineral-recyclables segment; distance captures the localized bulk construction system that dominates MF3 consumption. This distinction supports a material-specific interpretation of the spatial mechanisms. Spatial weights should be selected according to the economic geography of each material, rather than applied as interchangeable technical alternatives.

5.4 | Interpreting National Strategy Adoption

The policy analysis gives a different message from the convergence and network results. Formal national strategy adoption is nearly universal, leaving three never-treated countries and substantial overlap between the observed estimate and random-adoption-year placebos. The aggregate SDiD estimate is therefore informative about design limitations, not about a uniform EU-wide strategy effect. This finding is substantively consistent with research showing that national circular-economy plans differ in legal force, policy content, administrative capacity, and

implementation depth (Calisto Friant et al. 2021; European Court of Auditors 2023; Sanz-Torró et al. 2025). A common adoption indicator compresses these differences into one date.

The material-level results identify MF3 as the main area for instrument-level investigation. Construction materials are strongly affected by domestic public procurement, demolition requirements, landfill and sorting rules, permitting, and recycled-aggregate standards. These instruments are closer to national and subnational regulatory control than globally traded metal ores or fossil-energy inputs. The stronger early-adopter coefficient is compatible with longer implementation periods or pre-existing policy capacity, while the significant event-time -2 coefficient also indicates that part of the MF3 trajectory began before formal adoption. The empirical implication is to replace the binary strategy date with measures of policy content, enforcement, expenditure, and sectoral coverage.

5.5 | Policy Implications, Limitations, and Research Agenda

EU monitoring would be stronger if CMUR were embedded in a material and network dashboard. CMUR remains useful for communicating the share of secondary input, while material-specific DMC, intensity, import dependence, and club membership reveal where adjustment is occurring. A Member State can be a high-level country for one material and a low-level country for another, so a single leader-laggard classification can misdirect support. Club transitions could instead be used to identify material-specific peer groups and to evaluate whether lagging countries are moving toward the relevant frontier.

Policy instruments should also follow the spatial mechanism. For metals and traded mineral recyclables, priorities include harmonized end-of-waste criteria, quality certification, contamination thresholds, digital traceability, and cross-border treatment capacity. For localized construction minerals, priorities include selective demolition, recycled-content procurement, regional sorting infrastructure, and standards that permit safe substitution of primary aggregates. These measures align policy with the distinct frictions revealed by the trade and distance models.

The study also defines a clear empirical agenda. The 27-country panel limits precision in heavily parameterised spatial models, and trade links may co-evolve with circular performance and policy. The mineral basket covers traded recyclables but only part of construction-and-demolition flows. Strategy dates record formal adoption and omit implementation intensity. Future work should combine shipment-level material flows with prices, quality grades, treatment capacity, construction output, recycled-content use, and policy instruments. Dynamic network models could examine how trade links respond to policy and circular performance, while instrument-specific quasi-experiments could test procurement, landfill, sorting, and end-of-waste reforms in settings with stronger untreated or not-yet-treated support.

6 | Conclusions

Using EU-27 data for 2010–2024, this study finds material-specific rather than universal convergence. DMC-per-capita beta

convergence is detected for metal ores and fossil-energy materials, while non-metallic-mineral dispersion increases. Under fixed 2010–2012 total-waste trade, aggregate SDM is selected by BIC and LR, but ρ is small and imprecise; model fit comes mainly from network-weighted partner characteristics. MF3 is best represented by a parsimonious mineral-trade SAR under BIC, with SDM retained as a sensitivity.

National strategy adoption remains supplementary evidence. Aggregate SDiD does not provide a credible causal estimate because donor support is limited and placebo estimates overlap the baseline. The material-level CR2 association is concentrated in MF3, but event-time diagnostics and non-random adoption prevent a causal policy claim.

EU monitoring should combine CMUR with material-specific convergence indicators and network measures. Cross-border standards and secondary-material markets are especially relevant for metals and traded mineral recyclables, while construction procurement, sorting, and recycled-aggregate rules are more relevant for localized non-metallic-mineral use. Better bilateral construction-flow data and policy-intensity measures are the most important next steps for testing these mechanisms more directly.

Author Contributions

Pan Jiang: conceptualization, methodology, writing – original draft. **Shuaiyi Lu:** data curation, formal analysis, writing – review and editing. **Lianghan Cong:** conceptualization, methodology, writing – review and editing, writing – original draft.

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Appendix A: Temporal-Ordering and Specification Sensitivity Analyses

This appendix reports the full-sample sensitivity analyses summarized in Sections 4.4 and 4.5. The baseline uses the 2010–2012 total-waste matrix, $\ln(\text{CMUR})$, four covariates, and country and year fixed effects. SAR, SEM, and SDM comparisons are reported in Tables A4 and A6 focuses on timing and network alternatives.

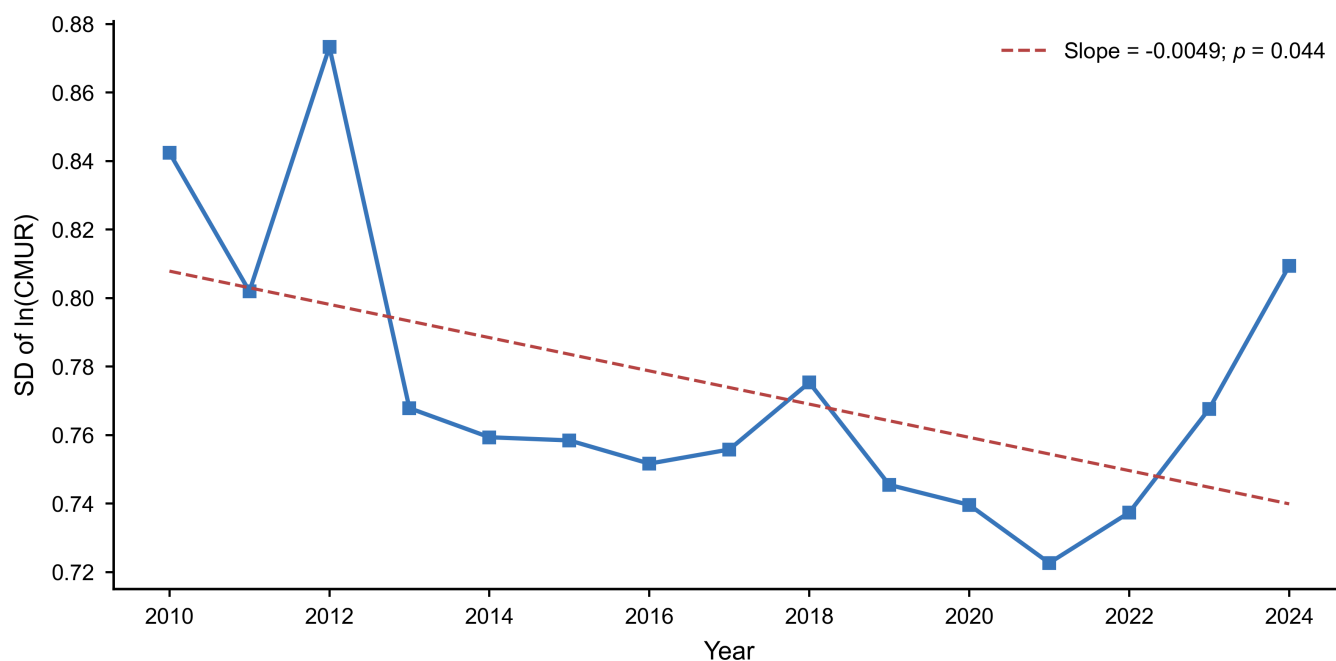


FIGURE A1 | Sigma convergence of aggregate *CMUR*. The figure reports the time trend in cross-country dispersion of aggregate *CMUR*. It provides a benchmark for the material-level results in the main text and shows that mild convergence in the aggregate indicator may conceal differences within materials.

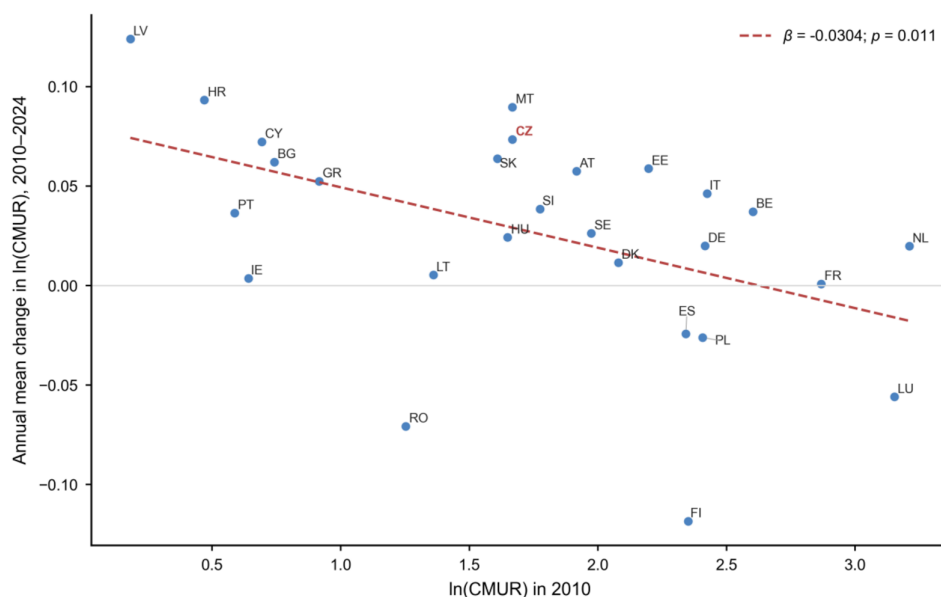


FIGURE A2 | Beta-convergence scatter plot for aggregate *CMUR*. The figure relates initial *CMUR* levels to growth over the sample period, testing whether initially low-level countries grow faster. The scatter plot provides visual evidence for conventional unconditional *beta* convergence.

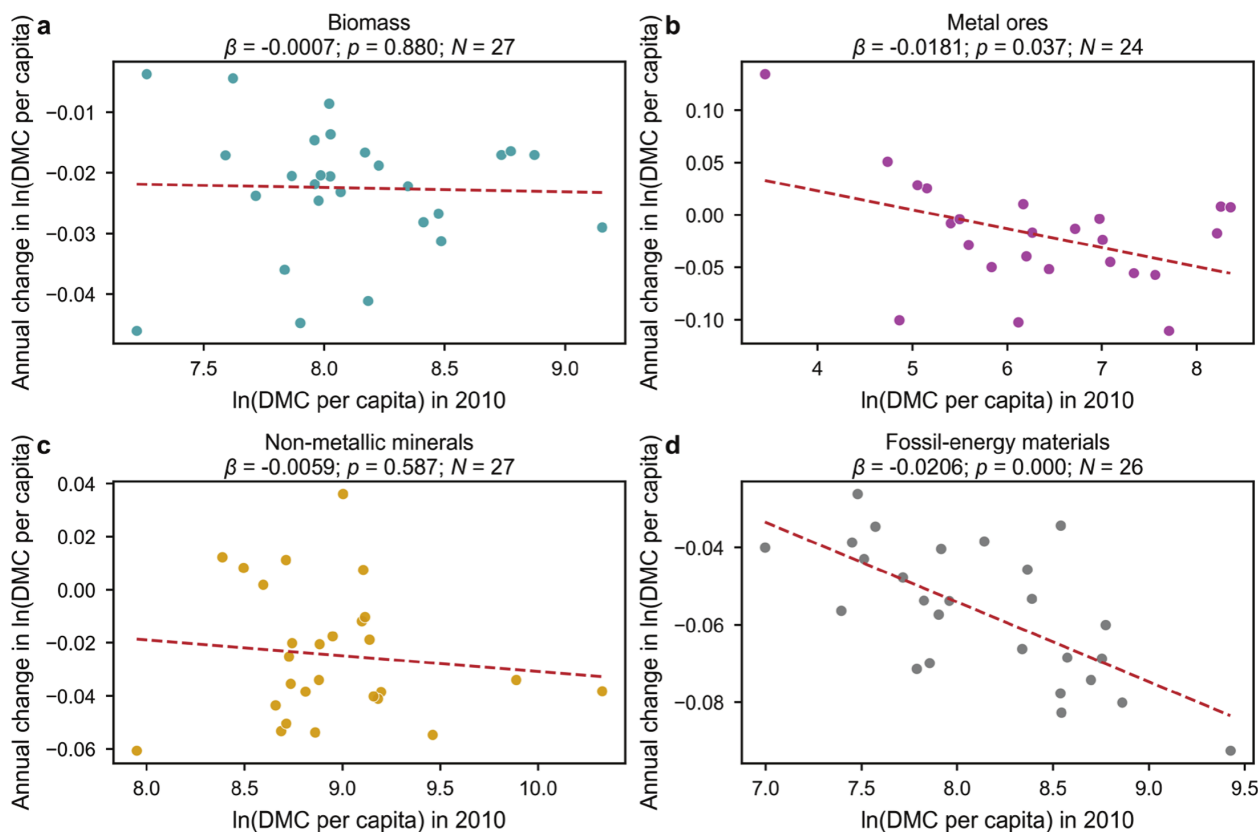


FIGURE A3 | Unconditional beta convergence for DMC per capita, 2010–2024. Each panel uses countries with complete positive paths; slopes, p -values, and N match Table 1.

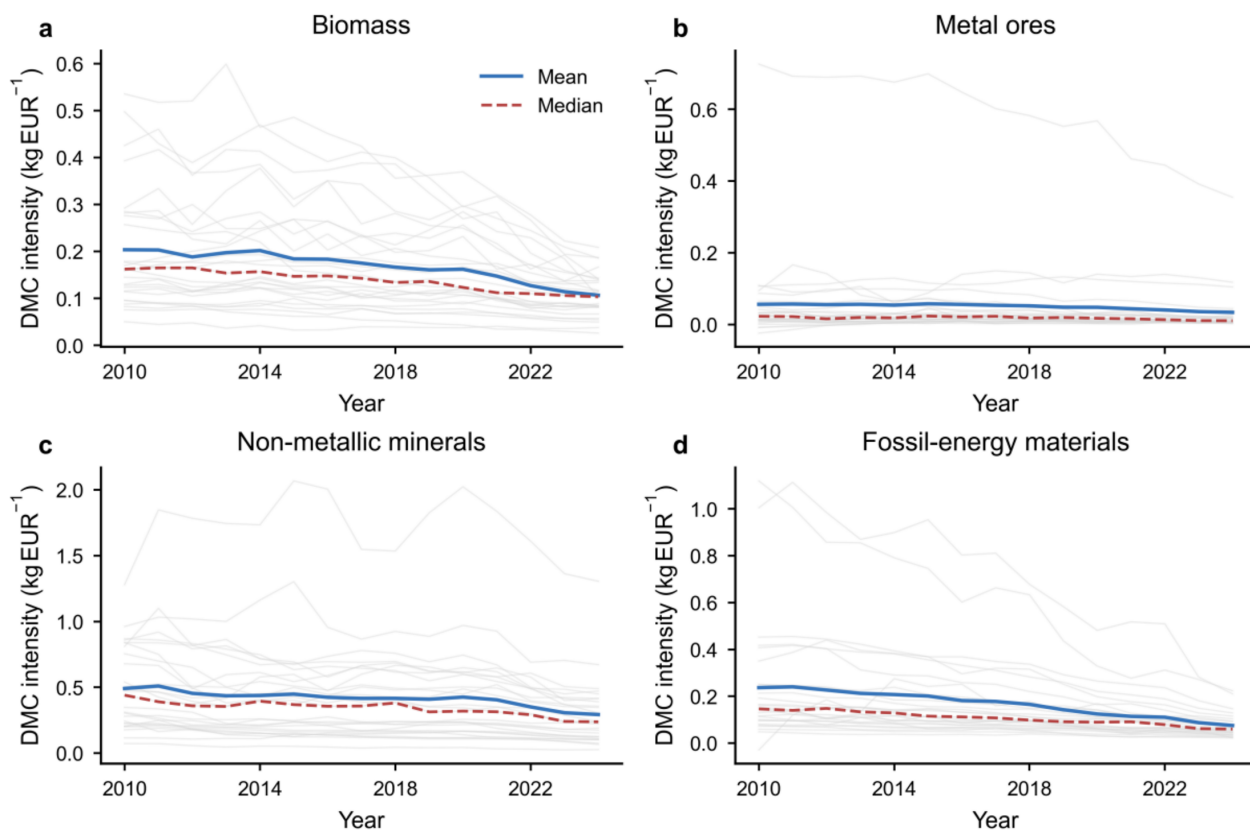


FIGURE A4 | Country trajectories of material intensity for the four material categories. The figure shows how material intensity changes over time across countries. Divergent paths reflect heterogeneous combinations of material consumption, industrial structure, and efficiency improvement.

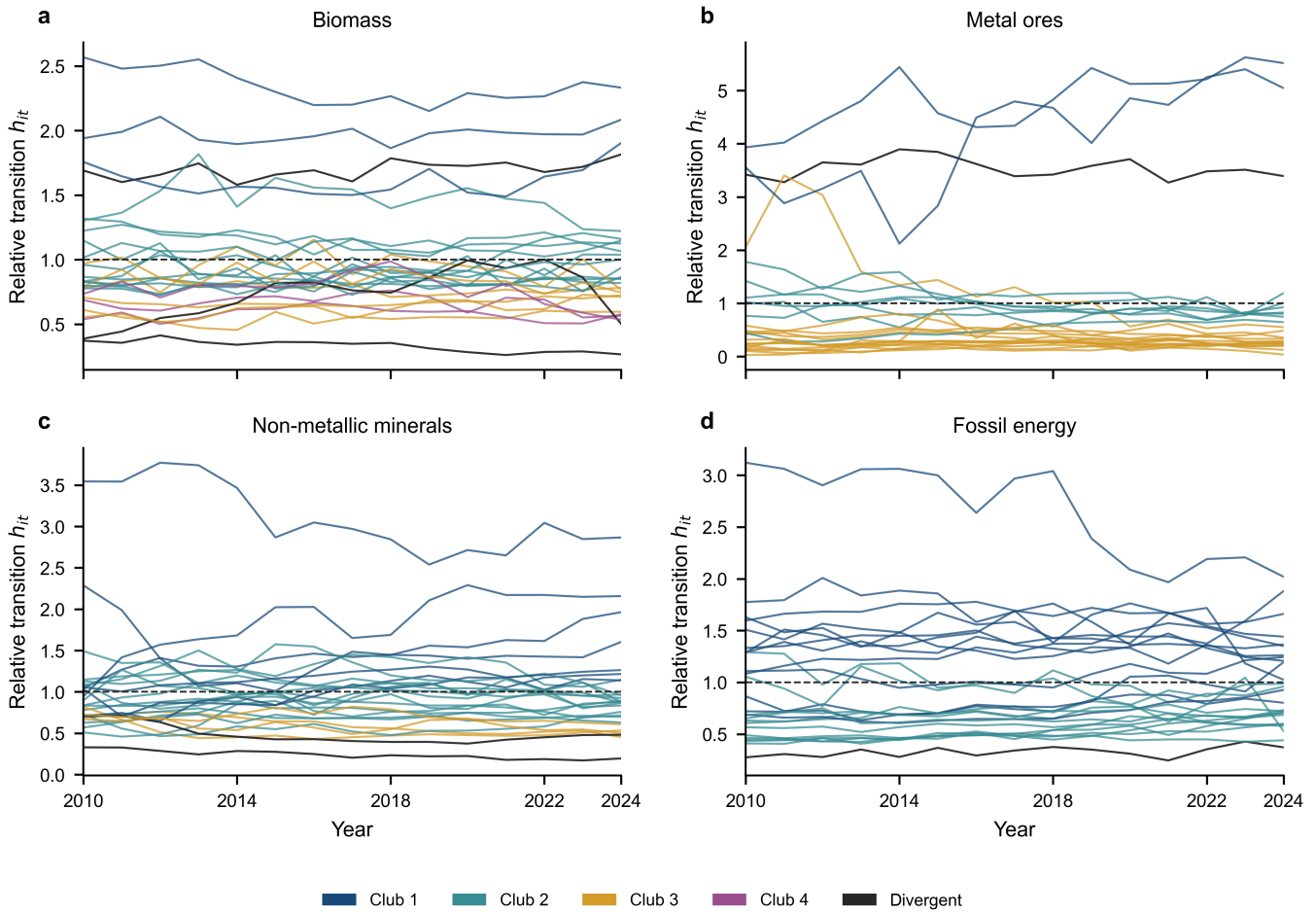


FIGURE A5 | Phillips-Sul relative transition paths for the primary complete-positive 2010–2024 DMC-per-capita sample with trim $r/T = 0.3$. Club labels are ordered by descending terminal transition level.

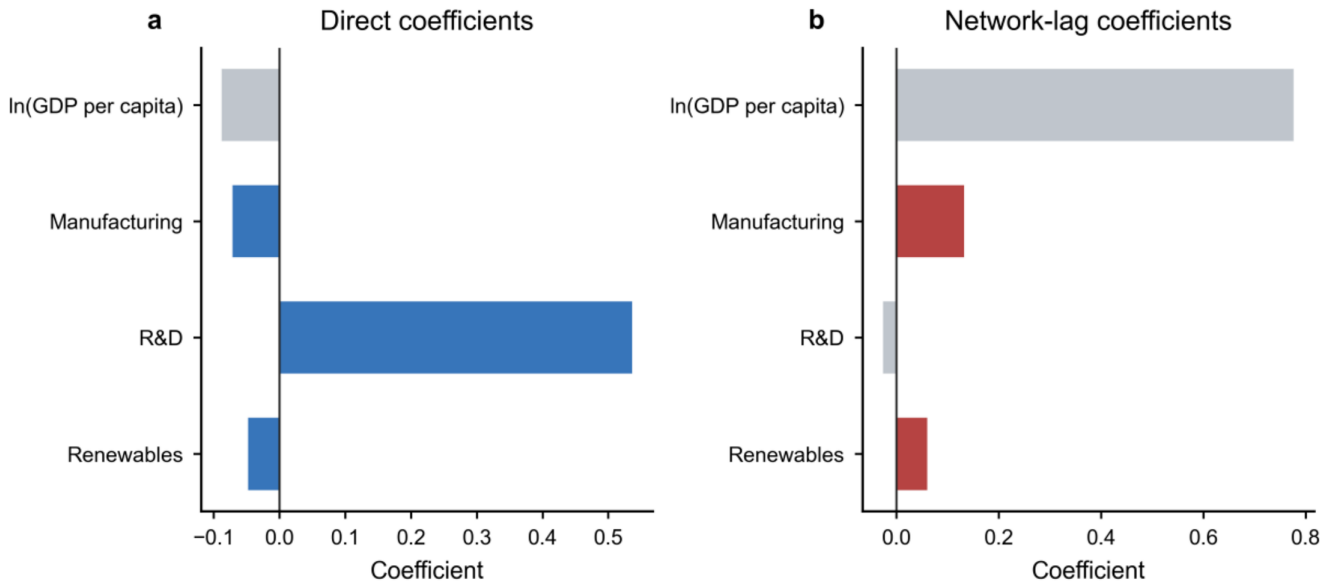


FIGURE A6 | Descriptive cross-sectional SDM coefficients based on late-period averages (2018–2024; $N = 27$). These level differences are not interpreted as dynamic spillovers.

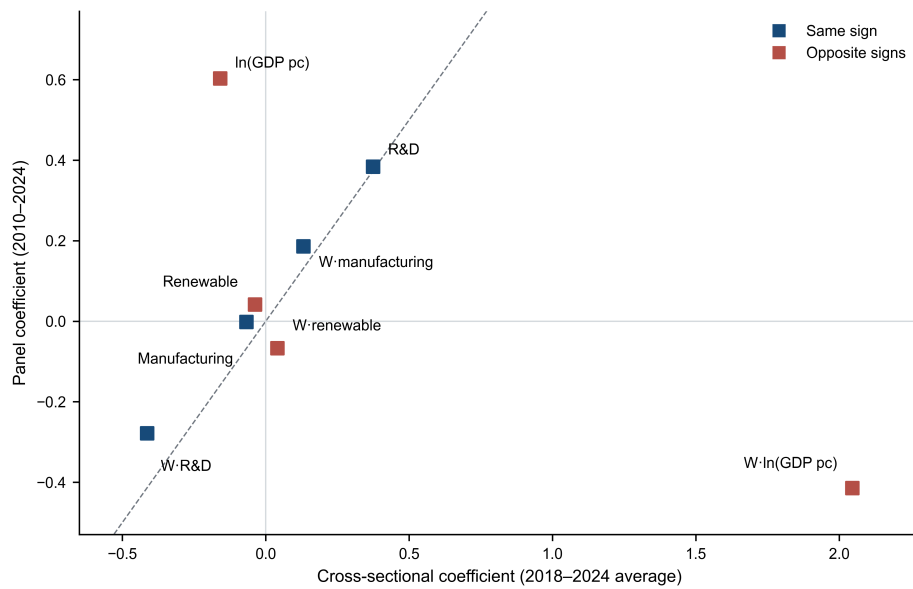


FIGURE A7 | Comparison of cross-sectional and panel *SDM* coefficients. The figure compares estimates based on long-run level differences with those based on within-country changes over time. The directions are not fully consistent, indicating that cross-sectional spatial correlation should not be interpreted directly as dynamic spillovers.

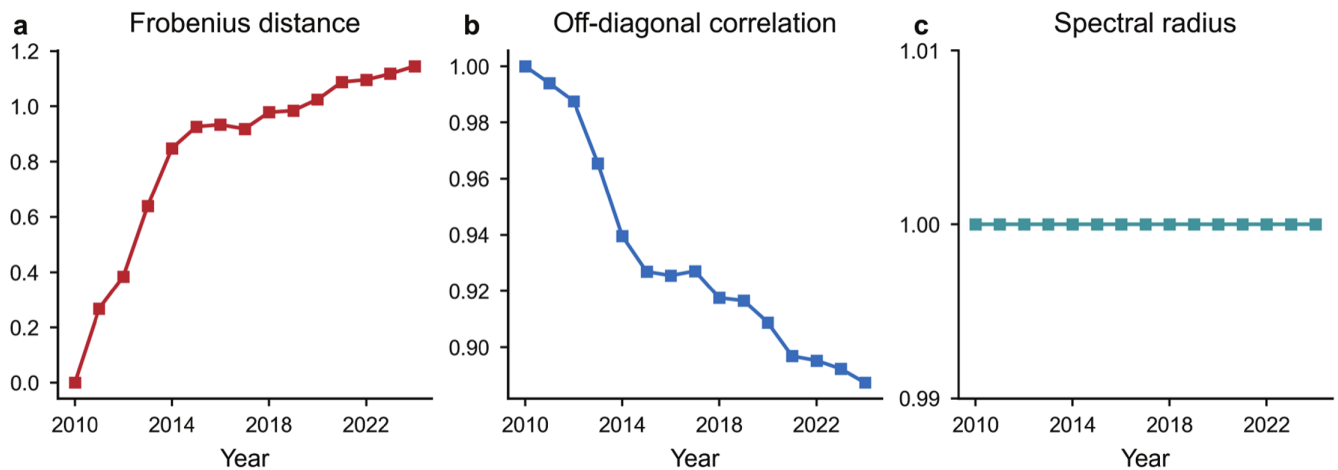


FIGURE A8 | Structural drift in the time-varying waste-trade weight matrix. Using the 2010 matrix as the benchmark, the figure shows the magnitude of network change in subsequent years. The rising Frobenius distance indicates substantial restructuring of EU waste-trade networks during the sample period.

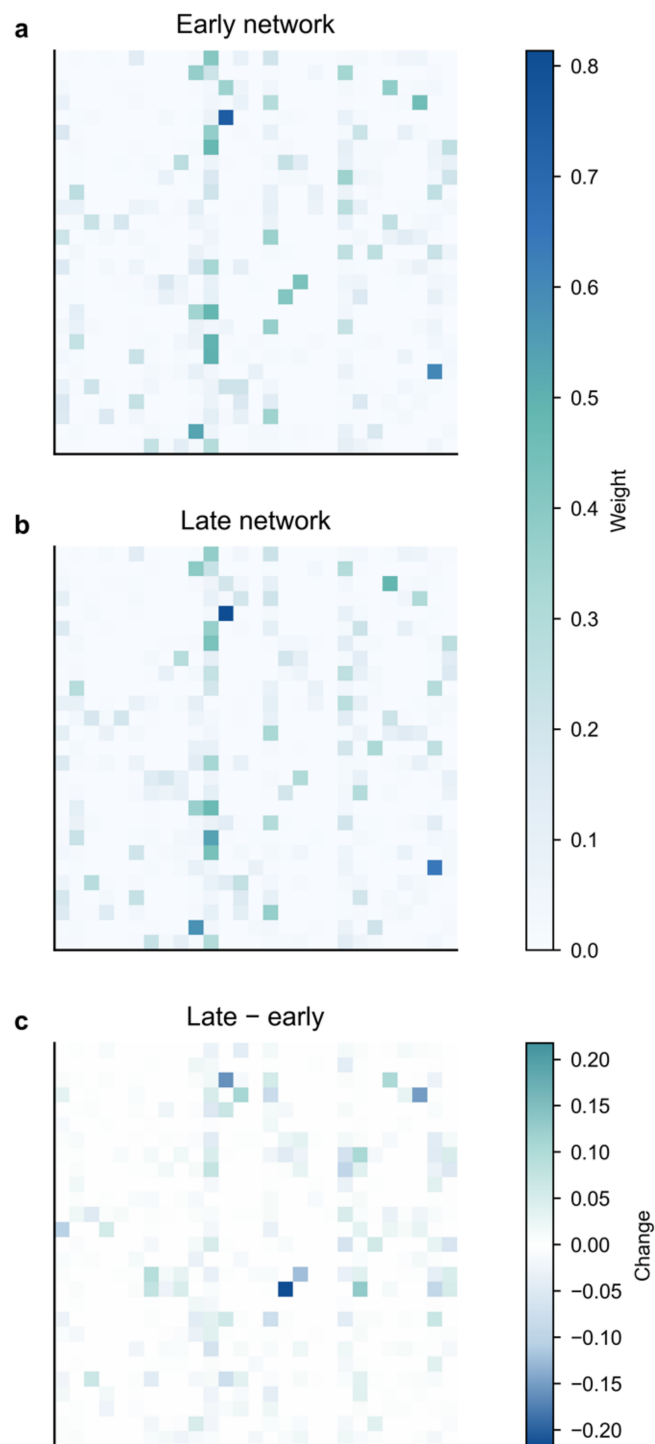


FIGURE A9 | Heat-map comparison of early- and late-period waste-trade weight matrices. The figure compares trade-network structures for 2010–2017 and 2018–2024. Changes in color patterns show that spatial weights are not a fixed background but adjust with secondary-resource markets.

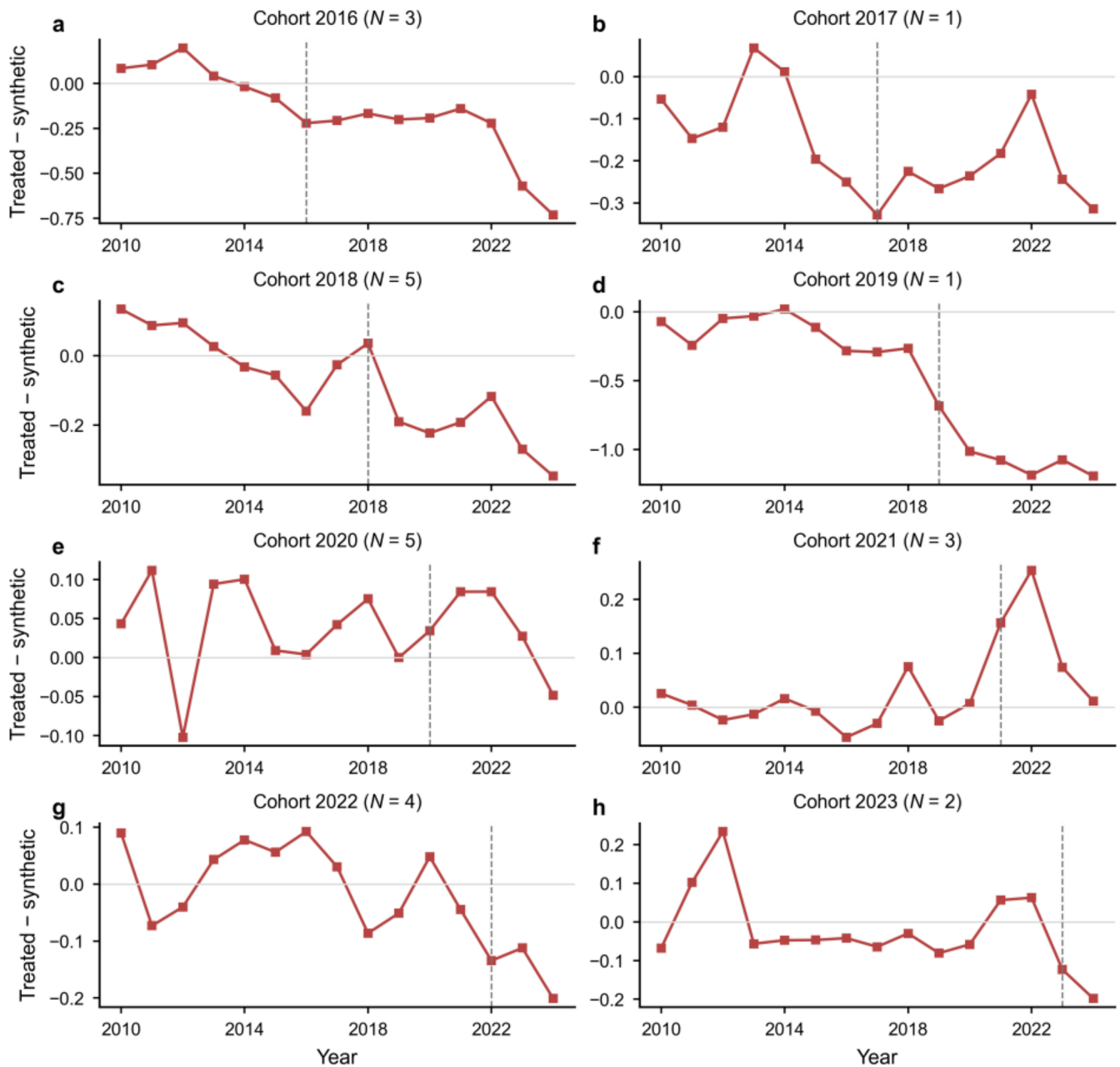


FIGURE A10 | Cohort-specific treated-minus-synthetic ln(CMUR) paths. Each panel plots the difference between the treated cohort and its synthetic counterfactual; the vertical dashed line marks strategy adoption. Variation in pre-treatment fit and post-adoption trajectories limits causal interpretation.

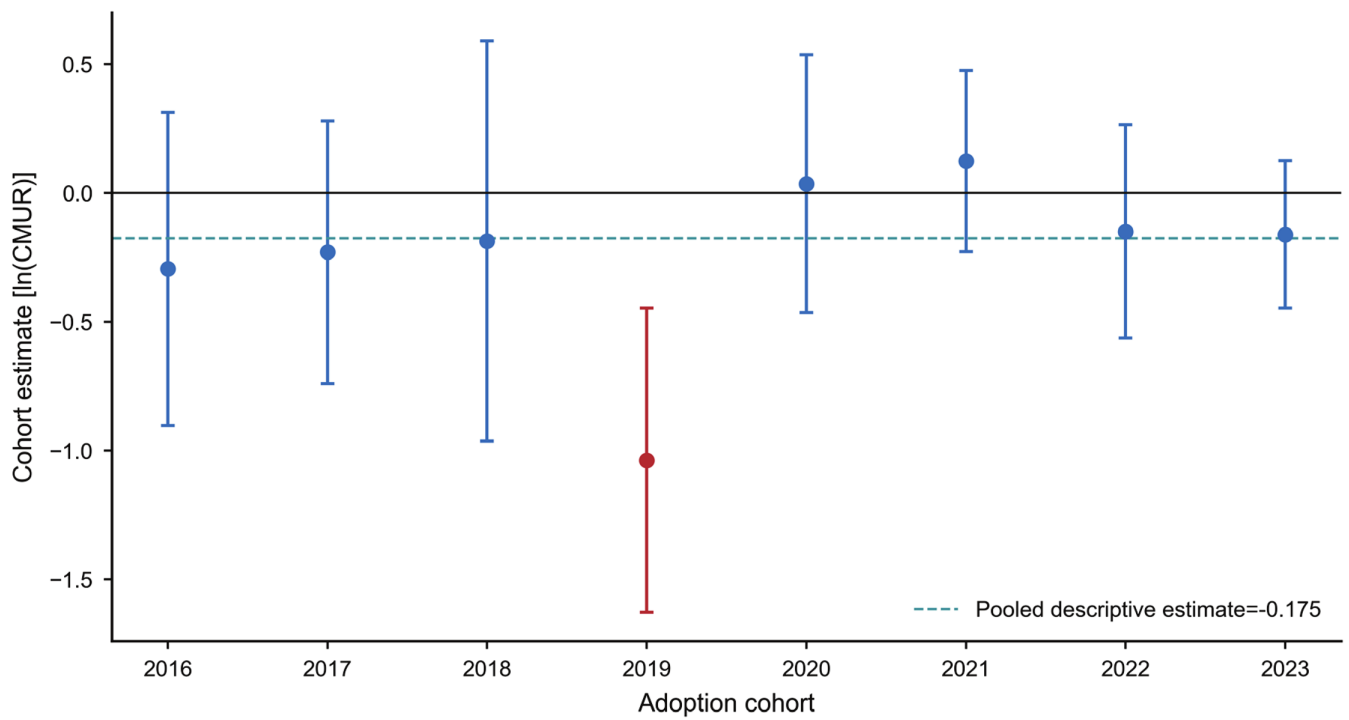


FIGURE A11 | *SDiD* treatment effects and confidence intervals by adoption cohort. The figure summarizes estimated effects for different adoption-year cohorts. Large between-cohort differences and wide confidence intervals indicate substantial heterogeneity and identification uncertainty in aggregate policy effects.

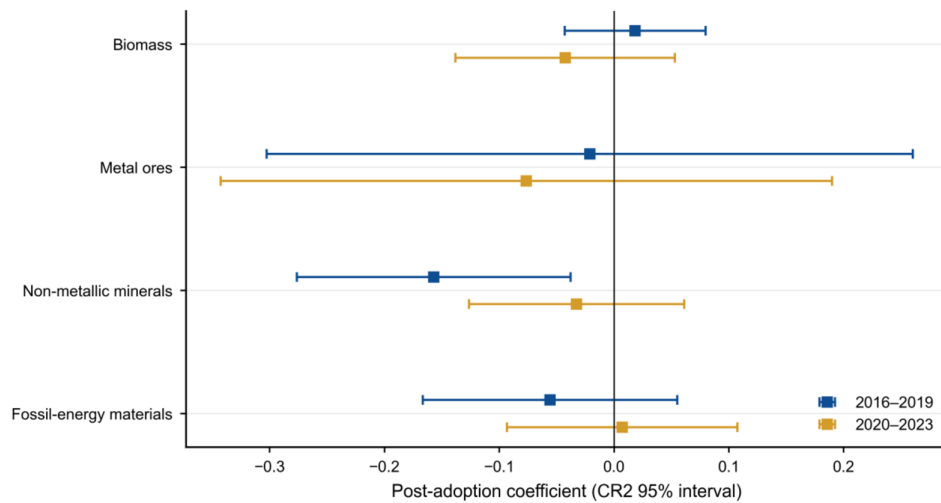


FIGURE A12 | Early- and late-adopter material associations with 2019 included in the early group. Points show log coefficients and CR2 95% intervals; early = 2016–2019, late = 2020–2023.

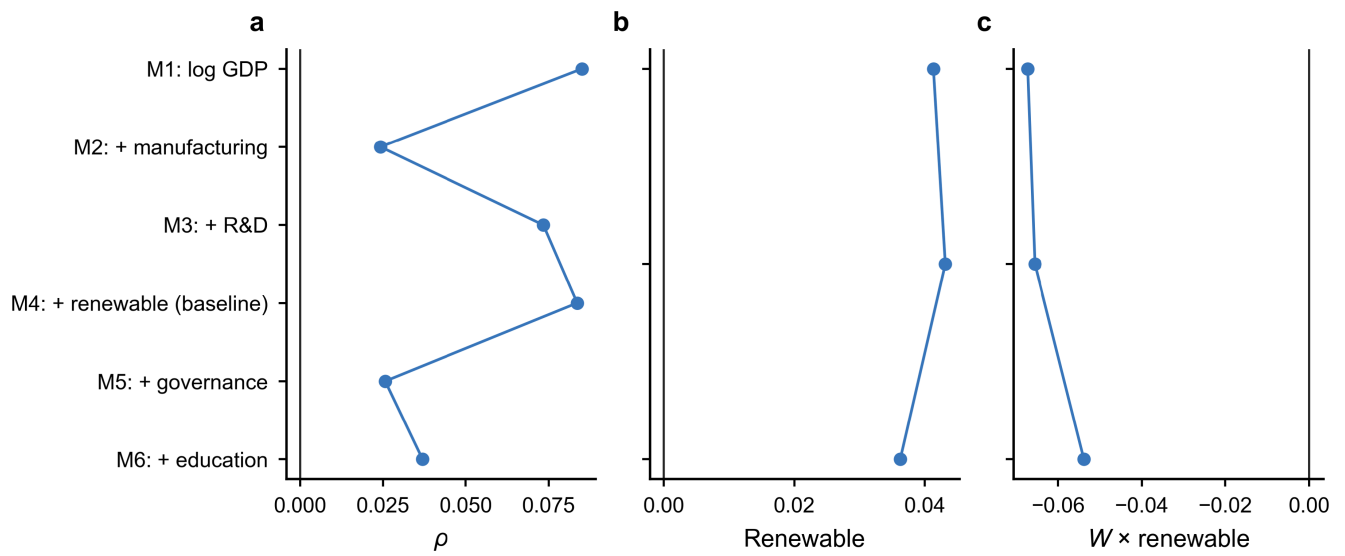


FIGURE A13 | Stepwise-control sensitivity under fixed 2010–2012 W_2 . The W -renewable coefficient remains negative after governance and ISCED 3–8 education controls.

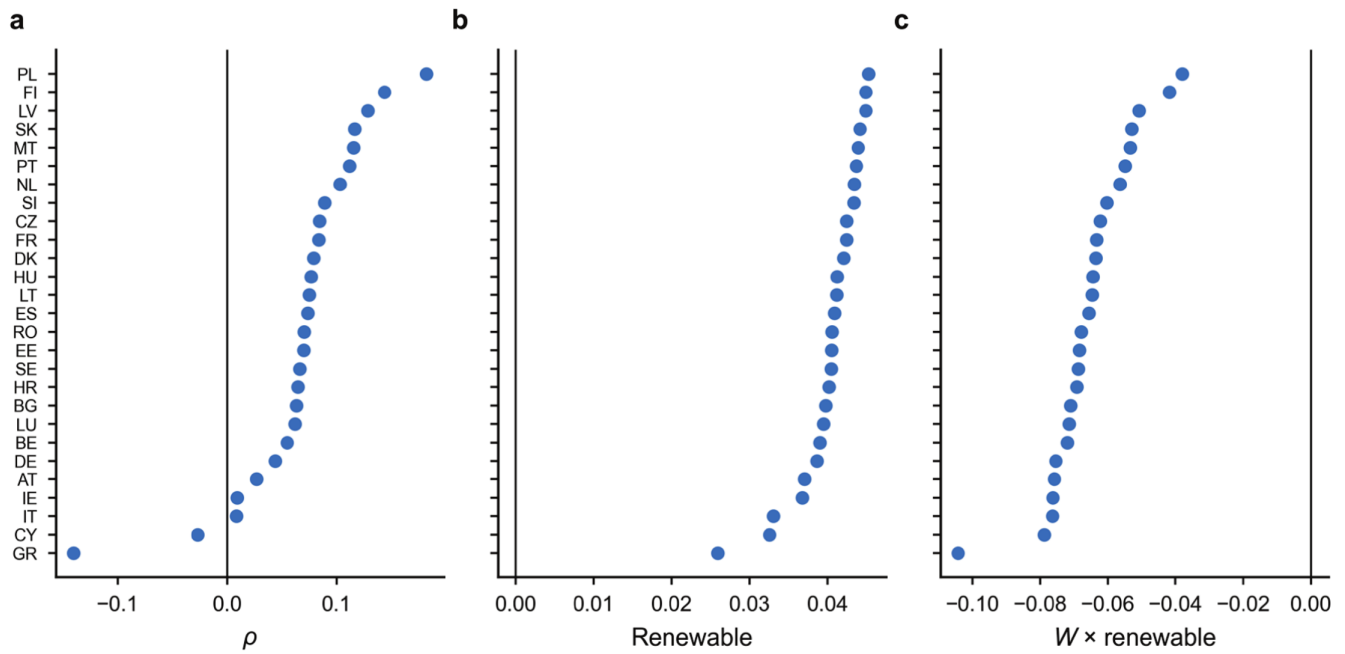


FIGURE A14 | Leave-one-country-out sensitivity under fixed 2010–2012 W_2 . W -renewable ranges from -0.104 to -0.038 and is distinguishable from zero in all 27 estimates.

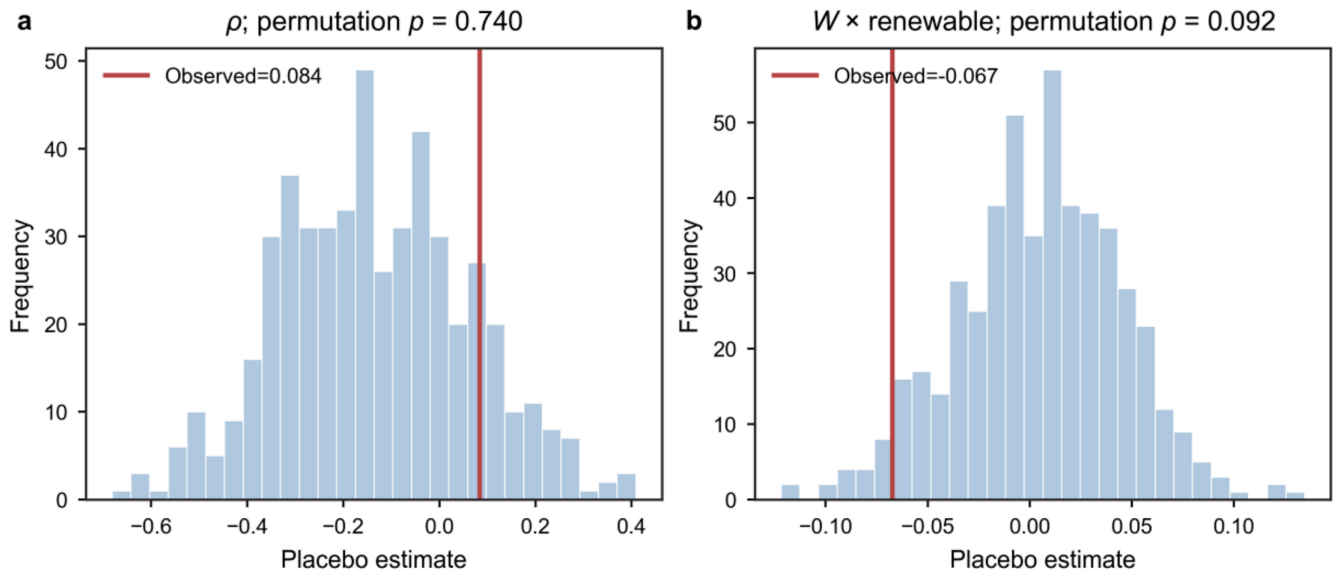


FIGURE A15 | W -label permutation placebo under fixed 2010–2012 W_2 (500 simultaneous row/column permutations; seed 20,260,825). Two-sided $p = 0.740$ for ρ and 0.092 for W -renewable.

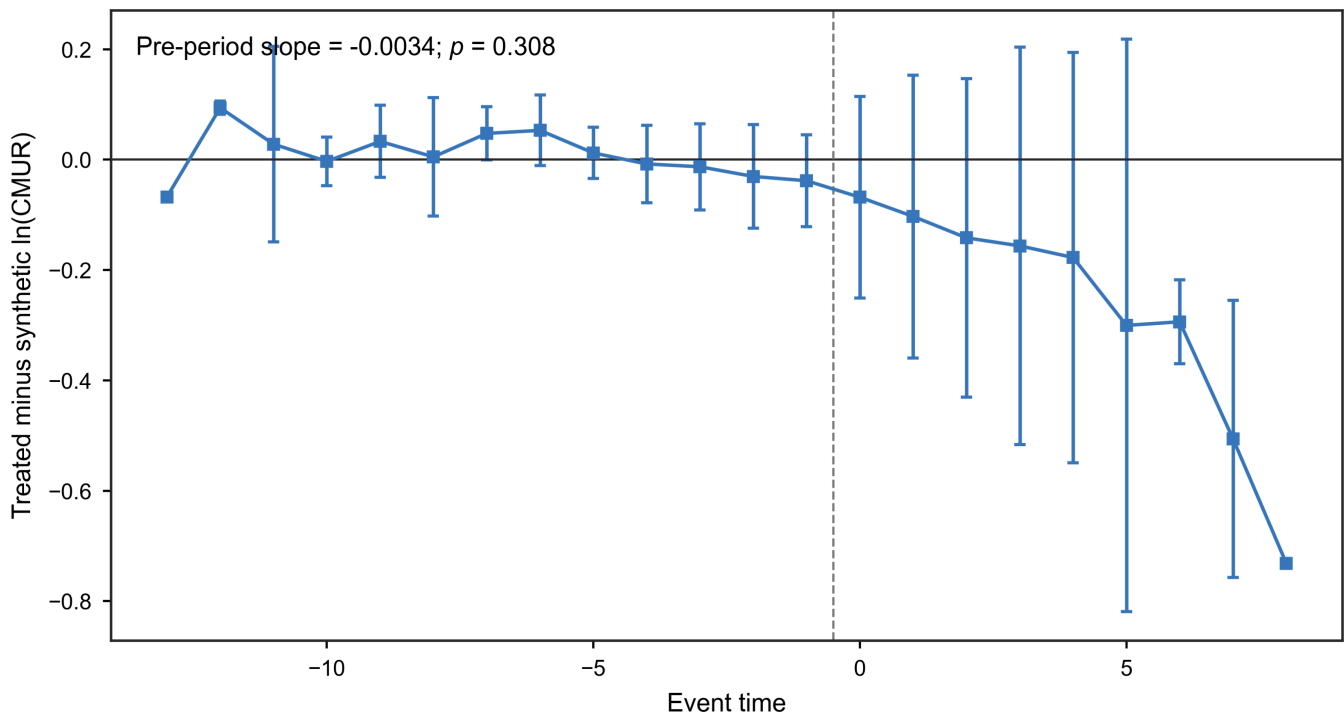


FIGURE A16 | Treated-count-weighted cohort-averaged aggregate SDiD path. The pre-period linear slope is -0.0034 ($SE = 0.0032$, $p = 0.308$; 13 event times).

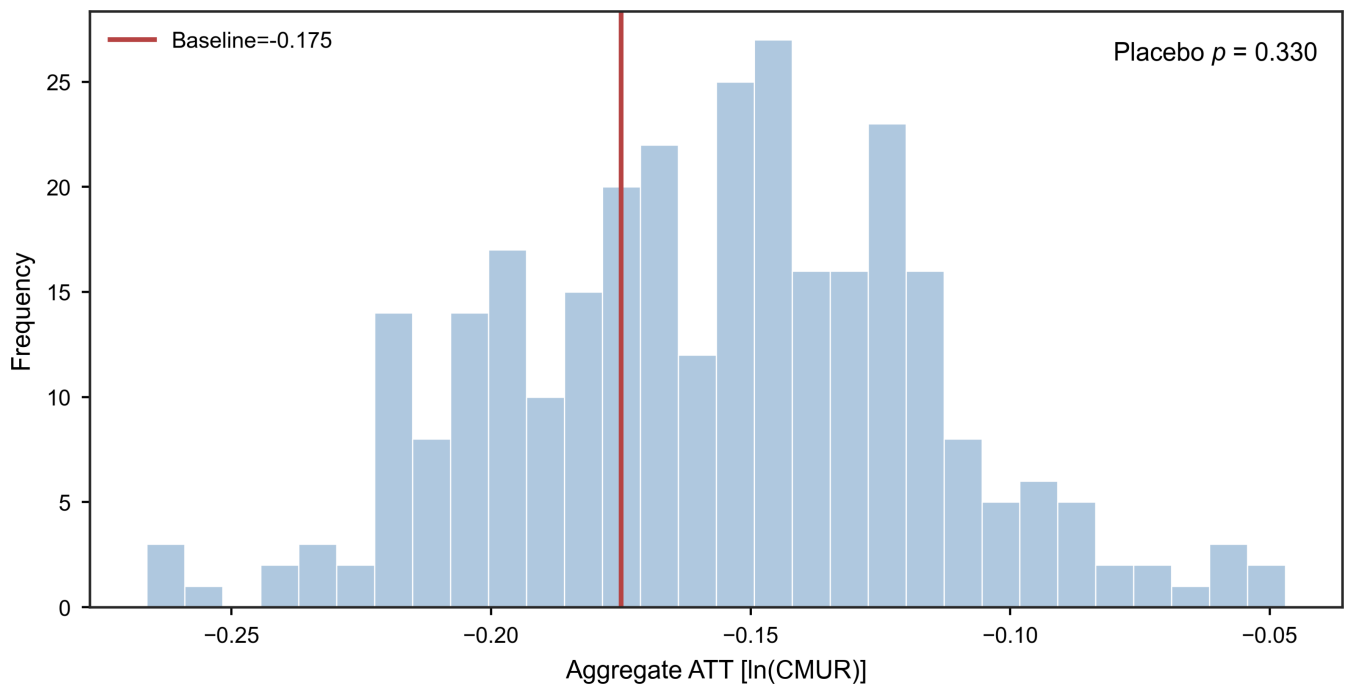


FIGURE A17 | Random-treatment-year placebo test for *SDiD*. The figure reports the placebo distribution obtained by randomly assigning adoption years. The placebo distribution is close to the baseline estimate, further weakening the causal interpretation of aggregate *SDiD*.

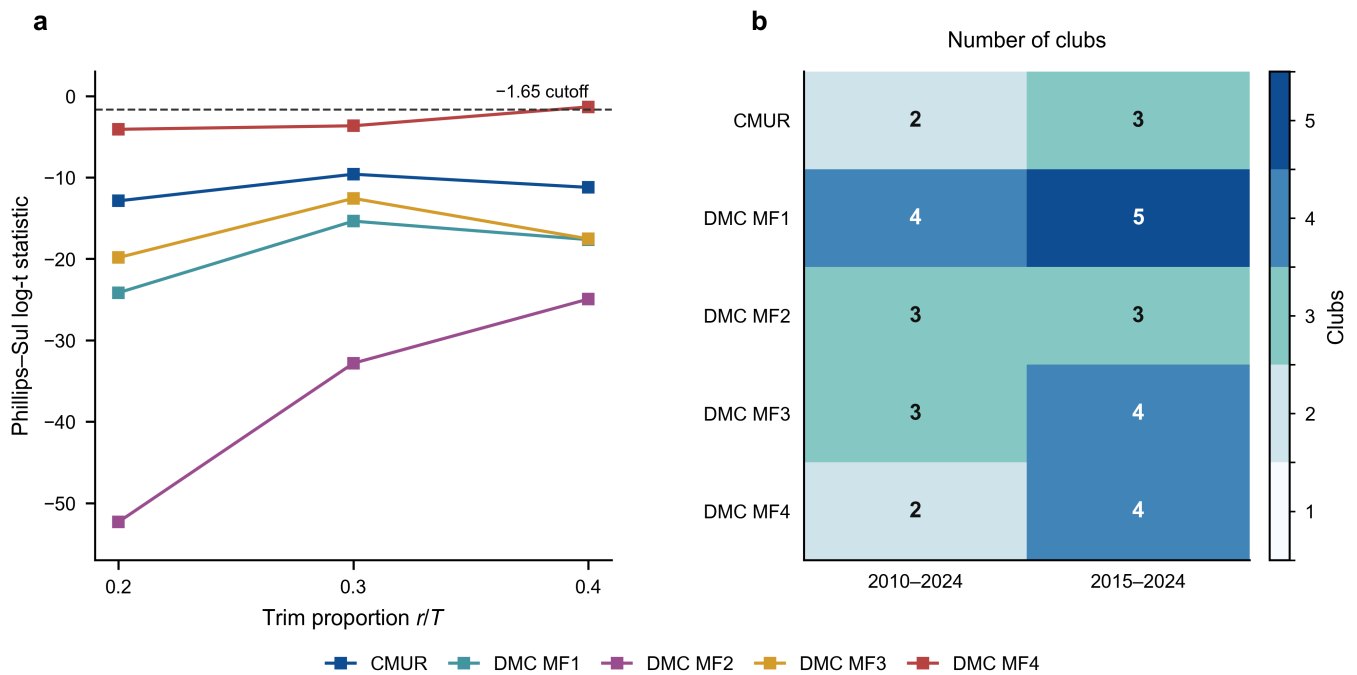


FIGURE A18 | Sensitivity of Phillips-Sul results to trim parameters and sample period. The figure compares club identification under different trim settings and time periods. Most indicators continue to reject single convergence, although results for metals and some other cases show moderate sensitivity.

TABLE A1 | Phillips–Sul club membership.

Country	Biomass (<i>MF1</i>)	Metal ores (<i>MF2</i>)	Non-metallic (<i>MF3</i>)	Fossil (<i>MF4</i>)	CMUR
AT	Club2	Club2	Club2	Club1	Club1
BE	Club2	Club2	Club3	Club2	Club1
BG	Club4	Divergent	Club2	Club1	Club2
HR	Club2	Club3	Club2	Club2	Club2
CY	Club3	Club3	Club1	Club1	Club2
CZ	Club4	Club3	Club2	Club1	Club1
DK	Club1	Club3	Club1	Club1	Club2
EE	Club2	Excluded	Club2	Club1	Club1
FI	Divergent	Club1	Club1	Club2	Club2
FR	Club2	Club3	Club2	Club2	Club1
DE	Club3	Club3	Club2	Club1	Club1
GR	Club2	Club3	Club2	Club1	Club2
HU	Club3	Club3	Club2	Club2	Club2
IE	Club1	Club2	Club1	Club2	Divergent
IT	Club3	Club3	Divergent	Club1	Club1
LV	Divergent	Excluded	Club2	Divergent	Club2
LT	Club2	Excluded	Club1	Club2	Club2
LU	Club2	Club2	Club2	Club1	Club2
MT	Divergent	Club3	Club3	Excluded	Club1
NL	Club2	Club3	Divergent	Club1	Club1
PL	Club2	Club2	Club2	Club1	Club2
PT	Club2	Club2	Club2	Club2	Club2
RO	Club4	Club3	Club1	Club2	Divergent
SK	Club3	Club3	Club3	Club2	Club1
SI	Club3	Club3	Club2	Club1	Club2
ES	Club2	Club2	Club3	Club2	Club2
SE	Club1	Club1	Club1	Club2	Club1

Note: Results are based on stepwise clustering with trim $r/T = 0.3$. Club 1 represents the higher-level club for the corresponding indicator, and Divergent denotes units that cannot be assigned to a stable convergence club.

TABLE A2 | Cross-sectional spatial Durbin model diagnostics.

Weight matrix	Moran's I	ρ ($W \cdot y$)	Log-lik <i>SDM</i>	Log-lik <i>SAR</i>	LR test	Pseudo- R^2
W_1 : distance	+0.025	−0.862	−13.02	−19.70	+13.35***	0.717
W_2 : total trade (2010–2012)	+0.310	−0.128	−12.07	−18.86	+13.57***	0.723
W_3 : sectoral (descriptive)	−0.035	Not estimable	Not estimable	Not estimable	Not estimable	Not estimable
$W_{2, MF1}$ paper	+0.126	−0.265	−12.47	−19.66	+14.37***	0.720
$W_{2, MF2}$ metals	+0.333	+0.055	−11.73	−19.10	+14.74***	0.732
$W_{2, MF4}$ plastics	+0.137	−0.407	−13.36	−19.95	+13.19**	0.703

Note: Descriptive outcome: 2018–2024 country-average, $\ln(\text{CMUR})$, $N = 27$. W_3 regression is not estimable because the WX design is near-collinear (condition number 844,651; maximum $|\text{corr}(X, WX)| = 0.990$) and the spatial solution reaches the -0.98 boundary. Six alternative networks remain estimable. Cross-sectional coefficients are descriptive late-period level associations. *** denotes $p < 0.01$.

TABLE A3 | Panel two-way fixed-effects *SDM* fit under alternative spatial weight matrices.

Weight matrix	ρ ($W \cdot y$)	Log-lik <i>SDM</i>	Log-lik <i>SAR</i>	LR test <i>SDM</i> vs. <i>SAR</i>
W_1 : distance	−0.478***	7.36	−24.80	+64.32***
W_2 : total trade (2010–2012)	+0.084	−3.05	−24.69	+43.28***
$W_{2, MF1}$ paper	+0.132	−10.89	−24.60	+27.42***
$W_{2, MF2}$ metals	+0.072	−8.45	−24.60	+32.32***
$W_{2, MF4}$ plastics	+0.093	−9.94	−24.73	+29.59***

Note: Outcome: $\ln(\text{CMUR})$; sample: EU-27, 2010–2024, $N = 405$; country and year fixed effects. W_2 is fixed from 2010 to 2012. W_3 is excluded from regression comparison because it is not estimable; its matrix is retained descriptively in Figure 3. *** denotes $p < 0.01$.

TABLE A4 | Full-sample model ladder under the fixed early-period 2010–2012 total-waste matrix.

Model	Spatial parameter (ρ)	Log-likelihood	AIC/BIC
TWFE	—	−25.41	60.81/80.83
SAR	$\rho = 0.106$ (0.230)	−24.69	61.39/85.41
SEM	$\lambda = 0.205$ (0.024)	−22.98	57.96/81.99
SDM	$\rho = 0.084$ (0.368)	−3.05	26.11/66.14

Note: All specifications use 405 observations from 27 countries over 2010–2024 with fixed 2010–2012 W_2 . BIC is the primary model-selection rule; SDM–SAR LR = 43.28 ($p < 0.001$) is an incremental-fit diagnostic.

TABLE A5 | Cohort-specific treatment effects from synthetic difference-in-differences.

Cohort	N	Treated units	τ (SE)	HR wt.	HU wt.	SK wt.	Pre-RMSPE	Pool wt.
2016	3	NL, BE, FI	−0.294 (0.310)	0.000	0.657	0.343	0.105	0.209
2017	1	PT	−0.230 (0.260)	0.245	0.403	0.352	0.144	0.062
2018	5	FR, DK, GR, SI, LU	−0.186 (0.396)	0.000	0.503	0.497	0.091	0.271
2019	1	PL	−1.038 (0.301)	0.079	0.305	0.617	0.187	0.047
2020	5	DE, ES, MT, SE, LV	+0.036 (0.255)	0.188	0.396	0.417	0.072	0.194
2021	3	CY, CZ, IE	+0.124 (0.179)	0.164	0.450	0.386	0.033	0.093
2022	4	AT, BG, IT, RO	−0.149 (0.212)	0.114	0.572	0.315	0.064	0.093
2023	2	EE, LT	−0.161 (0.146)	0.062	0.613	0.325	0.088	0.031

Note: Outcome: $\ln(\text{CMUR})$. Donors are HR, HU, and SK. Non-negative donor weights sum to one within cohort; pre-RMSPE is calculated over pre-adoption $\ln(\text{CMUR})$. Pool weights normalize N-treated $\times$ post-period count. Estimates are descriptive because only three donors are available. The donor-pool jackknife has limited support.

Design Considerations and Model Selection

The design separates model parsimony, early-period ordering of W_2 , and specification sensitivity. The early-period matrix establishes sequencing, while unobserved determinants of network formation remain part of the interpretation.

First, SAR, SEM, and SDM are estimated on the same full panel. Information criteria and the SDM–SAR LR test determine whether spatially lagged covariates add sufficient fit to justify the larger model.

Second, W_2 is fixed from 2010 to 2012, while the outcome panel continues through 2024. The full-period trade matrix is used as a sensitivity specification.

Third, country and year fixed effects absorb time-invariant country components and common annual shocks. Lagged covariates and distance provide additional timing and network checks, while remaining time-varying confounding is acknowledged in the interpretation.

Table A6 compares the fixed- W_2 baseline with lagged covariates, full-period W_2 , distance, and the strict 2013–2024 outcome sample.

Diagnostic Procedures

Lagged-Covariate Specifications

The lagged-covariate specifications assess whether the coefficient pattern depends on contemporaneous timing. All four covariates are replaced simultaneously by their 1- or 2-year lags, while W_2 remains fixed. The covariates are $\ln(\text{GDP per capita})$, manufacturing share, R&D intensity, and renewable-energy share. The 1-year lag specification uses 2011–2024 ($T = 14$, $n = 378$), and the 2-year lag specification uses 2012–2024 ($T = 13$, $n = 351$).

Baseline and Full-Period Trade Matrices

The baseline W_2 averages mirror-reconciled flows over 2010–2012. The 2010–2024 matrix is re-estimated as a sensitivity specification. Both matrices are row-standardized and applied to the full 2010–2024 outcome panel.

Alternative Geographic Network

W_1 uses inverse great-circle distance and is row-standardized. It tests whether the coefficient pattern under a geographic network differs from the pattern under waste-trade proximity.

Hausman Test: FE Versus RE

The (Hausman 1976) test compares fixed- and random-effects estimates in a non-spatial panel diagnostic. H is evaluated against χ^2 with K covariates. The spatially lagged dependent variable and WX terms are excluded from this auxiliary test.

Complete Results

TABLE A6 | Temporal-ordering and specification-sensitivity results.

Specification	Renewable share	<i>p</i>	<i>W</i> -renewable share	<i>p</i>	ρ	<i>p</i>	<i>n</i>
Baseline: W_2 2010–2012	+0.0413	< 0.001	−0.0673	< 0.001	+0.084	0.368	405
Lagged X, 1 year	+0.0489	< 0.001	−0.0826	< 0.001	+0.099	0.294	378
Lagged X, 2 years	+0.0587	< 0.001	−0.0892	< 0.001	+0.102	0.284	351
W_2 2010–2024 sensitivity	+0.0394	< 0.001	−0.0653	< 0.001	+0.088	0.375	405
W_1 distance	+0.0381	< 0.001	−0.2143	< 0.001	−0.478	0.009	405
Strict outcomes 2013–2024	+0.0325	< 0.001	−0.0464	0.0035	+0.162	0.098	324

Note: Outcome: $\ln(\text{CMUR})$. All rows use the two-way fixed-effects SDM. Baseline W_2 is fixed from 2010 to 2012; full-period W_2 and distance are network sensitivities. The strict row estimates outcomes only in 2013–2024 under fixed W_2 . Reported *p*-values are asymptotic and two-sided.

Hausman Test

The FE and RE coefficients from the non-spatial panel model differ as follows:

TABLE A7 | Hausman comparison between fixed effects and random effects.

Variables	FE coef	FE SE	RE coef	RE SE	FE–RE
$\ln(\text{GDP per capita})$	+0.6564	0.2126	+0.4462	0.1135	+0.2103
Manufacturing share	−0.0025	0.0087	−0.0054	0.0077	+0.0030
R&D intensity	+0.4463	0.0808	+0.3626	0.0673	+0.0837
Renewable share	+0.0221	0.0073	+0.0116	0.0036	+0.0105

The Hausman statistic is $H = 7.246$ ($p = 0.124$), so the auxiliary test does not distinguish FE and RE at the 5% level. FE is retained because persistent country characteristics, including geography, institutional history, and cultural patterns, are likely to correlate with the regressors (Wooldridge 2010). The Hausman result is treated as a specification diagnostic rather than the model-selection rule.

Interpretation

Table A6 shows that the domestic renewable coefficient is positive and the network-weighted renewable coefficient is negative across the reported timing and network alternatives.

Lagging covariates increase the magnitude of both coefficients, while replacing the fixed early-period matrix with the full-period matrix leaves them close to baseline.

The distance matrix produces a larger negative spatial-lag coefficient and negative ρ , showing that geographic proximity and waste-trade connectivity encode different dependence structures.

The trade-matrix ρ estimates remain small and imprecise after partner characteristics enter the SDM. Accordingly, the selected trade-network model is interpreted mainly through spatially lagged covariates rather than direct CMUR dependence.

Across the reported timing and network alternatives, the coefficient signs are stable. The estimates remain network-conditional associations.

Descriptive Statistics

Table A8 reports descriptive statistics for the country-year panel. The balanced EU-27 panel contains 405 observations from 2010 to 2024. *CMUR* is reported in percentage points in the descriptive table. The minimum observed *CMUR* is 1.2%, and no *CMUR* observation equals zero; therefore, the logarithmic transformation of *CMUR* used in the econometric analysis is well defined. In the sample, $\ln(\text{CMUR})$ ranges from 0.182 to 3.487 when *CMUR* is measured in percentage points.

Table A9 summarizes the 1620-observation material panel. Ordinary logs are used only for positive observations. MF2 DMC per capita has nine non-positive observations and MF4 has one; the log-positive regressions contain 396 and 404 observations. The asinh sensitivity retains all 405 observations per material after scaling by the material-specific median positive value.

TABLE A8 | Descriptive statistics for the country-year panel, EU-27, 2010–2024.

Variables	N	Mean	SD	Minimum	Median	Maximum
CMUR (%)	405	9.053	6.509	1.200	7.500	32.70
GDP per capita (EUR)	405	26,569.21	17,220.18	5080.00	21,780.00	86,890.00
Manufacturing share (%)	405	14.10	5.395	3.885	13.40	36.92
R&D intensity (%)	405	1.643	0.894	0.380	1.380	3.710
Renewable energy share (%)	405	21.73	12.16	0.979	18.90	66.39
Energy productivity	405	7.352	3.831	2.030	6.650	27.00
Share aged 15–64 with ISCED 3–8 attainment (%)	405	75.51	10.36	32.70	78.10	89.20
Population density	405	178.34	284.39	17.60	104.80	1817.40

TABLE A9 | Descriptive statistics for material-level indicators, EU-27, 2010–2024.

Materials	Indicator	N	Mean	SD	Minimum	Median	Maximum
Biomass	DMC per capita (kg)	405	3388.27	1583.09	718.31	2973.50	9434.99
Biomass	Material intensity (kg EUR ⁻¹)	405	0.168	0.107	0.026	0.135	0.599
Biomass	Import share	405	0.337	0.187	0.093	0.269	0.883
Metal ores	DMC per capita (kg)	405	926.11	1298.08	−264.93	425.58	5809.12
Metal ores	Material intensity (kg EUR ⁻¹)	405	0.050	0.112	−0.024	0.018	0.726
Metal ores	Import share	405	0.800	0.296	0.098	0.996	1.000
Non-metallic minerals	DMC per capita (kg)	405	7658.18	4360.21	1106.19	6750.79	30,718.38
Non-metallic minerals	Material intensity (kg EUR ⁻¹)	405	0.415	0.351	0.025	0.314	2.067
Non-metallic minerals	Import share	405	0.159	0.195	0.014	0.097	0.948
Fossil energy materials	DMC per capita (kg)	405	2995.18	1846.79	−474.07	2410.82	12,383.68
Fossil energy materials	Material intensity (kg EUR ⁻¹)	405	0.167	0.183	−0.029	0.104	1.120
Fossil energy materials	Import share	405	0.766	0.256	0.162	0.869	1.000

Note: CMUR is in percentage points. DMC per capita is kg person⁻¹; material intensity is kg EUR⁻¹ GDP; import share is imports/DMI. Ordinary logs exclude non-positive observations without flooring. The scaled asinh sensitivity retains all observations and is interpreted in transformed units.

TABLE A10 | Event-time joint tests and support.

Materials	N	Joint pre $F_{(4,26)}$	p	Post support	Interpretation
Biomass	405	0.901	0.477	$t = 0$: 24 countries; ≥ 5 : 10	No material-specific causal claim
Metal ores	396	1.047	0.402	$t = 0$: 24 countries; ≥ 5 : 10	No material-specific causal claim
Non-metallic minerals	405	1.587	0.208	$t = 0$: 24 countries; ≥ 5 : 10	MF3 post coefficients negative; −2 lead individually $p = 0.037$
Fossil-energy materials	404	0.183	0.945	$t = 0$: 24 countries; ≥ 5 : 10	No material-specific causal claim

Note: Outcome: log-positive DMC per capita. Country and year fixed effects; country-clustered CR2 inference with 26 denominator degrees of freedom. Event time −1 is omitted. Pre-period bins are ≤ -5 , -4 , -3 , and -2 . The MF3 ≥ 5 bin has 26 observations, 10 countries, and four cohorts; declining support bounds interpretation.

TABLE A11 | MF3 spatial model ladder under fixed 2010–2012 mineral-recyclables trade.

Models	Spatial parameter	p	Log-likelihood	AIC	BIC	Role
TWFE	—	—	274.809	−539.618	−519.599	Comparator
SAR	$\rho = +0.352$	< 0.001	298.324	−584.648	−560.625	Primary by BIC
SEM	$\lambda = +0.354$	< 0.001	290.946	−569.892	−545.869	Comparator
SDM	$\rho = +0.271$	< 0.001	304.259	−588.518	−548.479	Incremental sensitivity; LR vs. SAR = 11.87, $p = 0.018$

Note: Outcome: log-positive MF3 DMC per capita; $N = 405$; country and year fixed effects. BIC is the primary parsimony rule. SAR is the reported baseline; SDM is retained because spatially lagged covariates improve fit by LR.

TABLE A12 | Spatial-matrix construction and analytical role.

Matrix	Source	Window	Link rule	Direction	Standardization	Use/status
W_1 distance	CEPII GeoDist	Time-invariant	Inverse great-circle distance	Symmetric	Zero diagonal; row	Sensitivity
W_2 total waste	UN Comtrade mirror flows	2010–2012	Average reconciled bilateral flow	Directed	Zero diagonal; row	Aggregate baseline
W_2 full-period	UN Comtrade mirror flows	2010–2024	Average reconciled bilateral flow	Directed	Zero diagonal; row	Sensitivity
W_3 sectoral	Eurostat 11-sector VA shares	2010–2024 average	Cosine similarity	Symmetric	Zero diagonal; row	Descriptive; not estimable
$W_{2,MF1}$ paper	UN Comtrade	2010–2012	Paper recyclable trade	Directed	Zero diagonal; row	MF1
$W_{2,MF2}$ metal	UN Comtrade	2010–2012	Metal recyclable trade	Directed	Zero diagonal; row	MF2
$W_{2,MF3}$ mineral	Eurostat Comext DS-045409	2010–2012	Max(export, mirror import)	Directed	Zero diagonal; row	MF3 baseline
$W_{2,MF4}$ plastic	UN Comtrade	2010–2012	Plastic recyclable trade	Directed	Zero diagonal; row	MF4

Note: Trade matrices are fixed before most national strategy adoptions. Mean-mirror, symmetric, and 2010–2024 variants of $W_{2,MF3}$ are sensitivity cases. Early-period ordering addresses sequencing; endogenous network formation remains part of the interpretation.

TABLE A13 | Scaled-Asinh sensitivity of material-level policy associations.

Materials	Median-positive scale	N	Coefficient	CR2 SE	p
MF1: Biomass	2973.4963	405	−0.00001	0.01645	0.9993
MF2: Metal ores	431.3883	405	−0.01913	0.04997	0.7050
MF3: Non-metallic minerals	6750.7918	405	−0.07387	0.02653	0.0099
MF4: Fossil-energy materials	2412.2225	405	−0.02571	0.03267	0.4384

Note: The outcome is $\text{asinh}(\text{DMC per capita}/s_m)$, where s_m is the material-specific median among positive observations. Each material retains all 405 country-year observations and is estimated separately with country and year fixed effects. Coefficients are in transformed units. Inference uses the custom country-clustered CR2 implementation with 26 denominator degrees of freedom.

TABLE A14 | MF3 spatial sensitivity across mineral-recyclables matrices.

Matrix construction	Model	ρ	p	Log-likelihood	BIC
2010–2012 directed max-mirror	SAR	0.352	< 0.001	298.324	−560.625
2010–2012 directed mean-mirror	SAR	0.350	< 0.001	297.295	−558.567
2010–2012 symmetric	SAR	0.303	< 0.001	286.313	−536.604
2010–2024 directed max-mirror	SAR	0.336	< 0.001	292.943	−549.862

Note: Outcome: log-positive MF3 DMC per capita; $N = 405$; country and year fixed effects. SAR is selected by BIC for each matrix construction. The directed baseline uses max(export, mirror import); the alternatives use mean-mirror reconciliation, symmetrization, or the 2010–2024 averaging window.