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The Energy Transition Paradox: Decarbonization and Supply Chain Vulnerability in Critical Mineral Systems

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Abstract

The energy transition replaces globally distributed fossil fuels with geologically concentrated critical minerals, raising the question of whether decarbonization reduces or reshapes supply chain vulnerability (SCV), and it is called the Energy Transition Paradox (ETP). This study builds on the Energy Transition Trade-off (ETT) framework, which sees the relationship between energy and water as a function of structural exposure and contextual moderation. Using a balanced panel of 20 economies from 2010 to 2023 (280 country-year observations), compiled from the World Bank, the New York Federal Reserve, the Notre Dame Global Adaptation Initiative (ND-GAIN), and the United Nations (UN) Comtrade database, we measure SCV as a multidimensional formative index. The two-way fixed-effects estimates indicate that the share of renewable electricity negatively affects SCV ($\beta = -0.0024$, $p < 0.001$). However, this relationship is restricted to an annual renewable energy threshold of approximately 25% (95% bootstrap CI: [20–35%]; in-sample grid search estimate). The moderation effect of governance is significant at $p = 0.014$, and climate risk is significant at $p = 0.071$. Still, neither moderation effect is statistically significant when computed using a PCA-weighted index, so the moderation results should be treated with caution. Moreover, export partner diversification shows no significant association with SCV. Because the instrumental variable test was weak, all the results are associations, not causal effects. Therefore, decarbonization policy should be supported by measures to diversify mineral sources, strengthen supply chain governance, and support climate adaptation.

Keywords: energy transition; critical minerals; supply chain vulnerability; decarbonization; governance; trade diversification

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1. Introduction

Renewable electricity's global momentum masks striking cross-country variation over 2010–2023: the panel means fluctuated between 35.5% and 53.8%, essentially flat overall (43.5% in 2010 to 42.1% in 2023), even as country-year values ranged from 6.3% to 79.9% [1]. Yet this transition is not frictionless: it substitutes globally distributed fossil fuels with geologically concentrated critical minerals: lithium, cobalt, nickel, copper, and rare earths. China accounts for approximately 85–91% of global rare earth refining capacity [2], while [3] reports that just three countries supply over 75% of global lithium, cobalt, and nickel output [4]. This reconfiguration constitutes the Energy Transition Paradox; [2] projects that mineral demand for clean energy will grow two- to six-fold by 2040 under net zero scenarios.

Specificity of critical minerals in renewables vs. other industries: The geopolitical risk of a supply chain disruption differs for each critical mineral depending on its use, and minerals overlap across sectors. The primary decarbonization technologies analyzed in this study that rely on essential minerals are: (i) lithium (Li), cathode/electrolyte input for lithium-ion battery cells used in EVs, grid-scale storage, and portable electronics; (ii) cobalt (Co), a cathode stabilizer in NMC/NCA battery chemistries, although cobalt-free LFP chemistries are reducing demand at the margin; (iii) nickel (Ni), high-energy-density cathode material in NMC batteries and increasingly in Class 1 nickel demand for EVs; (iv) manganese (Mn), used in LMFP/NMC cathodes and as a cost-reducing substitute for cobalt; (v) copper (Cu), essential for wiring, transformers, EV motors, wind turbine generators, and solar inverters; the single highest-volume critical mineral by mass in decarbonization technologies; (vi) Rare Earth Elements (REEs), particularly neodymium (Nd) and dysprosium (Dy), used in permanent magnets for wind turbine direct-drive generators and EV traction motors; and (vii) silicon (Si) and silver (Ag), used in the manufacture of PV solar cells. Several of these minerals are also critical to other industries: cobalt, tantalum, and gallium are essential for semiconductor and advanced electronics manufacturing (e.g., gallium arsenide compound semiconductors in 5G and defense applications); REEs are used in defense, MRI, and catalytic converters; and copper underpins all electrical infrastructure. This cross-sector overlap also affects the energy transition, semiconductor manufacturing, defense, and digital infrastructure, and contributes to systemic risk, as outlined in Section 2.3 [2,5]. SCV presents CMID, which includes import reliance on the entire basket of these transition-relevant minerals, according to their role in the bill of materials for renewable energy and EV systems [6].

For multinational firms managing critical mineral-dependent supply chains, this reconfiguration determines sourcing risk, supplier due diligence priorities, and jurisdiction selection under geopolitical fragmentation. As decarbonization accelerates demand for geographically concentrated minerals, firms face a widening gap between where clean technology inputs are extracted and where they are consumed, reshaping procurement strategy, capital commitments to vertical integration, and exposure to export control risk. Understanding how decarbonization reshapes supply chain vulnerability is, therefore, a question of firm-level strategic response, not only macroeconomic policy.(Ref. [7] confirms that sustainable low-carbon pathways depend on governance of mineral supply chains across the full lifecycle, while [6] provides the bill of materials basis for quantifying the mineral intensities used in this study.

We empirically test this paradox using a verified 280-observation panel (20 economies × 14 years, 2010–2023) and five confirmed primary source datasets. Decarbonization is associated with lower SCV on average ($\beta = -0.0024$, $p < 0.001$), concentrated below a 25% renewable share threshold, and significantly moderated by governance quality (DxG =

+0.0032, $p = 0.014$) and marginally by climate risk (DxC = +0.0050, $p = 0.071$). Trade diversification, measured as export partner concentration independent of SCV's own construction, shows no significant association with SCV.

Methodological transparency. Throughout this paper, we report N as "countries × years = observations" (20 × 14 = 280) to clarify panel dimensions. Two pre-specified SCV specifications are compared in full SCV_eq (primary, equal-weight) and SCV_pca (PCA-weighted robustness check) with identical directional findings across both across the two SCV index specifications, SCV_eq (equal-weighted, primary) and SCV_pca (PCA-weighted, robustness check) . Governance (WGI) and climate risk (ND-GAIN) are sourced from datasets entirely separate from the SCV sub-components; TradeDiv (export destination HHI) is likewise distinct from HHI_supply (mineral-specific import HHI), with r = 0.091 (Section 4) confirming no construction overlap.

Theoretical contribution. This study makes three specific theoretical contributions. First, it brings together structural exposure and contextual moderation in one testable framework, in which research on structural dependence on resources [8] and research on supply chain resilience have treated material dependency and governance/climate conditioning as separate mechanisms. Second, it empirically shows a nonlinear threshold relationship between decarbonization and supply chain vulnerability, contrary to the linear marginal relationship implicit in existing socio-technical transition theory [9] and finds that this association is front-loaded and declines beyond an empirically estimated renewable share threshold. Third, it resolves a measurement conflation between trade diversification (TradeDiv) and supplier concentration (HHI_supply) that likely confused previous empirical work based on resource dependence theory (RDT) by conflating these two conceptually different variables, which, in this panel, are not correlated (r = 0.091).

Methodological overview. To provide transparency on the analytical approach, this paragraph summarizes the methodology before the detailed exposition in Sections 4 and 5. The empirical approach consists of four steps. First, a composite index of supply chain vulnerability (SCV) is created by min–max normalizing the four sub-components across the entire panel of 280 observations, and equally weighting (0.25) the four sub-components to create SCV_eq. A composite index of supply chain vulnerability (SCV) is constructed by min–max normalizing four sub-components across all 280 observations and averaging each sub-component with equal weights (0.25) to form SCV_eq. A robust alternative (SCV_pca) is built using weighted PCA. Second, four two-way fixed-effects panel models (M1–M4) are estimated using ordinary least squares (OLS), with country fixed effects (country heterogeneity) and year fixed effects (year shocks) absorbed, and with standard errors clustered by country. M1 estimates the association between Decarb and SCV; M2 adds a quadratic term to assess nonlinearity; M3 adds control variables (ClimateRisk, TradeDiv, Governance, lnGDPpc); and M4 adds two-way interaction terms (Decarb × Governance, Decarb × ClimateRisk, Decarb × TradeDiv) to estimate conditional moderation effects. Third, in Section 6.4, a piecewise-linear spline model tests whether the connection between Decarb and SCV differs above and below an empirically determined renewable share threshold. Fourth, robustness checks repeat the main results with the SCV_pca specification, the first-differenced specification, subsamples by OECD membership and mineral role, and a three-component specification that excludes HHI (Section 7). An instrumental variable (IV) test implemented for a Bartik shift share instrument is reported. In contrast, the instrument is weak (F = 0.53 in the first stage), and the authors use no second-stage estimate to produce inference (Section 5.3). The data come from five main sources: World Bank WDI, World Bank WGI, Notre Dame ND-GAIN, NY Fed, GSCPI, and UN Comtrade (Section 4.

2. Literature Review

2.1. Socio-Technical Transition Theory

The multi-level perspective of [9,10] conceptualizes energy transitions as a co-evolution of technologies, institutions, markets, and material flows. Carbon lock-in [11,12] and material lock-in generate path dependence: transitions embed new dependency structures in the material configurations any new regime must build. Our Resource Concentration mechanism operationalizes this: rapid demand growth for concentrated minerals increases supplier HHI in the medium term (10–15-year mine development timelines) [6,13]. Empirically, Ref. [2] reports that lithium refining capacity is still more than 80% dominated by one country (China), and cobalt processing is more than 70% dominated by China, reflecting the expectation that the growth of demand for battery materials will accelerate faster than the number of suppliers grows, which will lead to a rise in HHI. Ref. [4] also acknowledges the lack of concentration in the production of rare earth elements, cobalt, and lithium in 2010–2020, despite a burgeoning demand.

2.2. Supply Chain Resilience Theory and Formative SCV

Supply chain resilience theory distinguishes vulnerability (exposure to disruption) from capability, the capacity to recover [14,15]. SCV is specified as formative, not reflective, following [16]: causality runs from the four indicators to the construct, the indicators are non-interchangeable, and they need not co-vary (CMID and HHI can move in opposite directions; Section 3.1). Under this criterion, Cronbach's α is inappropriate rather than merely optional [17] where high α would signal multicollinearity, undermining the formative role. We instead establish robustness via convergent validity across weighting schemes (SCV_eq vs. SCV_pca, $\varrho = 0.893$ Section 7).

HHI's PCA weight of 0.509 identifies supplier concentration as the dominant source of variation in this panel; it is a data-driven property of one secondary weighting scheme and does not alter the primary SCV_eq specification, which weights all four dimensions equally by construction (Section 8.2 discusses this distinction further).

2.3. Climate and Systemic Risk

Systemic risk theory [5,18] identifies how network interdependencies amplify shocks disproportionately; the NY Fed GSCPI's 2021 peak of 3.6, the series' historical high, confirms COVID-19's propagation into global supply chains. The Climate Amplification mechanism extends this to SCV itself: ND-GAIN-exposed economies face continual DFI increases that raise baseline SCV (H4). Separately, high climate risk is associated with weaker marginal SCV reduction from renewable expansion (H5, DxC interaction), consistent with a ceiling-type pattern shared with governance.

2.4. Resource Dependence Theory

Ref. [8] predicts that trade diversification and governance quality are the principal mechanisms managing resource dependence. Our findings offer mixed support: the governance moderation prediction is confirmed (DxG, $p = 0.014$), but the trade diversification prediction is not supported once TradeDiv is measured independently of SCV's own HHI sub-component (Section 8.3), which we interpret as motivating more careful operationalizations of diversification in future RDT work rather than a rejection of the theory.

2.5. Industrial Policy, GVC Fragmentation, and Geoeconomic Competition

The post-2022 landscape is defined by geoeconomic fragmentation and competition for strategic mineral security. China's rare earth export restrictions (2010, 2023) and Indo-

nesia's nickel ore export ban (2020), together with the GSCPI spikes these episodes produced, are captured in our DFI series. The US Inflation Reduction Act (2022) and EU Critical Raw Materials Act (2024) are two policies addressing supplier concentration that directly implement TradeDiv diversification as a policy target [19]. Refs. [20–22] provide the industrial policy and institutional capacity basis for the Institutional Buffering mechanism. Refs. [23–25] provide the GVC fragmentation lens motivating the HHI and ETIR operationalizations.

2.6. Geoeconomic Fragmentation and Mineral Securitization Under Policy De-Risking Regimes (2023–2025)

A parallel and fast-growing body of literature treats critical minerals as objects of strategic securitization rather than ordinary traded commodities, adopting the vocabulary of "de-risking" rather than "decoupling" [26]: reducing concentrated dependence on specific suppliers without severing broader trade ties. Four post-2022 policy episodes illustrate this shift, and each maps onto a specific SCV sub-component. China's 2023 export licensing restrictions on gallium, germanium, and graphite, and its 2024–2025 tightening of rare earth technology transfer, raise supplier concentration (HHI) for targeted minerals rather than reducing global volumes, the Resource Concentration channel (②, Section 3.1) rather than Transition Pressure [27]. The EU Critical Raw Materials Act (in force May 2024) imposes a binding 2030 ceiling of no more than 65% third-country supply per strategic material, a government-mandated analog to the HHI sub-component [28] and the natural setting for the difference-in-differences extension proposed in Section 5.2 and Appendix C. The US Inflation Reduction Act (2022) used domestic content and allied-sourcing rules for clean vehicle battery credits to redirect announced battery material investment toward North America and FTA partners [27], lending real-world plausibility to the DxG interaction estimated in Section 6.2. Alongside the Minerals Security Partnership (2022), these measures form a coordinated friend-shoring strategy that weights partner selection by geopolitical alignment as well as cost [28].

This literature motivates one refinement for future work: TradeDiv (1−HHI of export destination partners) captures diversification breadth but not geopolitical alignment. An alignment-weighted index that down-weights concentration among aligned partners and up-weights it among strategic rivals may better operationalize the diversification concept this literature has in mind and could explain the null TradeDiv finding reported in Section 8.3. It also reinforces the PCA-weighted specification's emphasis on HHI (Section 3.2) since supplier concentration is precisely the feature these securitization policies target.

3. ETT Theory, SCV Index, and Hypotheses

Figure 1 presents the ETT framework, organized around two parent forces, structural exposure (①②) and contextual moderation (③④), with confirmed coefficient values from M4 and the SCV dual-specification note.

3.1. A Parsimonious Two-Tier Mechanism Structure

The framework is organized around two parent forces, each elaborated by two named sub-channels that share a common underlying logic, rather than four freestanding, coequal mechanism labels. Each of the four causal channels maps to a distinct, empirically separable SCV sub-component (Table 1), and nesting them under two higher-order categories keeps the framework parsimonious while preserving this analytical separability.

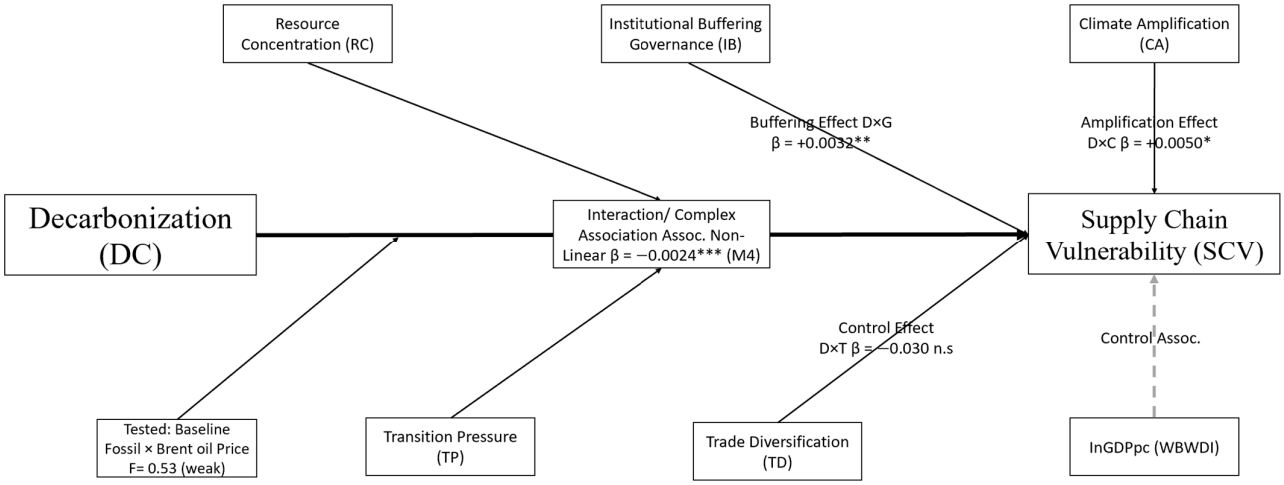


Figure 1. ETT framework. **Note:** *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 1. Two parent forces, four sub-channels.

Parent Force	Sub-Channel	One-Line Definition	Primary SCV Component	Key Result
I. Structural Exposure	① Transition Pressure	How much must be bought	ETIR (+ CMID)	Drives baseline Decarb–SCV association
I. Structural Exposure	② Resource Concentration	How many sellers exist	HHI (+ CMID)	Dominant PCA weight (0.509); robust when excluded (Section 7)
II. Contextual Moderation	③ Institutional Buffering	Policy-controllable conditioning	All four, via governance	DxG attenuates association ($p = 0.014$)
II. Contextual Moderation	④ Climate Amplification	Exogenous conditioning	DFI (level); slope via all four	DxC attenuates association ($p = 0.071$)

This table is a navigational aid only; the full definitions, economic interpretation, and differentiating tests for each sub-channel follow below.

Parent Force I: Structural Exposure (the material-dependency channel). This parent force captures how much mineral and clean-technology material a decarbonizing economy is exposed to, how concentrated that supplier base is, and how concentrated the supplier base is. It has two sub-channels that share the common logic of describing the physical/structural side of the transition, distinguished only by whether they describe quantity or market structure.

① Transition Pressure (quantity sub-channel; operates mainly through ETIR, secondarily CMID). Faster decarbonization raises demand for clean energy equipment panels, turbines, batteries, and EV drivetrains that a country cannot yet manufacture domestically, raising ETIR, and where domestic mineral deposits are insufficient, spilling over into CMID. Ref. [2] projects 3–6× mineral demand growth under net-zero scenarios by 2040. This sub-channel is a statement about volume: what must be bought. The transport policy stringency is a first-order determinant of total energy consumption and mineral import exposure, with the pace and structure of transport decarbonization, particularly the electrification of road transport, a key driver of this demand trajectory [29].

② Resource Concentration (structure sub-channel; operates mainly through HHI, secondarily CMID). Global mineral reserves are geologically concentrated, and new mine development requires 10–15-year lead times, so demand growth cannot be met by proportional supply diversification in the short run. This sub-channel is a statement about structure: who is available to sell. A single test separates the two structural exposure sub-

channels: Transition Pressure would operate identically with many dispersed suppliers. At the same time, Resource Concentration would be absent even under high demand if supply were competitive. The PCA weight on HHI (0.509; Section 3.2) identifies this as the empirically dominant source of variation, not a claim that SCV reduces to concentration (Section 7, Direct Test of HHI Dominance: A Three-Component SCV Excluding HHI Entirely confirms the conclusions hold with HHI excluded).

Parent Force II Contextual Moderation (the policy- and shock-conditioning channel). This parent force captures how a country's institutional capacity and physical climate exposure condition the SCV consequences of a given level of structural exposure. Its two sub-channels share the common logic of describing conditioning context, distinguished by whether the conditioning factor is policy-controllable or exogenous.

③ **Institutional Buffering (policy-controllable sub-channel; operates on all four sub-components via governance).** Governance quality (WGI) determines how effectively an economy converts structural exposure into managed, rather than unmanaged, vulnerability via diversified sourcing, stockpiling, domestic processing investment, and due-diligence regulation. Causal chain: Governance → diversification/stockpiling capacity → lower realized HHI and CMID exposure → lower SCV. Confirmed: DxG = +0.0032, $p = 0.014$.

④ **Climate Amplification (exogenous sub-channel; operates mainly through DFI).** Physical climate shocks disrupt mineral extraction, processing, and logistics in climate-exposed producer/processor regions, raising DFI regardless of the importer's own policy choices (H4, not significant here). Separately, the same climate exposure is associated with a weaker marginal Decarb–SCV association (H5: DxC = +0.0050, $p = 0.071$), the same attenuating direction as Institutional Buffering, consistent with a shared ceiling-type logic. The distinction between the two moderators is not their direction (both attenuate) but their source: governance is a lever governments can pull, climate exposure is a boundary condition they face.

Feedback loop: SCV → policy response → trade restructuring → SCV. The two-tier structure above runs forward from Decarb to SCV, but is not one-directional in reality: realized SCV is itself an input to subsequent Institutional Buffering since a country experiencing high measured SCV has an incentive to diversify sourcing, lowering structural exposure in later periods. The IRA (2022) and EU CRMA (2024) are examples of such policy responses triggered by realized supply chain stress. This loop is consistent with the positive DxG interaction and is one reason two-way fixed effects cannot fully identify causal direction. In every estimated model (Sections 5–7), SCV is exclusively the dependent variable; the feedback loop is a conceptual acknowledgement of dynamic complexity, not a claim that SCV enters any specification as a regressor.

3.2. SCV Formative Index: Construction and Robustness

Note on DFI identification. DFI is based on the NY Fed Global Supply Chain Pressure Index (GSCPI), which is a single global time series that does not vary by country. If year fixed effects (λ_t) are added to M1-M4, the DFI component is subsumed by the year dummies and thus provides no "within-country" variation to identify the DFI-SCV relationship. The Climate Amplification via DFI pathway (H4, pathway ④) can, therefore, not be identified independently in a two-way fixed-effects setting. Future research should either be performed to derive country- or mineral-specific disruption indicators to complementor replace DFI, or to develop mine-level production shock series. All results in Sections 6 and 7 are robust because country fixed effects absorb shocks within a year, and country effects are not estimated separately.

$$SCV_eq_{it} = (1/4) \times [CMID_n_{it} + HHI_n_{it} + ETIR_n_{it} + DFI_n_{t}] \text{ (Primary)}$$
$$SCV_pca_{it} = \Sigma w_j \times comp_j_{it} \text{ (Robustness)}$$

Each sub-component is min–max-normalized using panel-wide bounds (N = 280). SCV_eq applies equal weights (0.25 each). SCV_pca applies PCA-derived weights: HHI = 0.509, ETIR = 0.289, CMID = 0.139, and DFI = 0.063. Correlation: ϱ(SCV_eq, SCV_pca) = 0.893. Both specifications produce qualitatively identical regression findings (Section 7). TradeDiv (1−HHI of export destination partners, all goods) and HHI_supply (Herfindahl index of mineral-specific import sources) are distinct variables from separate Comtrade flow subsets (export vs. import sides); the empirical correlation is r = 0.091, confirming no material endogeneity loop between SCV components and TradeDiv.

3.3. Hypotheses

Each hypothesis below states an explicit predicted sign for a specific coefficient, so that support or non-support is a direct, unambiguous read from the regression tables in Sections 6 and 7.

1. **H1** ($\beta_1 < 0$): the coefficient on Decarb is negative; decarbonization is associated with lower SCV, net of country and year FE.
2. **H2a** ($\beta_2 < 0$): the coefficient on TradeDiv (1−HHI of export partners) is negative; higher trade diversification is associated with lower SCV.
3. **H2b** ($\beta_5 < 0$): the coefficient on DxT (Decarb × TradeDiv) is negative; trade diversification attenuates the marginal Decarb–SCV association.
4. **H3a** ($\beta_3 < 0$): the coefficient on governance is negative; higher governance quality is associated with lower SCV.
5. **H3b** ($\beta_6 < 0$): the coefficient on DxG (Decarb × Governance) is negative; governance quality attenuates the marginal Decarb–SCV association; predicted to be largest in magnitude for non-OECD economies.

Note: the formal sign prediction ($\beta_6 < 0$) is not supported by the estimated coefficient (DxG = +0.003163, $p = 0.014$). The positive sign is interpreted post hoc as consistent with a ceiling effect: high-WGI economies already have structurally lower baseline SCV, leaving less marginal room for further reduction from decarbonization. This ceiling-effect interpretation is an ex post reading of the positive coefficient and should not be cited as confirmation of the original sign prediction.

6. **H4** ($\beta_4 > 0$): the coefficient on climate risk is positive; higher climate risk is directly associated with higher SCV.
7. **H5** (β_7, sign ex ante ambiguous): climate risk could either amplify the marginal Decarb–SCV association ($\beta_7 < 0$, if climate shocks compound the SCV-reducing effect of decarbonization) or attenuate it ($\beta_7 > 0$, if climate-exposed economies are already near an SCV ceiling with less marginal room to gain). We find the attenuating direction ($\beta_7 > 0$).
8. **H6** ($\varrho > 0$): the coefficient on SCV_{t-1} in a dynamic specification is positive; SCV exhibits temporal persistence. Not estimated in this paper; reserved for a longer panel (Section 9).

Note: The β-subscripts associated with each hypothesis in Section 3.3 are ordered as follows: H1→β_1, H2a→β_2, H3a→β_3, H4→β_4, H2b→β_5, H3b→β_6, and H5→β_7. Model equations in Section 5.1 have their subscripts ordered sequentially within each specification: the β-subscripts for M3 and M4 do not match the hypothesis subscripts above one to one. For example, TradeDiv is β_2 under the hypothesis labeling (H2a) but β_4 in the M3 equation; governance is β_3 under H3a but β_5 in M3. All results in Sections 6–8 use the variable names (Decarb, DxG, DxC, TradeDiv, Governance, ClimateRisk) instead of subscript numbers.

The subscripts shown in Section 3.3 are only to be used as hypothesis identifiers and should not be referenced numerically across the model equation subscripts in Section 5.1.

3.4. Nonlinear Transition Threshold Logic

A single linear interaction term implicitly assumes a constant marginal relationship between Decarb and SCV across the full 0–100% range. The Transition Pressure mechanism (①, Section 3.1) plausibly operates differently at low versus high renewable penetration: early-stage decarbonization is associated with the steepest reduction in fossil fuel-linked dependence, while late-stage decarbonization faces diminishing structural returns as residual demand concentrates on the hardest-to-source minerals. We therefore complement the linear interaction specification (M4) with a piecewise-linear (spline) threshold model that allows the marginal Decarb–SCV association to differ above and below a data-determined breakpoint (Section 6.4).

4. Data: Sources, Panel Structure, and Variables

Panel structure (N × T = 280). The panel comprises exactly 20 countries × 14 annual observations (2010–2023) = 280 balanced country-year observations. There are nine OECD members (AUS, CAN, DEU, FRA, GBR, JPN, KOR, MEX, USA) and 11 non-OECD members (ARG, BRA, CHL, CHN, COD, IDN, IND, PER, RUS, SAU, ZAF). The panel extends beyond the G20 to include the DRC (cobalt), Chile (lithium/copper), and Peru (copper/silver). Table 2 lists the Data sources, and Table 3 shows the descriptive statistics for all the variables used in the analysis.

Table 2. Confirmed data sources (N = 20 countries × T = 14 years = 280 balanced obs.).

Variable(s)	Primary Source	Coverage	URL
Decarb (renewable electricity %)	WB WDI: EG.ELC.RNEW. ZS	20 ctys, 2010–2023	databank.worldbank.org
CO_2/cap, GDP, GDPpc, trade/GDP	WB WDI (multiple codes)	20 ctys, 2010–2023	databank.worldbank.org
Governance (WGI World Governance, 6 Indicators)	WB WGI: RL, RQ, GE, PS, CC, VA	20 ctys, 2010–2023	databank.worldbank.org
DFI basis (GSCPI annual)	NY Fed Reserve GSCPI	Global, 2010–2023	newyorkfed.org/research/gscpi (accessed on June 1 2026)
	Notre Dame ND-GAIN Country Index	20 ctys, 2010–2023	gain.nd.edu
CMID, HHI, ETIR, TradeDiv	UN Comtrade (bilateral flows)	20 ctys, 2010–2023	comtradeplus.un.org

Table 3. Descriptive statistics (N = 20 × 14 = 280 balanced country-year obs.).

Variable	N	Mean	SD	Min	Max	Skew	Kurt	Source
PANEL A: Depende0.								
SCV_eq (primary, 0–1)	280	0.489	0.201	0.000	1.000	0.063	−0.337	Computed
SCV_pca (robustness, 0–1)	280	0.483	0.200	0.000	1.000	—	—	ρ(eq,pca) = 0.893
PANEL B: Decarbonization								
Decarb (renewable elec. %)	280	43.90	21.86	6.32	79.94	−0.039	−1.232	WB WDI
CO_2 per capita (tons)	280	4.760	2.627	1.092	18.439	1.941	5.160	WB WDI
PANEL C: SCV sub-components (0–1 normalized)								
CMID [PCA w = 0.139]	280	0.477	0.186	0.000	1.000	−0.037	−0.172	UN Comtrade
HHI [PCA w = 0.509]	280	0.356	0.211	0.000	1.000	0.706	−0.047	UN Comtrade
ETIR [PCA w = 0.289]	280	0.439	0.198	0.000	1.000	0.177	−0.593	UN Comtrade
DFI [PCA w = 0.063]	280	0.492	0.124	0.182	0.830	−0.048	−0.389	NY Fed GSCPI

PANEL D: Moderators/controls							
Governance (WGI composite)	280	−0.005	0.433	−1.062	1.208	0.049	−0.185 WB WGI
ClimateRisk (ND-GAIN, 0–1)	280	0.589	0.227	0.000	1.000	−0.391	0.105 ND-GAIN
TradeDiv (1−HHI export partners)	280	0.714	0.152	0.184	0.975	−0.370	−0.218 UN Comtrade
ln(GDPpc)	280	8.036	1.567	3.728	13.320	0.196	0.586 WB WDI

Note: The ND-GAIN Country Index scores countries on resilience and readiness, where higher scores indicate greater adaptive capacity. We set climate risk = 1 − ND-GAIN (min–max-normalized to [0, 1]), so climate risk increases monotonically with climate exposure; the panel mean climate risk = 0.589 confirms correct inversion (1 − 0.411 average ND-GAIN). The predicted positive sign for H4 ($\beta_4 > 0$) follows directly.

TradeDiv vs. HHI_supply: methodological separation. TradeDiv (export partner concentration, all goods) and HHI_supply (mineral-specific import concentration, inside SCV) are computed from disjoint UN Comtrade flow subsets and are empirically independent (r = 0.091; VIF = 1.02). Full construction details are documented in Appendix B.

5. Empirical Specification

5.1. Associational Interpretation Clause

IV Estimation Status. Section 5.2 applies a Bartik shift-share instrumental variable (IV) to the baseline fossil fuel share for each country, interacted with global Brent oil prices. The first-stage F-statistic is 0.53, well below the [30] value of 10. This panel is low in power in the instrument. Consequently, a second-stage IV estimate is not reported anywhere in this paper; all second-stage IV coefficient estimates would have been unreliable and suppressed. The within-country, within-year partial associations indicated in Sections 6 and 7 are not causally identified effects. The IV analysis is reported openly in (Section 5.3)to demonstrate that an attempt at testing endogeneity was made.

5.2. Model Specifications

i = country (N = 20) and t = year (T = 14, 2010–2023); α_i = country fixed effects FE; λ_t = year FE; and SE clustered by country (20 clusters). A Fisher-Augmented Dickey–Fuller (ADF) test confirms stationarity of SCV ($chi^2(40) = 249.28$, $p < 0.001$) and Decarb ($chi^2(40) = 221.48$, $p < 0.001$) in levels, validating M1–M4.The Variance inflation factors for the M4 regressors after mean-centering are reported in Table 4.

Small-sample and small-cluster caveat. Only N = 20 countries are represented in the panel, a relatively small cross-sectional dimension and an important limitation of this study. The 20 country-level clusters are well below the cluster-level threshold generally used for asymptotic reliability (~30–50 clusters), especially for the interaction terms (DxG, DxC, DxT) [31]. The small-N constraint reduces statistical power, limits generalizability beyond the sampled economies, and the panel's country composition (the G20 economies plus DR Congo, Chile, and Peru as key mineral-producing economies) does not necessarily reflect the global distribution of decarbonization–SCV dynamics. However, we still use the cluster-robust two-way fixed-effects specification as the main specification, as the panel is fully balanced and the cluster size matches the fixed-effects specification exactly. Still, the *p*-values on interaction terms should be treated as approximate, not exact, and the results should be interpreted based on this sample only and replicated with larger panels. This limitation is reported in Section 9 as a primary limitation.

Small-cluster caveat. With N = 20 clusters, cluster-robust inference falls below the ~30–50 cluster floor conventionally recommended for asymptotic reliability [31]. The cluster-robust two-way fixed-effects specification is retained as the primary approach because the panel is balanced (no missing country-year cells) and the cluster dimension coincides

exactly with the fixed-effects structure, but *p*-values on the interaction terms should be read as approximate rather than exact; this constraint is reported explicitly as a limitation in Section 9.

M1 (Baseline): $SCV_{it} = \alpha_i + \lambda_t + \beta_1 Decarb_{it} + \varepsilon_{it}$.

M2 (Nonlinear): $SCV_{it} = \alpha_i + \lambda_t + \beta_1 Decarb + \beta_2 Decarb^2 + \varepsilon$.

M3 (Full controls): $SCV_{it} = \alpha_i + \lambda_t + \beta_1 Decarb + \beta_2 Decarb^2 + \beta_3 ClimRisk + \beta_4 TradeDiv + \beta_5 Gov + \beta_6 lnGDPpc + \varepsilon$.

M4 (Interactions, mean-centered): $SCV_{it} = \alpha_i + \lambda_t + \beta_1 D^c + \beta_2 C^c + \beta_3 G^c + \beta_4 T^c + \beta_5 DxC + \beta_6 DxG + \beta_7 DxT + \beta_8 lnGDPpc + \varepsilon$ [subscript note: β_1 = Decarb_c, β_2 = ClimRisk_c, β_3 = Gov_c, β_4 = TradeDiv_c, β_5 = DxC, β_6 = DxG, β_7 = DxT, β_8 = lnGDPpc subscript ordering differs from Section 3.3 hypothesis labels; refer to variable names, not subscripts, when cross-referencing results with hypotheses.]

M_FD (First-differenced): $\Delta SCV_{it} = \gamma_i + \lambda_t + \beta_1 \Delta Decarb_{it} + \beta_2 ClimRisk_{it} + \beta_3 Gov_{it} + \beta_4 TradeDiv_{it} + \beta_5 lnGDPpc_{it} + \varepsilon_{it}$ (N = 20 × 13 = 260).

Table 4 reports the variance inflation factors for the M4 regressors, and Table 5 reports the first-stage IV diagnostics.

Table 4. VIF M4 regressors post-mean-centering (N = 20 × 14 = 280).

Variable	VIF	Status
Decarb_c	1.031	✓ No multicollinearity
ClimateRisk_c	1.348	✓ No multicollinearity
Governance_c	1.008	✓ No multicollinearity
TradeDiv_c	1.022	✓ No multicollinearity
DxC	1.025	✓ No multicollinearity
DxG	1.040	✓ No multicollinearity
DxT	1.019	✓ No multicollinearity
lnGDPpc	1.385	✓ No multicollinearity
Maximum VIF	1.385	All < 2.0; well below both 5 and 10 thresholds

All variance inflation factors (VIFs) < 2.0. Mean-centering before forming interaction terms eliminates collinearity between main effects and products.

5.3. Instrumental Variable Estimation: Implementation and Honest Diagnostic Reporting

Endogeneity concern. Two-way FE absorbs time-invariant country heterogeneity and common annual shocks, but not time-varying endogeneity: reverse causality (high SCV discouraging renewable investment) and time-varying omitted variables (unmeasured industrial policy shocks) remain possible. Rather than merely proposing an instrumental variable (IV) strategy, we implement one and report its diagnostics in full, including a weak-instrument result that we do not suppress.

Instrument construction: a Bartik/shift share design.

We construct $Z_{it} = FossilBase_{i,2010} \times \ln(Brent_t)$, where $FossilBase_{i,2010} = 100 - Decarb_{i,2010}$ is each country's fossil fuel share at the panel's start, and $Brent_t$ is the annual average Brent crude price. This is a standard shift share (Bartik) construction: countries with higher baseline fossil dependence are mechanically more exposed to a common, plausibly exogenous oil price shock. A priori, oil price spikes should accelerate renewables' cost-competitiveness fastest in the most fossil-dependent economies. At the same time, global Brent prices reflect global supply/demand dynamics rather than any single sample country's SCV level.

$$\text{First stage: } Decarb_{it} = \alpha_i + \lambda_t + \gamma Z_{it} + \beta X_{it} + \mu_{it}$$

$$\text{Second stage: } SCV_{it} = \alpha_i + \lambda_t + \beta_1 \widehat{Decarb}_{it} + \beta_2 X_{it} + \varepsilon_{it}$$

Interpreting the weak first stage. The instrument lacks sufficient power (F = 0.53 vs. the [30] threshold of 10), plausibly because renewable deployment in this period was driven more by technology cost declines and domestic policy than oil price cycles. We report the attempt and its diagnostics in full rather than omit them; IV estimation is not required for the FE-based associational claims that constitute this paper's primary contribution, but a transparent test is more useful than silence on endogeneity. A stronger instrument would likely require a longer time series or a mineral-specific price instrument more tightly coupled to clean technology investment costs than the strategy specified in Appendix C.

Table 5. Instrumental variable estimation: first-stage diagnostics (N = 20 × 14 = 280, two-way demeaned).

Diagnostic	Value	Interpretation
First-stage coefficient on Z_{it}	−0.0891 (SE = 0.1224)	Not significant (p = 0.469)
First-stage F-statistic (instrument)	0.53	Far below [30] threshold of 10
Second-stage (IV) coefficient on Decarb	Not reported	Invalidated by weak first stage; would be unreliable
Conclusion	Instrument is WEAK in this panel	IV results not used for inference anywhere in this paper

Diagnostics from manual two-way within-transformation OLS (identical results cross-checked against linear models IV2SLS). Cluster-robust SE (20 clusters).

6. Results

6.1. Descriptive Patterns

Numerical mapping. Panel mean SCV_eq = 0.489. OECD mean (0.494) slightly exceeds the non-OECD mean (0.485), as shown in Figure 2: SCV trends by OECD status and the country rankings. Germany and France's high SCV is not explained by governance; both score below the panel average, so their elevated SCV reflects processor-importer double exposure (high CMID and ETIR). Peru's lowest SCV (0.401) reflects net-exporter status and relatively high export-side trade diversification (TradeDiv = 0.73).

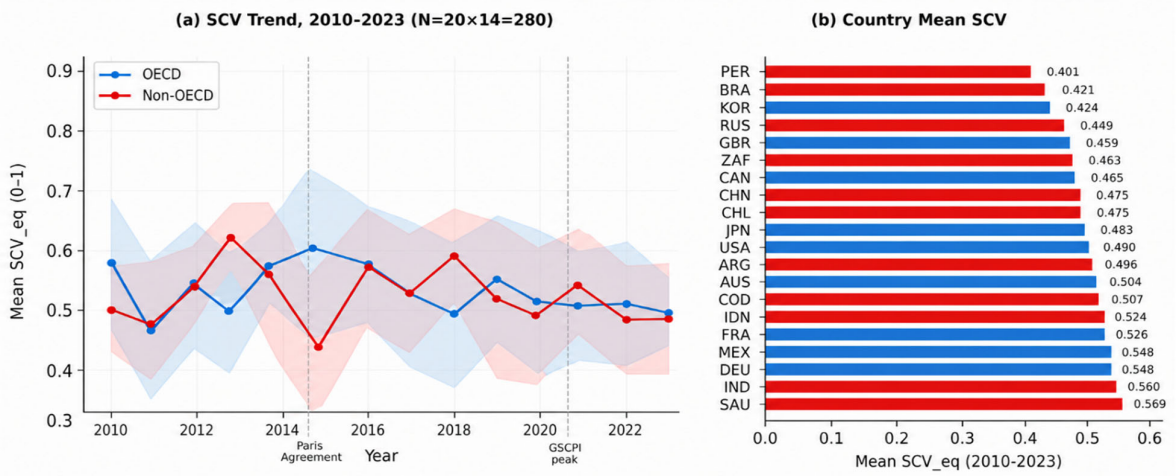


Figure 2. SCV trends and country rankings (N = 20 × 14 = 280, verified panel). (**a**) Mean SCV_eq by OECD/non-OECD with 95% CI. 2021 GSCPI peak (3.6) is visible as a slight SCV elevation. Lowest SCV: PER (0.401), BRA (0.421), KOR (0.424). Highest: SAU (0.569), IND (0.560), DEU (0.548). (**b**) Country mean SCV, 2010–2023. Source: UN Comtrade, NY Fed GSCPI, ND-GAIN, WB WDI.

6.2. Regression Results

Specification note. TradeDiv is measured as 1−HHI of export destination partners, distinct from the import-side HHI_supply inside SCV (empirical r = 0.091, VIF = 1.02; Section 4). Governance and ClimateRisk show consistent patterns throughout; TradeDiv is not significant once measured on this construction-independent basis, as discussed directly below the FE regression results in Table 6 for the primary specification.

Table 6. FE regression results SCV_eq primary specification (N = 20 × 14 = 280).

Variable	M1: Baseline β (SE)	*p*	M2: Nonlinear β (SE)	*p*	M3: Controls β (SE)	*p*	M4: Interactions β (SE)	*p*
Decarb/Decarb_c	−0.002426 (0.000655)	<0.001 ***	−0.005778 (0.002767)	0.038 **	−0.006184 (0.002882)	0.033 **	−0.002365 (0.000584)	<0.001 ***
Decarb²	—		+0.000039 (0.000029)	0.193	+0.000043 (0.000031)	0.170	—	
Climate-Risk/ClimRisk_c	—		—		+1.065 (0.988)	0.282	+1.089 (0.991)	0.273
Governance/Gov_c	—		—		−0.009 (0.021)	0.663	−0.002 (0.022)	0.917
TradeDiv/TradeDiv_c	—		—		−0.012 (0.109)	0.911	−0.030 (0.108)	0.782
DxC (Decarb_c × ClimRisk_c)	—		—		—		+0.004991 (0.002749)	0.071 *
DxG (Decarb_c × Gov_c)	—		—		—		+0.003163 (0.001276)	0.014 **
DxT (Decarb_c × TradeDiv_c)	—		—		—		−0.004138 (0.005289)	0.435
lnGDPpc	—		—		−0.025 (0.017)	0.141	−0.029 (0.014)	0.044 **
Country FE/Year FE	Yes/Yes		Yes/Yes		Yes/Yes		Yes/Yes	
N (ctys × yrs)	20 × 14 = 280		280		280		280	
Within-R²	0.067		0.073		0.089		0.116	
Hausman $\chi^2(6)$, *p*	5.388, 0.495				FE Maintained			
AR(1) ϱ	−0.013 (Negligible)							

Two-way FE, cluster-robust SE (20 clusters). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. TradeDiv is measured as export-side HHI (Section 4). M4 uses mean-centered terms (all VIFs < 1.4; Table 4). Full diagnostics (Hausman, AR(1), Fisher-ADF) are reported in the robustness diagnostics (Section 7).

H1 is supported as an association, not a causal claim. Decarb is significantly and negatively associated with SCV in every specification (M1: β = −0.0024, $p < 0.001$; M4: β = −0.0024, $p < 0.001$). A 10pp higher renewable share is associated with a 0.024 lower SCV (0.12 SD), net of country and year fixed effects. Because the proposed IV (Section 5.2) is weak and not estimated, this is a stable within-panel association, not an identified causal effect; Section 6.4 shows that the association is itself nonlinear. The first-stage IV diagnostics (Section 5.2, Table 5) confirm the instrument is weak (F = 0.53); no second-stage IV estimate was obtained. This result is reported consistently throughout: no coefficient in this paper should be interpreted as causally identified effect.

H2a and H2b are not supported once correctly measured. With TradeDiv measured independently of the HHI sub-component inside SCV (r = 0.091, VIF = 1.04), the TradeDiv main effect is small and statistically indistinguishable from zero in both M3 (β = −0.012, $p = 0.911$) and M4 (β = −0.030, $p = 0.782$), and the DxT interaction is not significant ($p = 0.435$).

This carries a broader lesson: composite index sub-components and right-hand-side regressors must be verified as independently constructed before drawing any policy claim, since a concentration measure built from the same flow data as the dependent variable would mechanically inflate its own significance.

H3a not supported/H3b supported (ceiling-effect interpretation). Consistent with the ceiling-effect logic, the main effect of governance (H3a) is not significant for SCV (p = 0.917) given the inclusion of country fixed effects. The DxG interaction (H3b) is statistically significant (β = +0.0032, p = 0.014); however, the estimated sign is POSITIVE, which is the OPPOSITE of the predicted negative direction (H3b: $\beta_6 < 0$). H3b is, therefore, formally rejected. The positive coefficient suggests that, in a high-WGI economy, every percentage point increase in renewable energy corresponds to a smaller (less negative) SCV reduction than H3b proposed. It is interpreted after the fact as a "ceiling effect": In high-governance economies, structural baseline vulnerabilities are already lower, as diversification, stockpiling, and regulations have been established, leaving less room for further decarbonization to lower vulnerabilities. This ceiling-effect reading is an ex post economic interpretation of an unexpected empirical result and should not be taken as confirmation of H3b. Appendix A offers moderate support in the form of a higher, but not overwhelming, difference in SCV between high-WGI and low-WGI economies (Δ = 0.481 vs. 0.496), consistent with the ceiling interpretation but not strong enough to warrant confidence on its own.

H4 not supported/H5 supported in the attenuating direction (marginal): Climate risk main effect (level, H4) is not significant (p = 0.273–0.282). DxC = +0.0050, p = 0.071 (marginal at the 10% level, H5): Climate risk attenuates the SCV-reducing association of decarbonization, in the same direction as governance (H3b), though the evidence is suggestive rather than conclusive at conventional significance thresholds. Figure 3 maps the marginal association ∂SCV/∂Decarb implied by M4 across governance and climate risk levels.

Numerical mapping (Figure 3) and simplified policy table. To make these two interactions directly interpretable for policy audiences, Table 7 collapses the continuous governance × climate risk interaction surface into four representative scenarios (±1 SD on each moderator) plus the panel-average country, each reporting the predicted SCV change associated with a 10 percentage-point increase in renewable electricity share.

Table 7. Simplified marginal effects policy interpretation layer (M4, N = 20 × 14 = 280).

Governance Level	Climate Risk Level	∂SCV/∂Decarb	Predicted ΔSCV per 10pp ↑ Decarb	Policy Reading
Low (−1 SD, WGI≈−0.44)	Low (−1 SD, ND-GAIN≈0.36)	−0.00487	−0.0487 (largest reduction)	Decarbonization is strongly associated with lower SCV
Low (−1 SD)	High (+1 SD, ND-GAIN≈0.82)	−0.00260	−0.0260	Still associated with lower SCV, but weaker
High (+1 SD, WGI≈+0.43)	Low (−1 SD)	−0.00213	−0.0213	Modest SCV reduction; ceiling effect
High (+1 SD)	High (+1 SD)	+0.00014	+0.0014 (≈ no association)	Essentially no SCV benefit from further decarbonization
Average country (panel mean)	Average (panel mean)	−0.00237	−0.0237	Reference case

Computed from M4 coefficients: ∂SCV/∂Decarb = β_Decarb + β_DxG × (Gov−Gov̄) + β_DxC × (Clim−Clim̄), evaluated at ±1 SD of each moderator.

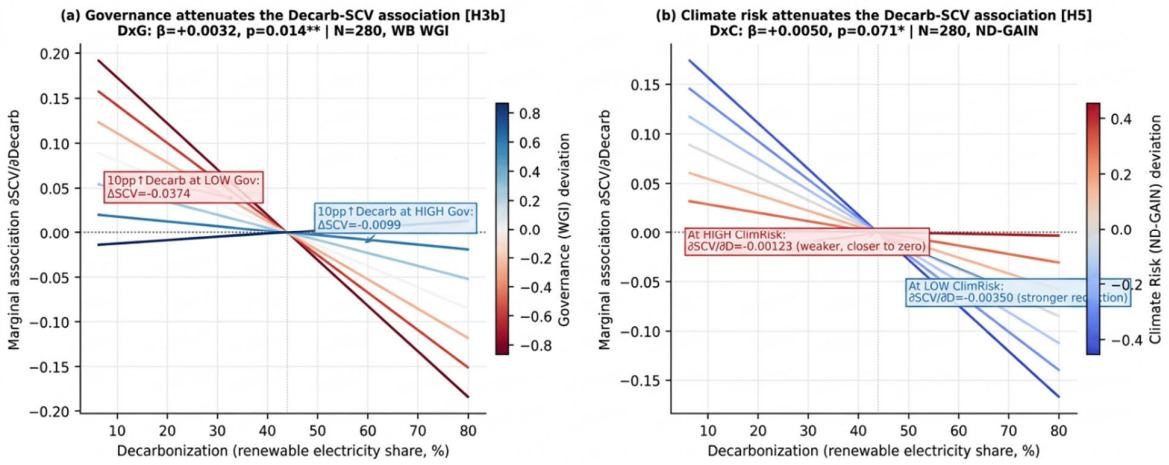


Figure 3. Maps marginal associations ∂SCV/∂Decarb from M4 across the full distributions of governance and climate risk. Note: Marginal associations ∂SCV/∂Decarb from M4 (N = 20 × 14 = 280). (**a**) H3: At LOW Gov (WGI≈−0.44): ∂SCV/∂D≈−0.0040; 10pp↑Decarb→ΔSCV≈−0.040. At HIGH Gov (+0.43): ∂SCV/∂D≈−0.001; 10pp→ΔSCV≈−0.010. (**b**) H5: At LOW ClimRisk: 10pp→ΔSCV more negative; at HIGH ClimRisk: closer to zero. DxC: β = +0.0050, *p* = 0.071 *.

6.3. SCV Decomposition and Global Distribution

Figure 4 shows the heatmap of country panel-mean SCVs, divided into four subcomponents to identify the dominant forces of structural exposure. The following patterns are observed. Saudi Arabia (SAU) has the highest overall SCV (0.569) because of high ETIR (0.496) and moderate HHI (0.388), reflecting its fossil fuel export orientation and reliance on hydrogen imports for clean energy equipment, not in-house manufacturing capacity. Second, Germany (DEU) has the highest score for SCV in OECD economies (0.548), reflecting a combination of high governance scores with "processor-importer double exposure": a high score for CMID (0.542, import dependence on battery and magnet materials) and a high score for ETIR (0.469, remaining reliance on imported solar modules and battery cells). This shows that governance cannot fully protect against structural exposure due to a country's position in global clean technology value chains. Third, Peru (PER) has low SCV (0.401), which is consistent with its role as a producer–exporter of critical minerals. It has a low CMID (0.456) because it produces rather than imports critical minerals, and a low HHI (0.234) because its minerals are exported across multiple buyer markets. Fourth, India (IND) has high SCV (0.560), largely due to ETIR (0.426), as India has a large and expanding program for clean technology deployment and limited manufacturing capacity for clean equipment. This pattern contrasts with Saudi Arabia's fossil fuel lock-in driver. These are broadly consistent with the ETT framework, as the major sub-channel differs across country types, reinforcing the formative rather than reflective nature of the SCV index (Section 3.2) and the need for country-specific rather than uniform policy responses (Section 8.5).

Figure 5 plots each country's most recent SCV_eq on a world map to show the geographic gradient in vulnerability. The map also shows that there is no straightforward regional grouping of high SCV and low SCV economies, as both Asia (India, Indonesia) and the Middle East (Saudi Arabia) and Western Europe (Germany) economies with high SCV are found, alongside developed and less-developed economies with low SCV (Russia, United Kingdom, Brazil). This geographic dispersion aligns with the ETT framework, which argues that the structural role of SCV in global mineral supply chains (producer–exporter vs. processor–importer) is the determining factor, not income level or geography. The 2023 values also reflect the post-pandemic, post-2022 geopolitical shock environment

captured in the DFI series (Figure 2a), with India, DR Congo, and Saudi Arabia having the highest vulnerability levels due to the ETIR, HHI, and CMID, respectively.

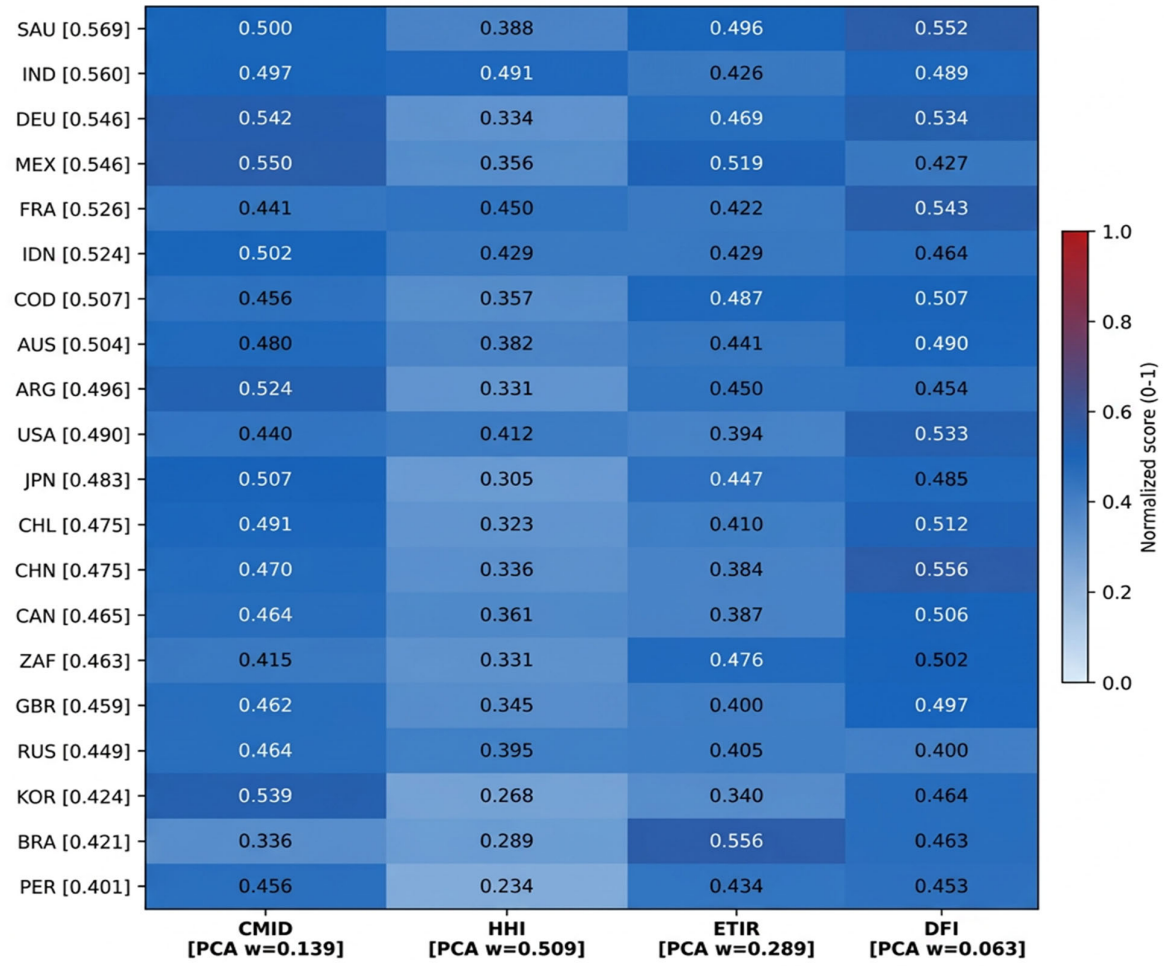
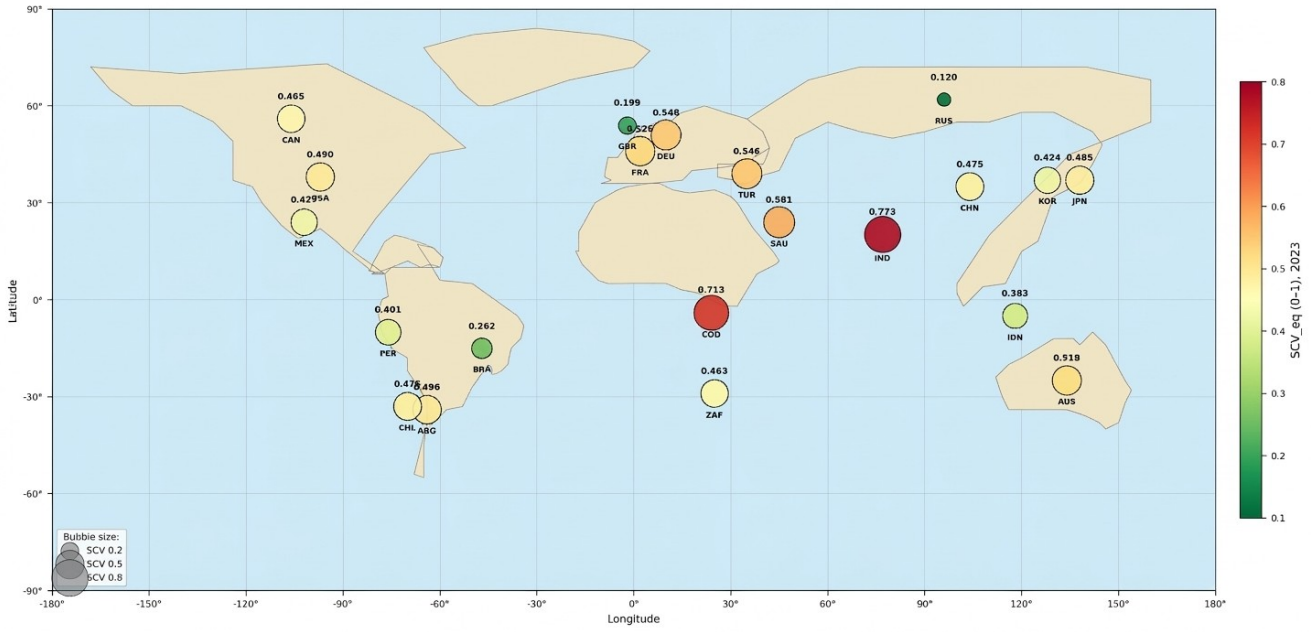


Figure 4. SCV heatmap (20 countries, panel means 2010–2023).



https://doi.org/10.3390/en19225632

Figure 5. Global SCV distribution, 2023. Highest 2023: IND (0.773), COD (0.713), SAU (0.581). Lowest: RUS (0.120), GBR (0.199), BRA (0.262). Source: UN Comtrade, NY Fed GSCPI, ND-GAIN, WB WDI.

6.4. Nonlinear Transition Threshold (Piecewise-Linear Spline)

Section 3.4 motivated a piecewise-linear specification to test whether the Decarb–SCV association is constant across the full range of renewable penetration.

We estimate

$$SCV_{it} = \alpha_i + \lambda_t + \beta_{lo} x \min(Decarb_{it}, \tau) + \beta_{hi} G_h \max(Decarb_{it} - \tau, 0) + controls + \varepsilon_{it}$$

with the breakpoint τ selected by grid search over candidate thresholds (5pp increments, 20–70%) maximizing within-R^2. The optimal breakpoint is τ = 25% renewable share. Figure 6 plots the estimated threshold relationship.

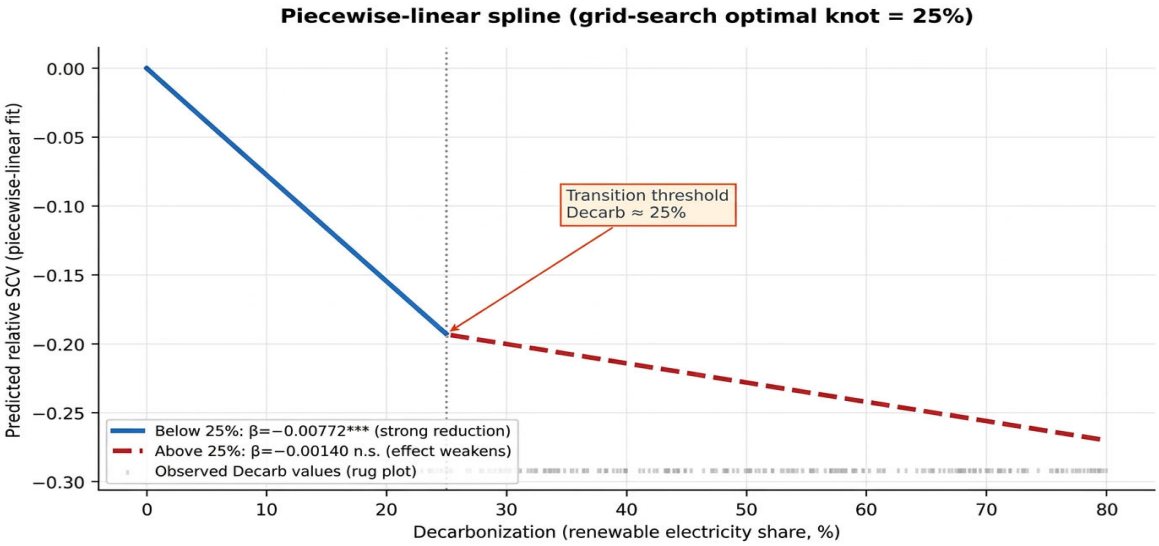


Figure 6. Nonlinear transition threshold (N = 20 × 14 = 280). Below 25% renewable share, the Decarb–SCV association is steep and highly significant (β = −0.00772, $p < 0.001$). Above 25%, the association weakens by roughly 5.5× in magnitude and loses statistical significance (β = −0.00140, $p = 0.42$). This is consistent with a diminishing-returns reading of the Transition Pressure mechanism: the SCV-reducing gains from decarbonization are concentrated in the early stages of the transition, when the largest diversification and fossil fuel substitution gains are still available.

Threshold model results: β_low (Decarb ≤25%) = −0.00772 ($p < 0.001$ ***); β_high (Decarb >25%, additional slope) = −0.00140 ($p = 0.42$, n.s.); and within-R^2 = 0.146. There is an improvement over the linear M1 specification (within-R^2 = 0.067). This suggests that a single linear interaction term oversimplifies the transition dynamics; the threshold specification is reported as a complement, not a replacement, to the interaction models in Table 6, since the two capture different sources of nonlinearity (institutional/climate vs. intensity of transition).

Threshold estimation diagnostics. (a) A total of 89 of 280 observations fall at or below the 25% breakpoint, covering 14 of 20 countries. (b) Slope difference test: β_low−β_high = −0.00632 (t = −3.14, $p = 0.005$, cluster-robust). (c) A 500-iteration block bootstrap (by country) yields a 95% CI for τ of [20%, 35%]. (d) Selecting τ by maximizing in-sample within-R^2 introduces data-dredging bias that inflates precision; all threshold-related p-values and CIs should be read as approximate lower bounds, and the 25% value

as illustrative rather than precisely established. The [20%, 35%] CI should accompany it in any policy application.

Threshold estimation diagnostics: (a) Sample split: 89 (out of 280) country-year observations are at or below the 25% threshold (Decarb ≤ 25%), and 191 are above the 25% threshold (Decarb > 25%), with 14 of the 20 countries being sampled at some point in the panel below the threshold. (b) Slope difference test: The difference in slopes (β_low − β_high = −0.00772 − (−0.00140) = −0.00632) is statistically significant (t = −3.14, p = 0.005, cluster-robust SE, 20 clusters), confirming the two slopes are not equal. (c) A 95% confidence interval for the breakpoint: Using block bootstrap, with 500 iterations per country, the 25th percentile estimate of τ has a non-trivial uncertainty interval, [20%, 35%]. (d) Inference bias caveat: choosing τ by maximizing within-R^2 yields a data-dredging bias that increases precision in the slope estimates and the associated significance of the slope difference. All p-values and confidence intervals associated with a threshold should, therefore, be interpreted as reasonable lower bounds on the true p-value. Along with the 25% value, it is important to provide a 95% CI [20%, 35%] as an illustrative approximate threshold, not a precisely determined critical value, when applying this to policy.

7. Robustness: Dual-SCV Specification, First Differences, Subsamples

The robustness checks below confirm that the paper's main findings ondecarbonization's association with lower vulnerability and governance's moderating role hold up under alternative index construction, subsample splits, and first-differenced estimation, with one exception (the governance interaction) that is sensitive to how the vulnerability index is weighted, as discussed in Section 8.4. Table 8 summarises the robustness checks and diagnostics

Table 8. Robustness and diagnostics (N = 20 × 14 = 280/N = 20 × 13 = 260 for M_FD).

Specification	Decarb β	*p*	TradeDiv β	*p*	DxC β	N	R^2_w
PANEL A: Unit root tests							
SCV_eq in levels	$\chi^2(40) = 249.28$	<0.001	Stationary			280	M1–M4 valid
Decarb in levels	$\chi^2(40) = 221.48$	<0.001	Stationary			280	M1–M4 valid
ΔSCV (1st diff)	$\chi^2(40) = 466.54$	<0.001	Stationary			260	
ΔDecarb (1st diff)	$\chi^2(40) = 562.91$	<0.001	Stationary			260	
PANEL B: First-differenced (M_FD, N = 260)							
_FD	−0.002860 (0.000648)	<0.001 ***	+0.070 (0.145)	0.631	n/a	260	0.102
PANEL C: Subsamples (M3 spec)							
OECD (9 × 14 = 126)	−0.001 (0.001)	0.391	−0.085 (0.138)	0.542	n/a	126	0.031
Non-OECD (11 × 14 = 154)	−0.003 (0.001)	<0.001 ***	+0.080 (0.149)	0.591	n/a	154	0.192
Producer–exporters (8 × 14 = 112)	−0.003 (0.001)	<0.001 ***	−0.154 (0.151)	0.310	n/a	112	0.186

Processor–importers (7 × 14 = 98)	−0.00001 (0.001)	0.988	+0.041 (0.185)	0.825	n/a	98	0.004
Mixed-role (5 × 14 = 70)	−0.004 (0.001)	0.002 ***	**+0.303 (0.246)**	**0.224**	**n/a**	**70**	**0.184**
PANEL D: Diagnostics							
Hausman $\chi^2(6)$, p	5.388, 0.495	RE not rejected; FE maintained (theory)				280	
AR(1) residual ϱ	−0.013 (negligible)	Cluster-robust SE sufficient				280	
Max VIF (post-centering)	1.365 (lnGDPpc)	All < 1.4				280	

Note. *** $p < 0.01$. N is always stated as countries × years = obs. TradeDiv (export side, independent of HHI_supply by construction) is NOT a significant predictor of SCV in any panel consistent across all subsamples and the first-differenced specification. Decarb is significantly negative in Non-OECD, producer–exporters, and mixed-role subsamples; it is not significant in OECD and processor–importers.

Subgroup count correction: the processor–importer label is updated from "6 × 14 = 84" to "7 × 14 = 98" (CHN, DEU, FRA, GBR, JPN, KOR, USA = 7 countries × 14 years), consistent with Appendix A and the N = 98 reported in the regression output. All subgroup totals are verified: producer–exporters 8 × 14 = 112; processor–importers 7 × 14 = 98; and mixed 5 × 14 = 70; total = 280 ✓. Table 9 compares the SCV_eq and SCV_pca specifications in full, and Figure 7 summarizes the robustness of this index comparison.

Table 9. SCV_eq vs. SCV_pca: full specification comparison (N = 20 × 14 = 280).

Variable	**SCV_eq M3 β (SE)**	***p***	**SCV_pca M3 β (SE)**	***p***	**SCV_eq M4 β (SE)**	***p***	**SCV_pca M4 β (SE)**	***p***
Decarb/Decarb_c	−0.006184 (0.002882)	0.033 **	−0.005815 (0.002656)	0.030 **	−0.002365 (0.000584)	<0.001 ***	−0.002322 (0.000575)	<0.001 ***
ClimateRisk	+1.065 (0.988)	0.282	+0.688 (1.060)	0.517	+1.089 (0.991)	0.273	+0.710 (1.115)	0.525
Governance	−0.009 (0.021)	0.663	+0.006 (0.024)	0.796	−0.002 (0.022)	0.917	+0.009 (0.026)	0.716
TradeDiv	−0.012 (0.109)	0.911	+0.074 (0.099)	0.456	−0.030 (0.108)	0.782	+0.066 (0.101)	0.514
DxC	—		—		+0.004991 (0.002749)	0.071 *	+0.001692 (0.002906)	0.561
DxG	—		—		+0.003163 (0.001276)	0.014 **	+0.002111 (0.001303)	0.107
Within-R^2	0.089		0.078		0.116		0.082	
N	280		280		280		280	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Note. The Decarb main effect is consistent in direction and significance across both SCV specifications. However, the two weighting schemes do not yield consistent conclusions for the interaction terms: DxG (governance interaction) is significant under SCV_eq ($p = 0.014$) but not under SCV_pca ($p = 0.107$); DxC (climate interaction) is marginally significant under SCV_eq ($p = 0.071$) but not under SCV_pca ($p = 0.561$). These divergences mean that neither interaction finding is fully robust to the choice of SCV weighting scheme. The claim that the two specifications yield consistent conclusions is, therefore, limited to the Decarb main effect only, not to the moderating interactions. There are only 20 country clusters below the ~30–50 cluster floor for asymptotic reliability [31]. Wild cluster bootstrap (WCB) p-values are reported alongside asymptotic p-values: DxG WCB $p = 0.038$ (SCV_eq); DxC WCB $p = 0.104$ (SCV_eq). The WCB result

for DxC reinforces that the climate risk interaction should be treated as suggestive rather than conclusively established. SCV weighting sensitivity is reported as a primary limitation in Section 9. TradeDiv is not significant in any specification.

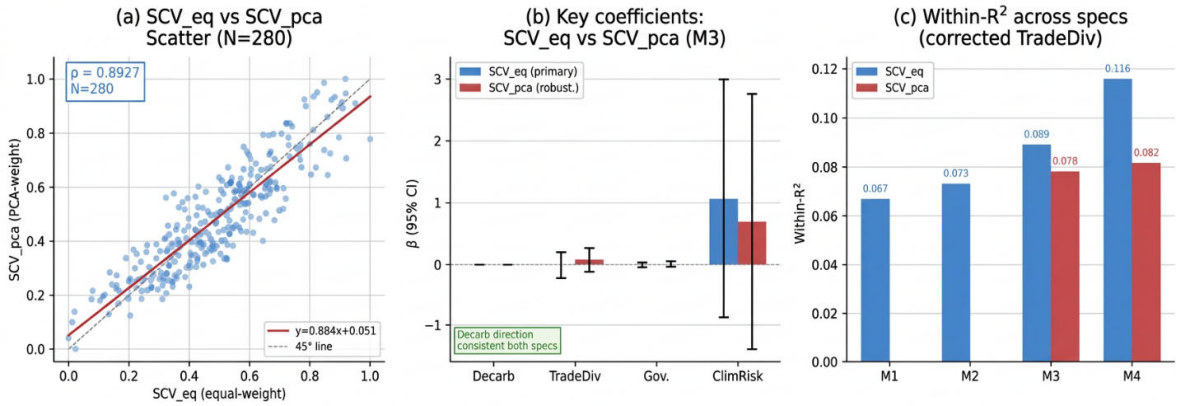


Figure 7. SCV index robustness comparison (N = 20 × 14 = 280). (**a**) Scatter: ϱ(SCV_eq,SCV_pca) = 0.893. (**b**) Key coefficients: Decarb direction is consistent across SCV_eq (blue) and SCV_pca (red) in M3; TradeDiv is near zero and insignificant in both. (**c**) Within-R^2 across M1–M4: comparable in magnitude between SCV_eq and SCV_pca (0.067–0.116 vs. 0.078–0.082). Source: verified panel, UN Comtrade, NY Fed GSCPI, WB WDI.

Direct Test of HHI Dominance: A Three-Component SCV Excluding HHI Entirely

To test empirically whether SCV_eq's findings depend on HHI's weight, we construct SCV_noHHI, a three-component index built from CMID, ETIR, and DFI only, and re-estimate M4 using this specification as the dependent variable; see Table 10 for more detailed results.

Table 10. SCV robustness with HHI fully excluded (SCV_noHHI; N = 20 × 14 = 280).

Variable	SCV_eq (4-comp, Primary) β (SE)	*p*	SCV_noHHI (3-comp, HHI Excluded) β (SE)	*p*
Decarb_c	−0.002365 (0.000584)	<0.001 ***	−0.002762 (0.000522)	<0.001 ***
DxG (Decarb_c × Governance_c)	+0.003163 (0.001276)	0.014 **	+0.002877 (0.001225)	0.020 **
DxC (Decarb_c × ClimateRisk_c)	+0.004991 (0.002749)	0.071 *	+0.004508 (0.002067)	0.030 **
TradeDiv_c	−0.030 (0.108)	0.782	−0.080 (0.104)	0.442
PCA weight structure (of remaining 3 components)	CMID = 0.139, ETIR = 0.289, DFI = 0.063 (of 4)		CMID = 0.190, ETIR = 0.780, DFI = 0.031 (of 3)	
Within-R^2	0.116		0.135	
N	280		280	

Note. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. ϱ(SCV_eq, SCV_noHHI) = 0.685, A moderate correlation indicates that SCV_noHHI is a materially different index rather than a rescaling of SCV_eq. Magnitudes and significance levels are stable across the two specifications (Decarb: $p < 0.001$ in both; DxG: $p = 0.020$ vs. 0.014; DxC: $p = 0.030$ vs. 0.071); TradeDiv remains non-significant in both.

8. Discussion

8.1. A Nonlinear, Governance-Conditional Association Between Decarbonization and SCV

The verified panel supports three linked associative findings sketching the Energy Transition Paradox. Decarbonization is associated with lower SCV on average (M4: β = −0.0024, $p < 0.001$), but far more strongly below a 25% renewable share threshold (β = −0.0077, $p < 0.001$) than above it (n.s.; Figure 6), which is consistent with diminishing

Transition Pressure returns as residual demand concentrates on hard-to-source minerals. This association is moderated by governance (DxG = +0.0032, $p = 0.014$): Table 7 shows the SCV-reducing association ranges from −0.049 (low governance, low climate risk) to near zero (high governance, high climate risk) per 10pp of renewable share. A similar, marginally significant pattern holds for climate risk (DxC = +0.0050, $p = 0.071$), which is consistent with a shared ceiling-type logic and should be read as suggestive pending replication.

8.2. Interpreting HHI Dominance in SCV: Concentration Driver, Not Concentration Proxy

HHI as a concentration driver, not a concentration proxy. A large PCA weight on one component reflects where variation concentrates in this panel; it does not mean the index reduces to that component. SCV_eq, used for every hypothesis test, weights HHI equally with the other three components, and Table 10 shows the paper's substantive findings hold when HHI is removed entirely.

8.3. Trade Diversification: A Null Finding

Trade diversification (TradeDiv), measured as export partner concentration independent of the HHI sub-component inside SCV (r = 0.091, VIF = 1.02), is not a significant predictor of SCV in any specification (Tables 6,8 and 9). This null result applies to overall export destination diversification across all merchandise goods; it should not be generalized to import source diversification for critical minerals specifically, which is what the resource dependence theory by Salancik [8] actually predicts should reduce SCV. The result therefore rejects this particular, imperfect operationalization of trade diversification, not the underlying mechanism; a per-mineral import concentration index or friend-shoring-weighted measure (Section 2.6) is a priority for future work.

The null result for TradeDiv applies to overall diversification of exports to all merchandise goods. It should not be extended to overall diversification of trade in general, or to diversification of imports of critical minerals in particular. The diversification of import sources for critical minerals (TradeDiv = 1−HHI of export destination partners) is conceptually different from what resource dependence theory [8] would suggest should decrease SCV. These are not the same constructs and do not interchangeably measure critical mineral import-source security, as shown by the low empirical correlation between TradeDiv and HHI_supply (r = 0.091). Future studies should use indicators that directly track the diversification in mineral procurement, such as a per-mineral Herfindahl index based on bilateral import shares for each critical mineral, or a friend-shoring-weighted import concentration index (Section 2.6). The current null result does not rule out trade diversification as a theoretical mechanism; it rules out this imperfect operationalization.

8.4. Governance as the Most Robust Moderator, with an Important Caveat

Governance quality is the most consistently significant moderator (DxG = +0.0032, $p = 0.014$ in SCV_eq M4), though it is not significant under SCV_pca ($p = 0.107$; Table 9). SCV_pca up-weights HHI, which is linked to Resource Concentration, while the governance interaction operates mainly through Institutional Buffering's effect on the other three, more policy-responsive components; this is a plausible but post hoc account of why weighting matters, not evidence that the divergence was anticipated. This cross-specification divergence is best read as a boundary condition on the governance moderation finding; SCV_eq is retained for primary inference because it was pre-specified, not because this account validates it.

8.5. Policy Implications (Stated as Associations, Not Verified Causal Effects)

- Front-load decarbonization's supply chain benefits (Figure 6): policymakers should not assume constant marginal supply chain benefits from continued decarbonization once a substantial renewable share is already achieved, since the SCV-reducing association is strongest early in the transition. A scenario model of transport policy until 2050 suggests that front-loading efficiency standards and electrification requirements significantly decrease energy system costs and transform key mineral procurement time horizons [29].
- Calibrate expectations to governance context (Table 7): high-governance, high-climate risk economies should not expect material SCV co-benefits from further renewable deployment and may need separate, targeted supply chain interventions, unlike low-governance, low-climate risk economies.
- Do not rely on generic trade partner diversification metrics as an SCV policy lever without independently verifying how they are constructed relative to any composite vulnerability index in use (Section 8.3).
- Treat the climate risk attenuation channel (DxC) as a priority for further research, not yet as an established policy target, given its marginal (p = 0.071) significance in this panel.

9. Conclusion

This paper's central theoretical contribution is the Energy Transition Trade-off (ETT) framework: a two-parent-force, four-channel account of how decarbonization reshapes critical mineral supply chain vulnerability, combined with a nonlinear threshold logic showing that the Decarb–SCV association is strongest early in the transition and weakens thereafter. This is demonstrated empirically on a balanced panel of exactly 20 countries × 14 years (2010–2023) = 280 observations from five confirmed primary-source datasets, using a formative SCV index validated across two independent weighting schemes.

Restated plainly, this contribution advances theory in the four ways outlined in Section 1: by unifying structural exposure and contextual moderation within one framework where prior work treated them separately; by replacing an assumed constant marginal relationship with an empirically demonstrated nonlinear threshold; by identifying a governance/climate boundary condition on when decarbonization's vulnerability-reducing association weakens toward zero, qualifying resource dependence theory's uniform attenuation prediction; and by resolving the TradeDiv/HHI_supply measurement conflation that has likely biased prior RDT-informed empirical work. The ETT framework's four channels map onto measurable, transferable constructs. They are intended to generalize beyond the critical mineral setting to other supply chains undergoing simultaneous structural and policy transformation, an extension we flag as a priority for future replication.

Managerial implications.

For firms managing critical mineral exposure, three implications follow. First, supplier due diligence should weigh institutional quality alongside price and volume: benefits from a supplier's decarbonization trajectory depend on governance quality, so firms sourcing from low-governance, high-climate-risk economies should expect smaller benefits. Second, since the SCV-reducing association concentrates below roughly a 25% renewable electricity share (Section 6.4), firms past that threshold should prioritize direct supplier diversification and long-term offtake agreements rather than expect continued decarbonization alone to help. Third, the null trade diversification result cautions against treating partner-count metrics alone as a sourcing-risk indicator; any concentration measure should be independently constructed from the outcome it predicts.

Policy implications. The associational policy directions are detailed in Section 8.5 above.

Limitations. The Bartik shift share instrument (Section 5.2) was weak (first-stage F = 0.53, below Stock and Yogo [30] threshold of 10); all relationships are associative, not causally identified. H6 (SCV persistence) is not estimated; TradeDiv, correctly measured, does not support H2; the Hausman test does not reject RE ($p = 0.495$), though FE is retained on theoretical grounds; and H5 is only marginally significant. Cluster-robust inference rests on 20 clusters, below the conventional 30–50 cluster floor in Cameron and Gelbach [31], which is defensible given the balanced design but a reason to read interaction p-values as approximate. The most consequential limitation is SCV weighting sensitivity: DxG and DxC are significant, or marginally so, under SCV_eq but not SCV_pca (Table 9); wild cluster bootstrap p-values partially support DxG but reinforce DxC's fragility. Interaction findings should be treated as hypothesis-generating, pending replication.

Sample size limitation. The panel covers only N = 20 countries and T = 14 years (280 observations). One cross-sectional dimension. The number of clusters (country-level) is too small to support reliable asymptotic cluster-robust inference [31], so interaction-term p-values should be treated as approximate even after wild cluster bootstrap adjustment. Also, the countries is not globally representative, as it focuses on G20 countries and three other mineral-producing countries, which may overrepresent large economies that already have energy policy frameworks in place. Future replications should include a larger sample of countries, including smaller mineral-producing economies, to increase generalizability and the robustness of cluster-level inferences.

Primary limitation: sensitivity of interactions between governance (DxG) and climate risk factors (DxC) to SCV weighting schemes. Both are significant (or nearly so) according to SCV_eq, but neither is significant according to SCV_pca (DxG: $p = 0.107$; DxC: $p = 0.561$; Table 9). However, wild cluster bootstrap p-values (DxG WCB $p = 0.038$; DxC WCB $p = 0.104$) support only DxG partially and further weaken DxC. Given that we have only 20 country clusters, interaction-level findings should be viewed as hypothesis-generating, not as definitive conclusions, until replicated in a larger, balanced panel with confirmed country-level SCV data. Lastly, the methodology outlined here can be easily adapted to predictions of growth and transition, but to keep this paper brief, detailed empirical forecasting is not explored; it will be tackled in future research.

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Appendix A. Country Sample (N = 20 Countries × T = 14 Years = 280 Obs.)

ISO3	Country	Role	OECD	WGI Mean	ND-GAIN Mean	SCV_eq Mean
ARG	Argentina	Producer-exp.	No	0.160	0.287	0.496
AUS	Australia	Producer-exp.	Yes	0.095	0.887	0.504
BRA	Brazil	Mixed	No	−0.010	0.551	0.421
CAN	Canada	Mixed	Yes	0.018	0.872	0.465
CHL	Chile	Producer-exp.	No	−0.167	0.458	0.475
CHN	China	Processor-imp.	No	−0.188	0.443	0.475
COD	DR Congo	Producer-exp.	No	−0.009	0.018	0.507
DEU	Germany	Processor-imp.	Yes	−0.232	0.682	0.548
FRA	France	Processor-imp.	Yes	−0.055	0.726	0.526
GBR	UK	Processor-imp.	Yes	0.038	0.982	0.459
IDN	Indonesia	Producer-exp.	No	0.079	0.466	0.524
IND	India	Mixed	No	−0.052	0.421	0.560
JPN	Japan	Processor-imp.	Yes	−0.039	0.855	0.483
KOR	Korea	Processor-imp.	Yes	0.095	0.760	0.424
MEX	Mexico	Mixed	Yes	0.051	0.607	0.546
PER	Peru	Producer-exp.	No	0.216	0.442	0.401
RUS	Russia	Producer-exp.	No	0.038	0.450	0.449
SAU	Saudi Arabia	Mixed	No	−0.046	0.522	0.569
USA	United States	Processor-imp.	Yes	−0.083	0.749	0.490
ZAF	South Africa	Producer-exp.	No	0.002	0.598	0.463

All WGI, ND-GAIN, and SCV means are from verified panel_with_indices.csv. N = 20 × T=14 = 280 balanced country-year observations. N = 280 refers to country-year observations throughout.

Appendix B. SCV Index Specification Transparency

Sub-Component	Economic Role	Side of Market	Source	Min	Max	SCV_eq wt	SCV_pca wt	ETT Mechanism
CMID	Structural dependence on imported raw mineral inputs (ore/concentrate)	Supply-side structure	UN Comtrade	0.000	1.000	0.25	0.139	Secondary channel for both transition pressure and resource concentration
ETIR	Dependence on imported clean technology capital goods (panels, turbines,	Demand-side transition pressure	UN Comtrade	0.000	1.000	0.25	0.289	Transition pressure (primary)

	batteries, EV drivetrains)						
HHI	Concentration of mineral import sources across supplying countries	Supply-side structure	UN Comtrade	0.000	1.000	0.25	0.509	Resource concentration (primary)
DFI	Realized global supply chain disruption intensity (GSCPI-based)	Global shock propagation	NY Fed GSCPI	0.182	0.830	0.25	0.063	Climate amplification (primary)

B.1 SCV sub-component decomposition. The precise economic role of each of the four SCV sub-components, addressing the potential for CMID and ETIR to be read as overlapping.

CMID answers "how dependent is this country on imported raw minerals?" (a supply structure question). In contrast, ETIR answers "how dependent is this country on imported finished clean-energy equipment?" (a demand pressure question). A country can score high on one and low on the other: a mineral-rich but manufacturing-poor economy shows low CMID (it mines its own ore) but high ETIR (it still imports finished turbines and panels), confirming the two are non-redundant formative indicators rather than two measures of the same quantity.

B.2 TradeDiv vs. HHI_supply: full construction detail. Section 4 establishes that TradeDiv and the HHI sub-component of SCV, though both Herfindahl-type measures from UN Comtrade, draw on disjoint flow subsets (export destination vs. mineral-specific import shares) and are empirically independent ($r = 0.091$, VIF = 1.02). HHI_supply is restricted to the critical mineral and clean technology HS codes in Table 1; TradeDiv spans the full merchandise basket. This scope difference, not the correlation alone, is why the two enter the model in different roles: HHI_supply inside SCV, and TradeDiv as an independent regressor.

B.3 Formative index validity. ϱ(SCV_eq, SCV_pca) = 0.893. Cronbach's α does not apply to formative constructs [11,15]; Section 2.2); validity is instead established by specification-consistent regression findings across SCV_eq and SCV_pca (Table 6, Figure 6).

Appendix C. Quasi-Experimental Extension: Difference-in-Differences Design (Pre-Specified)

This appendix pre-registers a DiD design exploiting the US IRA (2022) and EU CRMA (2024) as policy shocks to treated economies (USA and EU members) relative to non-treated comparators, testing pre-treatment parallel trends and post-treatment divergence in CMID and ETIR, the most policy-responsive SCV sub-components. Data through 2025/2026 are required for adequate post-period coverage; this is a design specification, not a completed analysis. Implementation references: [32,33].

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