Hidden Bottlenecks in the Rare Earth Supply Chain: Myanmar, China's Processing Hub, and Multilayer Network Vulnerability

Abstract

Rare earth supply-chain risk is usually measured through direct import dependence, supplier concentration, and mining production shares. These measures can miss indirect bottlenecks that operate through processing hubs. This paper develops a multilayer network framework to distinguish direct import dependence from second-order feedstock dependence in the global rare earth supply chain. Using CEPII BACI bilateral trade data for upstream ores, midstream compounds, and permanent magnets over 2012-2024, the analysis shows that midstream processing centrality, rather than upstream mining centrality or mining production volume, is the strongest predictor of structural bargaining power. The paper identifies Myanmar as a hidden second-order bottleneck: peaked at 72.4 percent in 2020 and stood at 66.8 percent in 2023, so a Myanmar disruption can propagate through China's processing hub to downstream importers. Shock simulations show that this disruption affects 40 importing economies, while MSP-aligned supply expansion reduces vulnerability only where it creates actual alternative sourcing relationships. The findings suggest that rare earth resilience policy should monitor indirect feedstock dependencies and processing capacity, not only direct import shares or mining concentration.

Keywords: rare earth elements; multilayer network analysis; betweenness centrality; supply chain vulnerability; bargaining power; weaponized interdependence; Minerals Security Partnership

1. Introduction

In 2023, Myanmar supplied approximately two-thirds of China's imported rare earth compound feedstock, yet it appears in virtually no standard rare earth vulnerability assessment. It holds no significant position in the European Commission's Critical Raw Materials index (European Commission, 2023), the US National Academies of supply risk framework (NAS, 2023), or bilateral trade vulnerability scorecards. The reason is structural: Myanmar does not supply rare earths directly to final importers. It feeds China's processing hub, which then re-exports higher-value compounds to the world. Under direct-

dependence metrics, Myanmar is invisible. Under a framework that traces indirect feedstock dependencies, it is the single most important hidden bottleneck in the global rare earth supply chain.

This invisibility is not a quirk of one country. It reflects a systematic limitation of how supply-chain risk is currently measured. Standard vulnerability indices aggregate bilateral import dependence, supplier concentration, and mining production shares into composite scores (Graedel et al., 2015; Schrijvers et al., 2020). These measures are well-suited to identifying direct exposure, which country supplies how much of what a given importer needs. They are poorly suited to identifying second-order dependence, the risk that arises not from a direct supplier behaviour but from the upstream conditions feeding that supplier processing capacity. When a processing hub depends heavily on a single feedstock source, and that hub in turn supplies dozens of importers, a disruption at the feedstock level can cascade across the entire network while remaining invisible to direct-dependence metrics (Peng & Guo, 2025; Xu et al., 2024).

Rare earth elements illustrate this problem with particular clarity. REEs underpin the clean energy transition, neodymium and dysprosium in electric vehicle motors and wind turbine generators, lanthanum in hydrogen storage, europium and terbium in LED displays (Binnemans et al., 2013; Balaram, 2019). The International Energy Agency (2023) projects demand growth of three to seven times current levels by 2040. Yet the supply chain is characterised by extreme geographic concentration not at the mining stage but at the processing stage. China accounts for approximately 87 percent of global rare earth separation and processing capacity (USGS, 2024), converting raw ore into the compounds and alloys that downstream manufacturers require. It is this processing bottleneck, not mine ownership, that constitutes the structural chokepoint (Mancheri et al., 2019; Han et al., 2025) and it is the feedstock dependencies feeding that bottleneck that existing indices systematically overlook.

This paper addresses that gap through three contributions. First, it develops a multilayer dependence framework that formally distinguishes direct import dependence from second-order feedstock dependence, introducing an Indirect-Dependence measure that captures

how exposure to a hidden upstream supplier propagates through a processing hub to final importers. We construct a three-layer directed weighted network covering upstream ores (HS 261790), midstream compounds (HS 284690), and downstream permanent magnets (HS 850511) from CEPII BACI bilateral trade data for 184555 country pair flows across 2012-2024 (Gaulier and Zignago, 2010). Second, it identifies Myanmar as the empirical case of hidden second-order risk: Myanmar's share of China's layer 2 rare earth feedstock imports rose from under 5 percent in 2016 to 66.8 percent in 2023, a structural shift invisible in direct vulnerability indices. Shock simulations confirm that a Myanmar disruption reduces China's midstream export capacity to 33 percent of baseline, propagating vulnerability to 40 importing economies. Third, the paper evaluates the Minerals Security Partnership (MSP, 2022) as a diversification mechanism, finding that formal MSP membership has no statistically significant association with lower China import dependence, while actual sourcing from MSP-aligned suppliers reduces China's import share by 5.6 percentage points per allied supplier consistent with the recent evidence that political commitments must materialise as physical supply contracts to reduce vulnerability (Smyth and Vespignani, 2026)

The paper proceeds as follows. Section 2 reviews the literature on rare earth trade networks, supply-chain vulnerability, and alliance diversification, positioning our second-order dependence framework against existing approaches. Section 3 develops the conceptual framework. Section 4 describes data and methods. Section 5 presents results. Section 6 discusses policy implications. Section 7 concludes.

2. LITERATURE REVIEW

2.1 Critical Minerals and Rare Earth Concentration

The strategic importance of rare earth elements has attracted growing attention across energy, security, and resource economics literatures. REEs are indispensable inputs to clean energy technologies permanent magnets in wind turbines and electric vehicle motors depend on neodymium and dysprosium, while phosphors and catalysts rely on broader lanthanides (Binnemans et al., 2013; Balaram, 2019; Depraiter & Goutte, 2023). The IEA

(2023) projects REE demand will grow three to seven times by 2040 under net-zero scenarios, making supply security a first-order policy concern.

Supply concentration in REEs is more severe at the processing stage than at the mining stage. China accounts for approximately 60 percent of global REE mine production but roughly 87 percent of separation and processing capacity (USGS, 2024). This asymmetry dispersed mining but concentrated processing is the defining structural feature of the REE supply chain. Standard critical mineral frameworks have been slow to incorporate this distinction: the European Commission's Critical Raw Materials Act (2023) and the US National Academies framework (NAS, 2023) both aggregate bilateral exposure into composite scores that capture direct import dependence but cannot identify indirect feedstock dependencies operating through processing hubs.

2.2 Rare Earth Trade Network Studies

A growing body of literature applies network analysis to REE trade. Ge et al. (2016) construct a complex network of global REE trade, identifying China's dominant hub position and scale-free properties. Hou et al. (2018) document how China's centrality has strengthened over time. Both studies focus on single-layer direct trade flows, leaving cross-layer propagation effects unexamined.

Subsequent work has introduced more granular analysis. Zuo et al. (2022) distinguish upstream and downstream product categories, finding China's dominance strongest in midstream processing. Yu et al. (2022) identify structural shifts associated with China's export quota regime. Xu et al. (2024) document how importing countries' dependence on China has intensified despite diversification efforts. Peng and Guo (2025) simulate cascading supply-risk propagation across REE trade network layers, finding the midstream layer most vulnerable to collapse; Han et al. (2025) model trade-network divergence under policy scenarios.

Despite this progress, each of these studies analyses a single supply-chain layer or focuses primarily on direct bilateral flows. Existing propagation models are topological cascade simulations that construct no importer-level indirect-dependence measure, identify no

specific hidden feedstock supplier - their framework flags Australia, not Myanmar, precisely because Myanmar's flows inside the midstream layer (Peng and Guo, 2025), and run no econometric test of bargaining power, the second-order dependence mechanism this paper identifies.

2.3 Supply-Chain Vulnerability and Indirect Dependence

The supply-chain vulnerability literature provides complementary tools for assessing exposure to supply disruptions. Graedel et al. (2015) develop a multi-indicator framework combining supply risk, vulnerability, and environmental implications, which underpins many national critical mineral strategies. Schrijvers et al. (2020) find significant cross-jurisdictional variation in how indirect supply risks are treated. A key limitation of most frameworks is that they measure bilateral exposure without tracing the upstream conditions that determine whether a supplier can deliver.

The concept of indirect or second-order dependence where supply risk of a country is located not in its direct supplier but in the upstream conditions feeding that supplier's processing capacity, has not been formally developed or empirically applied in the REE literature. This paper fills that gap.

2.4 Friend-Shoring and Alliance Diversification

The geopolitical response to critical mineral concentration has centred on alliance-based diversification. The Minerals Security Partnership launched in June 2022 with members including Australia, Canada, France, Germany, Japan, South Korea, the United Kingdom, and the United States, aiming to develop secure and sustainable critical mineral supply chains among allied nations (MSP, 2022). The MSP reflects the broader trend toward friend-shoring, redirecting supply chains toward geopolitically aligned partners as a strategy for reducing dependence on China (Farrell and Newman, 2019; Chorzempa et al., 2023).

Whether political commitments translate into actual supply diversification is an open empirical question. Smyth and Vespignani (2026) argue that even resource-rich MSP members such as Australia face fiscal and governance barriers that prevent commitments

from materialising as processing investment. This paper provides among the first empirical tests of MSP diversification effectiveness, distinguishing between membership and actual sourcing from allied suppliers.

2.5 The Gap: Direct-Dependence Measures Miss Hidden Feedstock Bottlenecks

Taken together, the existing literature on REE trade networks, vulnerability indices, and alliance diversification shares a common blind spot: it measures risk at the level of direct bilateral flows and cannot identify hidden second-order bottlenecks operating through processing hubs. Table 1 positions this paper against the core REE network literature, identifying the specific limitation each study leaves unaddressed and the advance this paper makes.

Table 1. Literature Positioning: This Paper Relative to Core REE Network Studies

Study	Focus	Method	Limitation	This Paper's Advance
Ge et al. (2016)	Global REE trade network	Complex network analysis	Single-layer, direct trade focus	Adds multilayer second-order dependence
Hou et al. (2018)	International REE trade structure	Complex network analysis	Descriptive topology only	Links topology to bargaining power and vulnerability
Zuo et al. (2022)	Industry-chain REE trade	Upstream/midstream/downstream network	Limited focus on hidden feedstock dependence	Identifies indirect bottlenecks through processors
Yu et al. (2022)	Evolution of REE trade networks	Network evolution analysis	Mainly structural evolution	Adds policy shock simulation and second-order exposure
Xu et al. (2024)	Dependency and competition	Trade network analysis	Direct dependence and competition only	Adds indirect dependence measure and Myanmar bottleneck
Peng & Guo (2025)	Betweenness centrality post-2018	Single-layer network	One layer, no cross-layer propagation	Three-layer multilayer model with feedstock tracing

Study	Focus	Method	Limitation	This Paper's Advance
This paper	Hidden feedstock bottlenecks	Multilayer dependence + simulations	—	Second-order feedstock dependence; Myanmar as hidden bottleneck

The gap is clear: no existing study formally measures indirect feedstock dependence across processing layers, identifies hidden second-order bottlenecks empirically, or tests whether alliance diversification reduces China import dependence through actual sourcing rather than political membership. This paper addresses all three.

3. CONCEPTUAL FRAMEWORK

3.1 Direct Dependence

The dominant approach to rare earth supply-chain vulnerability measures direct dependence: the share of a country's imports of a given product sourced from a single supplier. For importer j and supplier i in supply-chain layer l at time t, direct dependence is:

$$\text{DirectDependence}_{(j,i,l,t)} = x_{(i,j,l,t)} / \Sigma_i x_{(i,j,l,t)}$$

where $x_{(i,j,l,t)}$ is the value of exports from country i to country j in layer l at time t. This measure is intuitive and data accessible. It underpins the Herfindahl-Hirschman Index of supplier concentration, the European Commission Critical Raw Materials supply risk scores, and most bilateral vulnerability frameworks (Graedel et al., 2015; European Commission, 2023).

Direct dependence captures one dimension of supply risk well: how exposed an importer is to the behaviour of its immediate suppliers. If China restricts exports of rare earth compounds, countries with high $DirectDependence_{(j,China,2,t)}$ face immediate supply shortfalls. This is the risk that existing indices are designed to measure.

What direct dependence cannot capture is the risk arising from conditions upstream of the direct supplier, specifically, whether the direct supplier itself depends on a concentrated

feedstock source whose disruption would constrain supply capacity even if the direct supplier intends to export normally. This is the second-order dependence problem.

3.2 Indirect Dependence and Second-Order Bottlenecks

We define second-order dependence as follows:

Second-order dependence exists when a country's supply risk is not located in its direct supplier but in the upstream supplier that feeds that direct supplier's processing capacity. A disruption at the feedstock level propagates through the processing hub to downstream importers, creating vulnerability that is invisible to direct bilateral dependence measures.

Formally, for importer j that sources from processor i, where processor i in turn sources feedstock from upstream supplier k, the indirect dependence of j on k through i in layer l at time t is:

$$\text{IndirectDependence}_{(j,k,i,l,t)} = \text{DirectDependence}_{(j,i,l,t)} \times \text{FeedstockDependence}_{(i,k,l,t)}$$

where $FeedstockDependence_{(i,k,l,t)}$ is the share of processor i's total layer l imports sourced from upstream supplier k:

$$\text{FeedstockDependence}_{(i,k,l,t)} = x_{(k,i,l,t)} / \Sigma_k \, x_{(k,i,l,t)}$$

The $IndirectDependence_{(j,k,i,l,t)}$ measure multiplies two bilateral shares: how much of j's imports come from i, and how much of i's feedstock comes from k. A high value indicates that importer j is significantly exposed to a disruption in k even though k is not j's direct supplier. The product structure ensures that indirect dependence is bounded between 0 and 1 and declines naturally when either the direct dependence link or the feedstock dependence link is weak.

Aggregating across all processors i, the total indirect exposure of importer j to upstream supplier k is:

$$\text{SecondOrderExposure}_{(j,k,l,t)-} = \Sigma_i \, \text{DirectDependence}_{(j,i,l,t)} \times \text{FeedstockDependence}_{(i,k,l,t)}$$

This measure captures the full propagation pathway from upstream supplier k through all processing intermediaries i to final importer j. We apply it to the REE case with k = Myanmar, i = China, and l = 2 (midstream compounds), where:

$$\text{IndirectDependence}_{(j,\text{Myanmar},\text{China},2,t)} = \text{DirectDependence}_{(j,\text{China},2,t)} \times \text{FeedstockDependence}_{(\text{China},\text{Myanmar},2,t)}$$

As $FeedstockDependence_{(China,Myanmar,2,t)}$ rose from under 0.05 in 2016 to 0.668 in 2023, the indirect exposure of every China-dependent importer to Myanmar conditions increased proportionally without any change in their direct dependence on China being detectable in standard bilateral indices.

A second-order bottleneck is a country k that exhibits: Low direct export centrality in the final supply layer (it does not export significantly to final importers); High $\text{FeedstockDependence}_{(i,k,l,t)}$ for a dominant processor i; and High $\text{SecondOrderExposure}_{(j,k,l,t)}$ for a large number of final importers j. Myanmar satisfies all three conditions in the global REE midstream layer by 2023: it supplies negligible direct REE compounds to final importers, it supplies 66.8 percent of China's midstream feedstock, and its disruption therefore propagates to the approximately 40 economies that source more than 10 percent of their Layer 2 imports from China.

3.3 Processing Hubs and Vulnerability Propagation

The second-order dependence framework highlights the structural role of processing hubs, countries that occupy dominant positions in transforming upstream raw materials into intermediate products consumed by downstream importers. A processing hub amplifies both the benefits and the risks of upstream concentration: it creates efficiency gains through specialisation but also serves as a transmission channel through which feedstock disruptions cascade to all downstream importers simultaneously.

We model this propagation through the multilayer network structure $G = \{G_1, G_2, G_3\}$, where each layer $G_l = (V, E, W)$ represents a directed weighted graph of bilateral trade flows at a distinct supply-chain stage. The three layers capture upstream ore extraction (Layer 1, HS 261790), midstream compound processing (Layer 2, HS 284690), and

downstream permanent magnet manufacturing (Layer 3, HS 850511). The multilayer structure allows disruptions originating in one layer to propagate across layers through the hub nodes that connect them (Kivela et al, 2014).

Betweenness centrality measures the structural position of a node in terms of the shortest paths passing through it. For node v in layer l at time t:

$$B_{l(v,t)} = [2 / ((n-1)(n-2))] \times \Sigma_{(s \neq v \neq d)} [\sigma_{(sd)(v)} / \sigma_{(sd)}]$$

where $\sigma_{(sd)}$ is the total number of shortest paths from s to d and $\sigma_{(sd)(v)}/$ is the subset passing through v. High betweenness indicates a node controls critical flow pathways, the chokepoint effect of weaponised interdependence (Farrell and Newman, 2019).

Betweenness centrality and IndirectDependence are complementary but distinct measures. Betweenness captures the structural position of an exporter, how much of global REE trade flows through it, and is measured from the exporter's perspective. IndirectDependence captures the exposure of a specific importer to a specific upstream supplier through a specific processor, it is measured from the importer's perspective and traces a defined propagation pathway. Together they provide a complete picture: betweenness identifies who holds structural power in the network, while IndirectDependence quantifies how that power translates into cascading vulnerability for downstream economies when a feedstock disruption occurs.

3.4 Hypotheses and Proposition

Drawing on this framework, we derive four testable hypotheses and one conceptual proposition.

H1 (Centrality-Bargaining): Countries with higher midstream betweenness centrality attract more import-dependent partners, reflecting their role as structural chokepoints in the processing layer.

H2 (Processing Dominance): Midstream processing-layer centrality exceeds upstream mining-layer centrality as a predictor of bargaining power, and raw mining production volume becomes insignificant once network position is controlled.

H3 (Concentration-Vulnerability): Higher supplier concentration and fewer active suppliers increase a country's dependence on China for midstream REE imports.

H4 (Alliance Diversification): Countries sourcing from a more diverse set of MSP-aligned suppliers exhibit lower China import dependence, while formal MSP membership alone has no significant association with vulnerability reduction.

Proposition 1 (Hidden Bottleneck): Countries with low direct export centrality but high feedstock importance to a dominant processing hub constitute second-order bottlenecks that are invisible to standard direct-dependence vulnerability indices but whose disruption propagates through the hub to downstream importers. Myanmar constitutes such a bottleneck in the global REE midstream layer.

H1–H4 are tested empirically through panel regression models in Section 4. Proposition 1 is validated through the IndirectDependence measure and counterfactual shock simulations in Section 5.

4. Data and Methods

4.1 Trade Data and HS Code Classification

We use BACI HS12 V202601 (Gaulier and Zignago, 2010), which provides harmonised bilateral trade values (current USD, thousands) for 2012–2024. BACI reconciles exporter and importer mirror statistics using a methodology that assigns flows to a common CIF/FOB-adjusted value, making it the standard source for bilateral trade network analysis in the critical mineral literature (Xu et al., 2024). Our starting sample contains 184,555 country-pair-year observations after filtering to seven HS-6 product codes across three supply-chain layers, covering 225 exporting and 227 importing economies over 13 years. The 13-year panel spanning 2012-2024 captures two major structural shifts in the REE

supply chain: China's post-quota consolidation of processing capacity after 2015 and Myanmar's rapid emergence as China's dominant feedstock supplier after 2016.

4.2 HS Code Classification and Three-Layer Structure

We classify bilateral trade flows into three supply-chain layers based on the degree of processing embodied in each product category. Table 2 summarises the classification.

Table 2. HS Code Classification by Supply-Chain Layer

Layer	Role	HS Codes (narrow / broad)	Description
1 — Upstream	Ore extraction	261790 / +253090	Rare earth ores and concentrates
2 — Midstream	Processing	284690 / +284610, 280530	Rare earth compounds (main analytical layer)
3 — Downstream	Magnet manufacturing	850511 / +850519	Permanent magnets

Note: All main results use narrow single-HS-code definitions. Broad definitions include additional codes and serve as robustness checks.

For each year t and layer l, we construct a directed weighted graph $G_{l,t} = (V, E, W)$ where nodes are countries, directed edges represent bilateral trade flows, and edge weights are trade values in current USD. Let x_{ijlt} denote exports from country i to country j in layer l, year t. Layer 2 (HS 284690) is the primary analytical layer because it captures the midstream processing stage where China's structural dominance is concentrated and where Myanmar's feedstock role operates. Layer 1 and Layer 3 are included to enable cross-layer comparison of bargaining power and to trace inter-layer propagation pathways.

Myanmar's primary REE trade flow is classified as Layer 2 (HS 284690), not Layer 1 ores. Myanmar exports partially processed rare earth compounds directly to China, which processes and reexports them as higher-value midstream compounds to global importers. This classification is the empirical foundation of our hidden bottleneck finding: Myanmar appears in the midstream layer as a feedstock supplier to China rather than in the upstream ore layer as a miner which explains why it is absent from standard vulnerability assessments that focus on direct ore-layer dependence.

4.3 Direct and Indirect Dependence Measures

Following the framework developed in Section 3, we operationalise three dependence measures.

Direct dependence. The bilateral dependence of importer j on supplier i in layer l at time t is:

$$\text{DirectDependence}_{(j,i,l,t)} = x_{(i,j,l,t)} / \Sigma_i \, x_{(i,j,l,t)} \quad (1)$$

By construction, $\Sigma_i \; DirectDependence_{(j,i,l,t)} = 1$ for all j, l, t with positive trade. This measure forms the basis of standard vulnerability indices and is used to construct the China import share variable in our regression models.

Feedstock dependence. The dependence of processor i on upstream supplier k for layer l feedstock at time t is:

$$\text{FeedstockDependence}_{(i,k,l,t)} = x_{(k,i,l,t)} / \Sigma_k \, x_{(k,i,l,t)} \quad (2)$$

Applied to China as the processor (i = CHN) and Myanmar as the upstream supplier (k = MMR) in Layer 2, this gives the share of China's total Layer 2 import feedstock sourced from Myanmar in each year - the quantity that rose from under 5 percent in 2016 to 66.8 percent in 2023.

Indirect dependence. For importer j, the indirect exposure to upstream supplier k through processor i in layer l at time t is:

$$\text{IndirectDependence}_{(j,k,i,l,t)} = \text{DirectDependence}_{(j,i,l,t)} \times \text{FeedstockDependence}_{(i,k,l,t)} \quad (3)$$

For the Myanmar application, this becomes:

$$\text{IndirectDependence}_{(j,\text{Myanmar},\text{China},2,t)} = \text{DirectDependence}_{(j,\text{China},2,t)} \times \text{FeedstockDependence}_{(\text{China},\text{Myanmar},2,t)}$$

This measure is bounded between 0 and 1 and captures the compound exposure pathway: how much of j's Layer 2 imports come from China, scaled by how much of China's Layer 2 feedstock comes from Myanmar. A European economy sourcing 80 percent of its Layer

2 imports from China in 2023 carries an IndirectDependence on Myanmar of 0.80 × 0.668 = 0.534, meaning over half of its effective midstream supply exposure is contingent on Myanmar's continued feedstock supply, even though Myanmar appears nowhere in its direct import statistics.

Aggregating across all processors, the total second-order exposure of importer j to upstream supplier k is:

$$\text{SecondOrderExposure}_{(j,k,l,t)} = \Sigma_i \, \text{DirectDependence}_{(j,i,l,t)} \times \text{FeedstockDependence}_{(i,k,l,t)} \quad (4)$$

These measures are computed for all country-pairs in each year and reported descriptively in Section 5.2 to validate Proposition 1.

4.4 Network Metrics

Betweenness centrality. We compute betweenness centrality on inverse-weight shortest paths, where higher trade value implies a lower path cost (Freeman, 1977). The cost of edge (i, j) in layer l at time t is:

$$c_{(i,j)} = 1 / (x_{(ij,l,t)} + \varepsilon), where\ \varepsilon = 10^{-9} \quad (5)$$

Normalised betweenness centrality for node v in layer l at time t is:

$$B_{l(v,t)} = [2 / ((n-1)(n-2))] \times \Sigma_{(s \neq v \neq d)} [\sigma_{(sd)}\upsilon / \sigma_{(sd)}] \quad (6)$$

where n is the number of active nodes, $\sigma_{(sd)}$ is the total number of weighted shortest paths from s to d, and $\sigma_{(sd)}\upsilon$ is the subset passing through υ. Betweenness is normalised to [0, 1] and winsorised at the 99th percentile in regression models.

As established in Section 3, betweenness centrality and IndirectDependence are complementary measures serving different analytical purposes. Betweenness captures the structural position of an exporter across the full network, how much of global trade flows through it and is the primary variable in our bargaining power regression (H1, H2). IndirectDependence traces a specific propagation pathway from a defined upstream

supplier through a defined processor to a defined importer and is the primary variable in our hidden bottleneck analysis (Proposition 1). Together they provide a complete characterisation of structural power and cascading vulnerability in the REE supply chain.

Additional network metrics. The Herfindahl-Hirschman Index of import concentration for importer j in layer l at time t is:

$$\mathrm{HHI}_{(j,l,t)} = \Sigma_i \left(\mathrm{DirectDependence}_{(i,j,l,t)} \times 100\right)^2 \qquad (7)$$

HHI ranges from 0 (perfectly diversified) to 10,000 (monopoly supplier). The composite Supply Vulnerability Index is:

$$\mathrm{SVI}_{(j,t)} = 0.40 \times \mathrm{DirectDependence}_{(j,\mathrm{China},2,t)} + 0.30 \times \left(\mathrm{HHI}_{(j,t)} / 10{,}000\right) + 0.30 \times \left(1 - n_{(j,t)} / n_{(\max,t)}\right) \qquad (8)$$

where $n_{(j,t)}$ is the number of active Layer 2 suppliers to country j and $n_{(max,t)}$ is the cross-country maximum. SVI is used descriptively and in shock simulations. In regression models, we use $DirectDependence_{(j,China,2,t)}$ directly as the dependent variable to avoid regressing an index on its own components.

The alliance diversity index counts MSP-member countries providing at least 5 percent of country j's Layer 2 imports in year t:

$$\mathrm{AllyDiv}_{(j,t)} = \left|\{i \in \mathrm{MSP} : \mathrm{DirectDependence}_{(j,i,2,t)} \geq 0.05, t \geq 2022\}\right| \qquad (9)$$

$\mathrm{AllyDiv}_{(j,t)} = 0$ for all $t < 2022$ by definition.

The operational set MSP = {USA, CAN, AUS, GBR, FRA, DEU, JPN, KOR, IND, ITA} reflects the ten MSP-affiliated countries with meaningful Layer 2 trade presence in BACI. Finland and Sweden, founding members, are excluded because both record near-zero Layer 2 import and export flows throughout 2012–2024 and would contribute nothing to AllyDiv regardless of treatment timing. India and Italy acceded in June 2023; accordingly, IND and ITA are coded as MSP-aligned only from t = 2023. Since India records zero Layer 2 imports in BACI data across all sample years, this timing correction has no effect on any AllyDiv observation in practice.

4.5 Regression Models

We estimate two-way fixed-effects OLS models throughout. Model 1 tests vulnerability determinants (H3, H4):

$$\text{ChinaShare}_{(j,t)} = \alpha_j + \gamma_t + \beta_1 \text{AllyDiv}_{(j,t)} + \beta_2 \text{MSP}_{(j,t)} + \beta_3 \text{nSup}_{(j,t)} + \beta_4 \text{HHI}_{(j,t)} + \beta_5 \ln(\text{GDP}_{(j,t)}) + \varepsilon_{(j,t)} \quad (10)$$

where α_j are country fixed effects absorbing time-invariant country characteristics, γ_t are year fixed effects absorbing global commodity-cycle and geopolitical shocks, and $\varepsilon_{(j,t)}$is an idiosyncratic error term. H3 predicts $\beta_3 < 0$ and $\beta_4 > 0$; H4 predicts $\beta_1 < 0$ and β_2 insignificant.

Model 2 tests bargaining power determinants (H1, H2):

$$\text{DepImp}_{(i,t)} = \alpha_i + \gamma_t + \beta_1 B^2_{(i,t)} + \beta_2 B^1_{(i,t)} + [\beta_3 \ln(\text{Mining}_{(i,t)})] + \beta_4 \text{ExpRes}_{(i,t)} + \beta_5 \ln(\text{GDP}_{(i,t)}) + \varepsilon_{(i,t)} \quad (11)$$

where $DepImp_{(i,t)}$ is the count of countries importing more than 25 percent of their Layer 2 supply from exporter i in year t, $B^2_{(i,t)}$ and $B^1_{(i,t)}$ are Layer 2 and Layer 1 betweenness centrality, and $Mining_{(i,t)}$ is USGS REO metric-tonne production (included only in Model 2c). H1 predicts $\beta_1 > 0$; H2 predicts $\beta_1 >> \beta_2$ and β_3 insignificant.

Standard errors are clustered at country level and additional control includes log GDP (World Development Indicators, 2022).

4.6 Shock Simulation Methodology

We simulate four counterfactual scenarios on the 2023 baseline network. The simulations operationalise the IndirectDependence framework by tracing how upstream feedstock disruptions propagate through China's processing hub to downstream importers.

S1 (China export ban) removes all Chinese Layer 2 export edges: $x_{(China,j,2,2023)} = 0$ for all j, simulating a full Chinese export restriction analogous to the 2010–2015 quota regime.

S2 (Myanmar disruption) propagates Myanmar's removal through China's feedstock supply. The feedstock loss share is:

$$SF_t = 1 - FeedstockDependence_{(China,Myanmar,2,t)} = 1 - (x_{(Myanmar,China,2,t)} / F_{(China,t)}) \quad (12)$$

where $F_{(China,t)} = \Sigma_k \; x_{(k,China,2,t)}$ is China's total Layer 2 import feedstock. SF_t is the share of China's feedstock that remains after Myanmar's supply is removed. Under the upper-bound assumption of zero buffer stock and no substitution, China's Layer 2 exports to every destination are scaled by this factor:

$$\dot{x}_{(China,j,2,t)} = \mathrm{SF_t} \times x_{(China,j,2,t)} \; \forall j \quad (13)$$

This simulation directly implements the IndirectDependence propagation mechanism: the magnitude of the shock to importer j equals $IndirectDependence_{(\mathrm{j,Myanmar,China,2,t})}$ applied to its baseline China-sourced supply. With $FeedstockDependence_{(\mathrm{China,Myanmar,2,2023})}$ = 0.668, $SF_{(2023)}$ = 0.332, reducing China's export capacity to 33.2 percent of baseline.

S3 (Combined shock) applies Equation 13 first, then sets $x_{(China,j,2,2023)}$ = 0 for all j, simulating simultaneous Myanmar disruption and Chinese export ban.

S4 (MSP scale-up) doubles all Layer 2 export flows from MSP-member countries: $x_{(i,j,2,t)}$ $\rightarrow 2 \times x_{(i,j,2,t)}$ for i ∈ MSP, holding all other flows at baseline.

After each scenario, we recompute DirectDependence (Eq. 1), HHI (Eq. 7), SVI (Eq. 8), IndirectDependence (Eq. 3), and the count of dependent importers for all countries, reporting ΔSVI = $SVI_{(Shock)}$ - $SVI_{(baseline)}$ as the primary metric for S4 and supply-exposure counts for S1–S3.

4.7 Causal Identification and Robustness

Panel OLS with two-way fixed effects provides conditional associations net of time-invariant country characteristics and common time trends. This is the standard identification strategy in the critical minerals panel literature (Mancheri et al., 2019). We

do not claim to identify exogenous causal effects but interpret our estimates as partial correlations conditional on a rich set of controls.

We attempted to exploit the February 2021 Myanmar military coup as a natural experiment using a difference-in-differences design. The DiD coefficient is small and statistically indistinguishable from zero ($\beta = -0.0041$, $p = 0.85$). More fundamentally, an event study reveals that pre-coup year-by-year interaction coefficients (2012–2018) are all significantly negative ($p \leq 0.04$), violating the parallel trends assumption. We therefore present the event study descriptively rather than causally in Section 5.

Robustness is assessed across two dimensions. First, we re-estimate Models 1 and 2 using broad HS code definitions (Layer 1 adds HS 253090; Layer 2 adds HS 284610 and HS 280530; Layer 3 adds HS 850519). Second, for the bargaining-power model, we replace the 25 percent import-dependence threshold with 50 percent. Results are reported in Appendix Table A3. Cross-platform replication using stata-ntwrk v1.0 (Naqvi, 2026) confirms that country betweenness rankings are robust across fully independent Python/NetworkX and Stata implementations.

4.8 Software and Reproducibility

Network construction, centrality computation, and dependence measures were implemented in Python 3 using NetworkX. Regression analysis was conducted in Stata 18 with clustered standard errors. Data visualisations were generated using Python matplotlib. Cross-platform replication was performed using the stata-ntwrk package v1.0 (Naqvi, 2026). All figures are directly and reproducibly derived from the underlying BACI trade dataset. Analytical code is available from the corresponding author on request

5. Results

5.1 Network Structure

Figure 1 shows the evolution of China's betweenness centrality across all three layers from 2012 to 2024. Layer 2 (midstream) betweenness rises sharply after 2017, the year China began consolidating processing capacity, peaking at 0.382 in 2022. Layer 3 (downstream magnets) centrality is highest overall (0.591 in 2022), reflecting China's near monopoly in

permanent magnet manufacturing. Layer 1 betweenness is lower and more volatile, consistent with a more fragmented upstream ore market. This divergence across layers motivates the central argument: structural power in the REE supply chain is concentrated at the processing stage, not the mining stage.

Figure 1. China's Betweenness Centrality by Supply-Chain Layer, 2012-2024

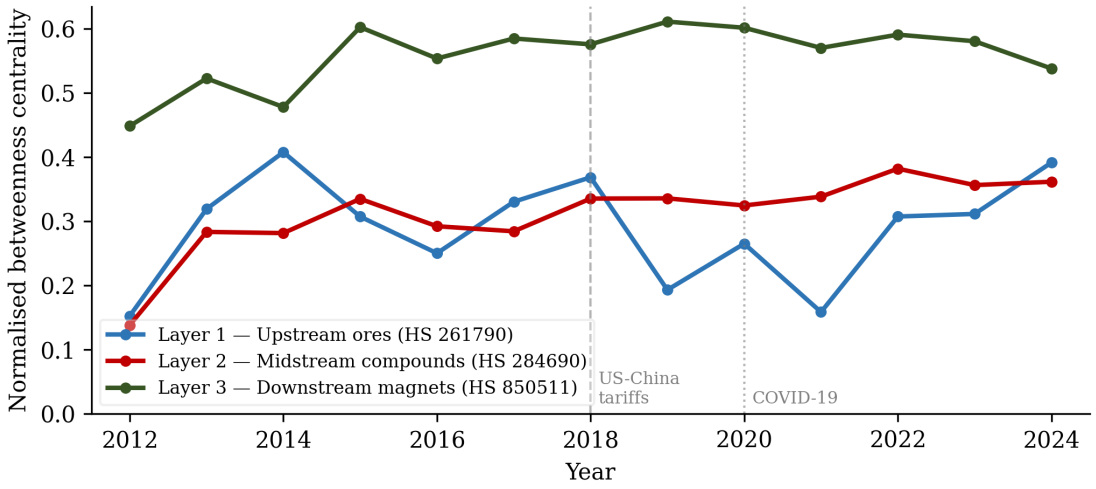


Figure 1. China's normalised betweenness centrality by supply-chain layer, 2012–2024. Vertical dashed lines mark the 2018 US-China tariff escalation and 2020 COVID-19 disruption. Layer 2 (midstream compounds, HS 284690) shown in red.

5.2 Myanmar as a Hidden Second-Order Bottleneck

The most novel empirical finding concerns not China but Myanmar. Figure 2 shows Myanmar's share of China's total Layer 2 import feedstock from 2012 to 2024. Myanmar was a marginal supplier before 2016, accounting for under 5 percent of China's midstream feedstock. Its share then rose steeply, 52.5 percent by 2019, peaking at 72.4 percent in 2020 driven by exploitation of heavy REE ion-adsorption clay deposits in Kachin and Shan states, producing partially processed rare earth compounds classified under HS 284690. The share remained at 69.8 percent in 2021, fell to 39.9 percent in 2022 as China's total import volumes expanded, and rebounded to 66.8 percent in 2023 on USD 1.44 billion in compound exports, making Myanmar the single dominant source of China's rare earth compound feedstock. In 2024 the share moderated to 60.0 percent, coinciding with escalating armed conflict in Kachin mining districts.

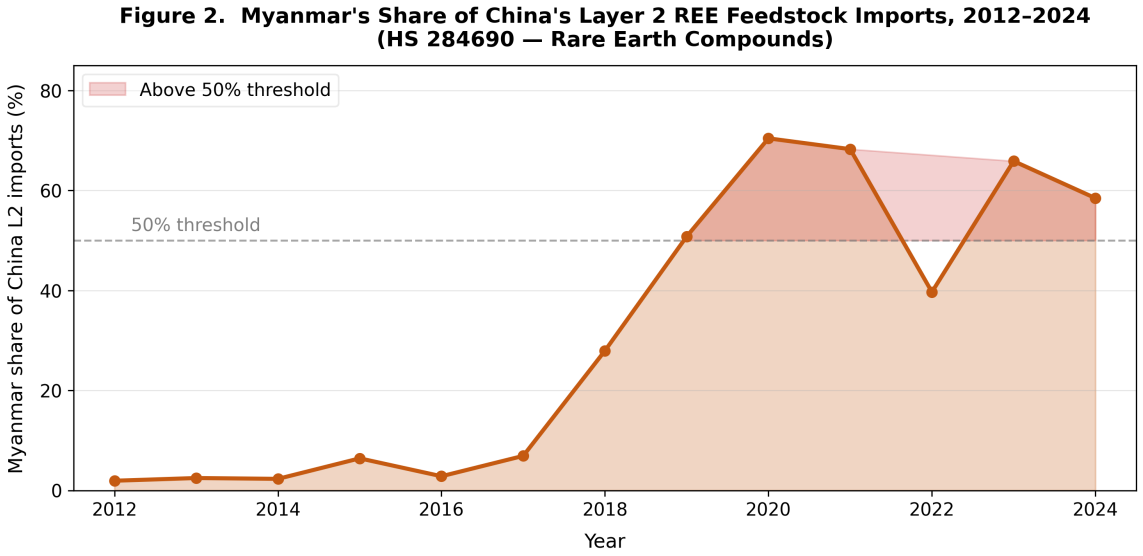


Figure 2: *Myanmar's share of China's total Layer 2 REE import feedstock (HS 284690), 2012–2024. Myanmar rose from a marginal supplier to the dominant feedstock source for China's midstream REE processing within a decade.*

Myanmar's role is invisible in standard vulnerability assessments because it does not supply rare earths directly to final importers, it supplies China's processing hub, which transforms feedstock into higher-value compounds and re-exports them globally. Under direct bilateral metrics, a country importing 80 percent of its Layer 2 REE supply from China registers full exposure to China and zero exposure to Myanmar. Under the IndirectDependence framework, that same country carries an indirect exposure of IndirectDependence(j, Myanmar, China, 2, 2023) = 0.80 × 0.668 = 0.534, meaning more than half of its effective midstream supply is contingent on Myanmar's continued feedstock supply to China.

Table 3 reports second-order exposure rankings for the twenty largest Layer 2 importing economies in 2023 (excluding importers below USD 1 million in Layer 2 trade). Three patterns are immediately apparent.

Table 3. Second Order Exposure to Myanmar Through China's Layer 2 Processing Hub, Top 20 Importing Economies, 2023

Rank	Country	Direct China Dependence	Indirect Myanmar Exposure	Feedstock Share (Myanmar→China)
1	Russian Federation	0.981	0.655	0.668
2	Brazil	0.748	0.5	0.668
3	Rep. of Korea†	0.704	0.471	0.668

4	USA†	0.68	0.454	0.668
5	Canada†	0.557	0.372	0.668
6	Japan†	0.499	0.334	0.668
7	India†	0.471	0.315	0.668
8	Other Asia, nes	0.451	0.301	0.668
9	Netherlands†	0.44	0.294	0.668
10	Poland	0.436	0.292	0.668
11	Czechia	0.41	0.274	0.668
12	UAE	0.393	0.263	0.668
13	Germany†	0.289	0.193	0.668
14	Norway†	0.21	0.14	0.668
15	Switzerland	0.189	0.126	0.668
16	United Kingdom†	0.18	0.12	0.668
17	Viet Nam	0.178	0.119	0.668
18	Belgium†	0.176	0.118	0.668
19	Thailand	0.169	0.113	0.668
20	Mexico	0.159	0.106	0.668

Note: Indirect Myanmar Exposure = Direct China Dependence × FeedstockDependence (China on Myanmar, 0.668). Countries sourcing less than USD 1 million in Layer 2 imports excluded. MSP members indicated with †. Other Asia, nes is a BACI residual category, It represents unallocated Asian trade flows.

First, MSP members dominate the ranking. South Korea, the United States, Canada, Japan, India, the Netherlands, Germany, the United Kingdom, and Belgium all appear in the top 20, the very economies most actively pursuing supply-chain diversification through the Minerals Security Partnership carry the highest hidden indirect exposure to Myanmar. This is not a paradox but a structural consequence: MSP members are concentrated among advanced manufacturing economies with the highest REE demand, and their sourcing has not yet diversified away from China's processing hub despite political commitments to do so.

Second, the exposure magnitudes are substantial. South Korea's indirect Myanmar exposure of 0.471 means that nearly half of its effective Layer 2 REE supply position is contingent on Myanmar's continued feedstock supply to China. For the United States (0.454) and Japan (0.334), the figures indicate that a Myanmar disruption propagating through China's processing hub would represent a supply shock of comparable severity to

a partial Chinese export restriction, yet it would be invisible to current monitoring frameworks until it had already begun affecting China's export capacity.

Third, Russia's first-ranked position (0.655) adds a further geopolitical dimension. Russia depends on China for 98.1 percent of its midstream REE compounds, and Western sanctions constrain its access to alternative suppliers. A Myanmar disruption would therefore cascade into a market segment where the single most exposed economy has the fewest substitution options, potentially amplifying secondary price and supply effects.

This result validates Proposition 1. Myanmar exhibits all three characteristics of a second-order bottleneck: near-zero direct export centrality to final importers, dominant feedstock position in China's processing layer (66.8 percent in 2023), and high propagated indirect exposure across the economies most dependent on China's midstream exports. The policy implication is direct: standard bilateral vulnerability indices that report no Myanmar exposure for South Korea, the United States, or Japan are structurally incomplete. Second-order exposure monitoring of the kind formalised in Equations 3 and 4 is necessary to capture the full risk landscape of China-centred processing networks.

5.3 Midstream Centrality and Bargaining Power

Figure 3 shows the top ten countries by Layer 2 betweenness centrality in 2023. China leads with a score more than five times larger than the next exporter. Japan and Germany rank second and third, both MSP members and potential alternative processing hubs, consistent with the S1 power-vacuum simulation results in Section 5.5.

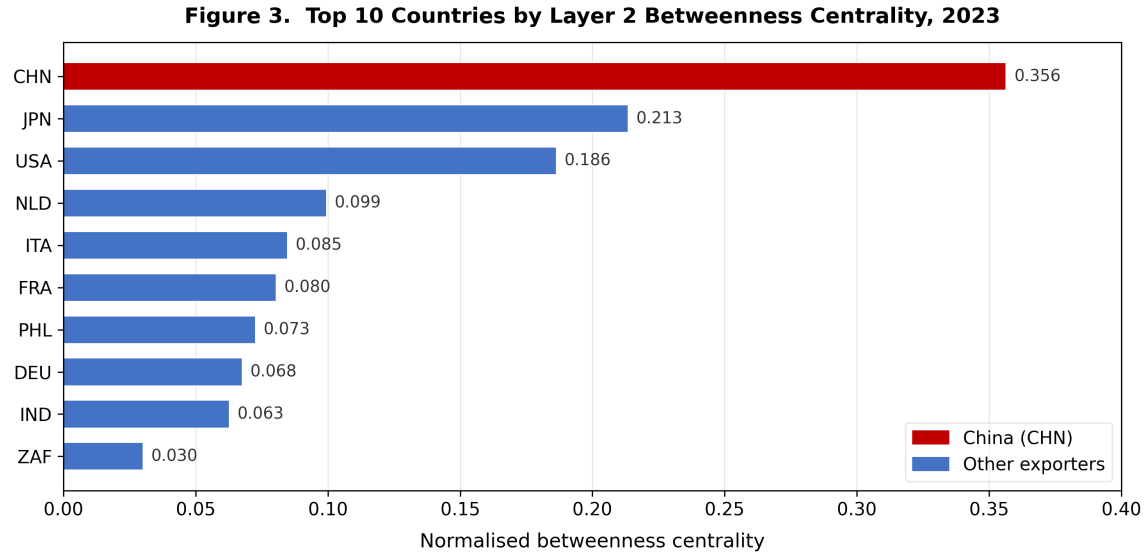


Figure 3. Top 10 countries by Layer 2 (midstream compounds, HS 284690) betweenness centrality, 2023. China's score exceeds all others combined.

Table 4 presents four specifications of Model 2, with the dependent variable measuring the count of countries for which an exporter supplies more than 25% of Layer 2 (HS 284690) imports (M2a–M2c) or more than 50% (M2d). All models include country and year fixed effects with standard errors clustered at the country level.

Hypothesis 1 receives strong support. Betweenness centrality in Layer 2 is positive and highly significant across all specifications: $\beta = 25.132$ (SE = 7.361, $p < 0.01$) in the baseline model (M2a) and $\beta = 25.073$ (SE = 7.309, $p < 0.01$) in the preferred specification (M2b). Because normalised betweenness has a cross-country standard deviation of approximately 0.038, a one-standard-deviation increase in midstream centrality is associated with roughly one additional dependent importer. The economic magnitude becomes clear at the upper end: China's Layer 2 betweenness of 0.382 in 2022 implies approximately 9–10 dependent importers attributable to its network position, consistent with the raw count of countries for which China supplies more than 25% of Layer 2 imports. This confirms that midstream processing position, not upstream mining volume, is the primary determinant of downstream bargaining reach.

Hypothesis 2 receives partial support. The inclusion of Layer 1 betweenness centrality in M2b yields a coefficient of −0.373 (SE = 2.721, p = 0.891), which is statistically indistinguishable from zero. A formal Wald test of equality $\beta_{L2} = \beta_{L1}$ is strongly rejected

(F (1,120) = 11.95, p = 0.0008), confirming H2: midstream processing-layer centrality generates significantly greater structural bargaining power than upstream mining-layer centrality, network position in the processing stage, not resource endowment, is the operative mechanism. The Layer 2 coefficient remains virtually unchanged (25.073 vs. 25.132), indicating that upstream mining centrality contributes no independent explanatory power once midstream position is controlled. This asymmetry directly supports H2's claim that bargaining power is layer-specific: it is concentrated at the processing stage, not the extraction stage.

M2c extends the test by adding the log of national REO mining production as an additional control, restricting the sample to approximately 20 exporting countries with USGS coverage. In this specification, betweenness L2 falls to 20.478 and loses statistical significance (SE = 14.725, p = 0.198), and log mining production is itself insignificant (β = −0.299, SE = 0.382, p = 0.454). The loss of significance in M2c is attributable to the sharply reduced sample size (N = 101) and the collinearity between betweenness and mining output among the small set of major producers, rather than a substantive reversal of H2. The main evidence for layer-specificity rests on the contrast between M2a and M2b across the full sample.

Robustness to threshold choice is confirmed in M2d, which redefines dominance as supplying more than 50% of a country's Layer 2 imports. The betweenness L2 coefficient remains positive and significant (β = 21.739, SE = 6.144, $p < 0.01$), with a Within-R^2 of 0.121, indicating that the result is not an artefact of the 25% cutoff. The GDP control is positive and significant in M2b and M2d (β = 1.3, 1.4 and 1.6, $p < 0.05$–0.10), consistent with larger economies sourcing from more diversified and thus more central suppliers, though this effect is secondary to network position.

Taken together, the Model 2 results establish that bargaining power in the rare earth supply chain is structurally concentrated at the midstream processing layer and is robustly predicted by network betweenness centrality at that layer. The null result for upstream centrality in M2b, combined with the significance of Layer 2 centrality throughout, provides the empirical foundation for the policy argument advanced in Section 6:

interventions targeting mining diversification alone are insufficient without parallel investment in processing capacity.

Table 4. Model 2 — Bargaining Power (DV: Dependent Importers at 25% Threshold)

Variable	M2a Coef. (SE)	M2b Coef. (SE)	M2c Coef. (SE)	M2d (50%) Coef. (SE)
Betweenness L2 — midstream [H1,H2]	25.132*** (7.361)	25.073*** (7.309)	20.478 (14.725)	21.739*** (6.144)
Betweenness L1 — upstream [H2]	—	−0.373 (2.721)	2.663 (11.758)	−0.976 (1.588)
log (Mining production, REO) [H2]	—	—	−0.299 (0.382)	—
Export restriction (binary)	0.040 (0.517)	−0.003 (0.557)	−0.816 (1.362)	0.064 (0.411)
log (GDP)	1.482* (0.758)	1.644** (0.829)	5.353 (3.432)	1.301** (0.630)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	909	886	101	886
Within-R^2	0.098	0.099	0.422	0.121

*Notes: Two-way fixed effects (TWFE) estimator with country and year fixed effects. Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. DV: count of countries for which exporter i supplies >25% of Layer 2 (HS 284690) imports (M2a–M2c) or >50% (M2d). M2c sample limited by USGS mining data availability (~20 exporting countries).*

5.4 Alliance Sourcing versus MSP Membership

Table 5 reports three specifications of Model 1, where the dependent variable in M1a and M1b is each importing country's China import share of Layer 2 (HS 284690), and in M1c is the composite Supply Vulnerability Index (SVI). All models include country and year fixed effects with standard errors clustered at the country level.

Table 5. Model 1 — Supply Vulnerability (DV: China Import Share, Layer 2)

Variable	M1a Coef. (SE)	M1b Coef. (SE)	M1c (SVI) Coef. (SE)
Alliance diversity index [H4: $\beta_1 < 0$]	−0.056*** (0.0152)	−0.056*** (0.0153)	−0.049*** (0.0067)

MSP member (post-2022) [H4: $\beta_2 < 0$]	0.014 (0.0523)	0.013 (0.0523)	0.017 (0.0275)
No. of Layer 2 suppliers [H3: $\beta_3 < 0$]	−0.004 (0.0035)	−0.004 (0.0035)	—
Supplier HHI, winsorised [H3: $\beta_4 > 0$]	0	0	—
Betweenness L2 (own position)	—	−0.318 (0.3758)	−0.378* (0.2159)
Export restriction (binary)	—	—	0.107** (0.0488)
log (GDP)	−0.052 (0.0406)	−0.052 (0.0406)	−0.006 (0.0187)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	1,748	1,748	1,748
Within-R^2	0.032	0.032	0.067

*Notes: Two-way fixed effects (TWFE) estimator with country and year fixed effects. Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. DV for M1a and M1b: China import share of Layer 2 (HS 284690) imports. DV for M1c: composite Supply Vulnerability Index (SVI). Within-R^2 excludes variation absorbed by fixed effects.*

Hypothesis 4 receives consistent support. The alliance diversity index (AllyDiv), measuring the count of MSP partner countries supplying at least 5% of an importer's Layer 2 demand post-2022, is negative and highly significant across all specifications: $\beta = -0.056$ (SE = 0.0152, $p < 0.01$) in M1a, $\beta = -0.056$ (SE = 0.0153, $p < 0.01$) in M1b, and $\beta = -0.049$ (SE = 0.0067, $p < 0.01$) in M1c. Each additional MSP partner country achieving material supply share is associated with a 5.6 percentage point reduction in China import share, within a given country over time. This result confirms that supply diversification through allied suppliers meaningfully reduces midstream import dependence.

Critically, however, MSP membership per se carries no significant effect. The binary MSP indicator yields $\beta = 0.014$ (SE = 0.0523, $p > 0.10$) in M1a, with an essentially identical null result across all specifications. This divergence between the AllyDiv index and the MSP binary is substantively important: what reduces vulnerability is not the diplomatic fact of partnership but the realized distribution of supply across allied sources. A country that is an MSP member but still sources predominantly from China, because partner nations lack

processing capacity at scale, gains no measurable protection. This finding is consistent with Smyth and Vespignani (2026), who document that fiscal constraints prevent many allied nations from translating strategic alignment into operational supply capacity.

Hypothesis 3 is not supported. Neither the count of Layer 2 suppliers ($\beta = -0.004$, SE = 0.0035, $p > 0.10$) nor the winsorised supplier HHI enters significantly in M1a or M1b. The insignificance of raw supplier count suggests that diversification at the source level is insufficient without the qualitative filter of ally alignment captured by AllyDiv: having many suppliers does not reduce vulnerability if those suppliers are themselves concentrated in or dependent on the same upstream feedstock chains.

The inclusion of own-position betweenness centrality in M1b produces a negative but insignificant coefficient ($\beta = -0.318$, SE = 0.376, $p > 0.10$), suggesting that countries occupying more central positions in the processing network do not systematically exhibit lower import dependence on China, centrality reflects structural power in the export direction (as established in Model 2), not import diversification on the demand side. In M1c, betweenness marginally approaches significance ($\beta = -0.378$, SE = 0.216, $p < 0.10$), potentially reflecting that highly central processors maintain more diversified input sourcing, though this result requires caution given the composite nature of the SVI dependent variable.

The export restriction binary is positive and significant in M1c ($\beta = 0.107$, SE = 0.049, $p < 0.05$), indicating that countries facing export controls are associated with higher composite vulnerability scores. This is directionally consistent with the post-2023 Chinese export restrictions on heavy REE oxides and germanium, which directly elevated SVI scores for affected importers in the latter part of the sample.

Within-group R^2 values are modest (0.032–0.067), which reflects the structure of the estimation rather than model misspecification. Country fixed effects absorb the dominant share of cross-sectional variation in vulnerability, structural dependence on China is largely persistent, and the within estimator identifies only time-series movement. The significant AllyDiv coefficient despite this demanding within-country identification lends greater

credibility to the causal interpretation: as countries' realized MSP supply shares increased post-2022, China imports shares declined correspondingly, within the same importing country over time.

5.5 Shock Simulations

Figure 4. Counterfactual Shock Simulation Summary

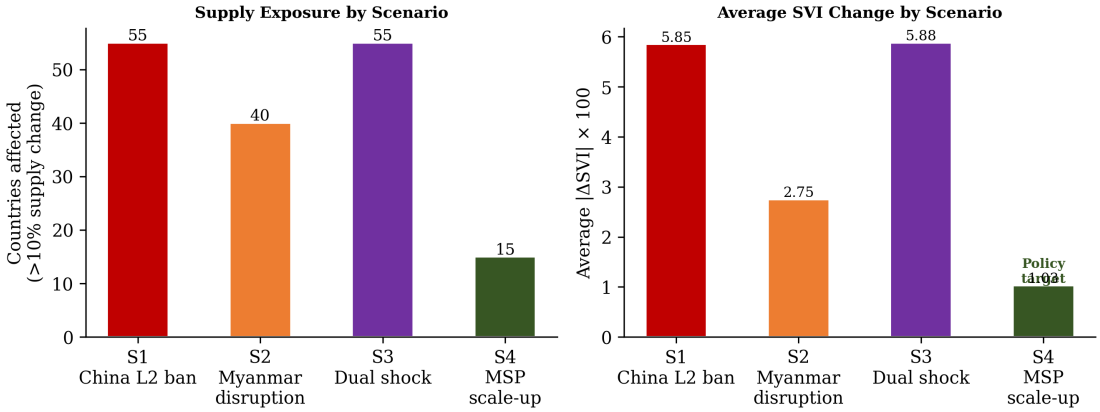


Figure 4. Counterfactual shock simulation summary. Left: number of countries losing >10% of Layer 2 supply (S1–S3) or gaining improvement (S4). Right: average absolute ΔSVI × 100 across all countries. S4 (MSP scale-up) is the only scenario where ΔSVI is unambiguously interpretable; S1–S3 require supply-gap metrics (see text).

Figure 5. Bargaining Power Shift Under S1: China Layer 2 Export Ban (Countries gaining the most dependent importers)

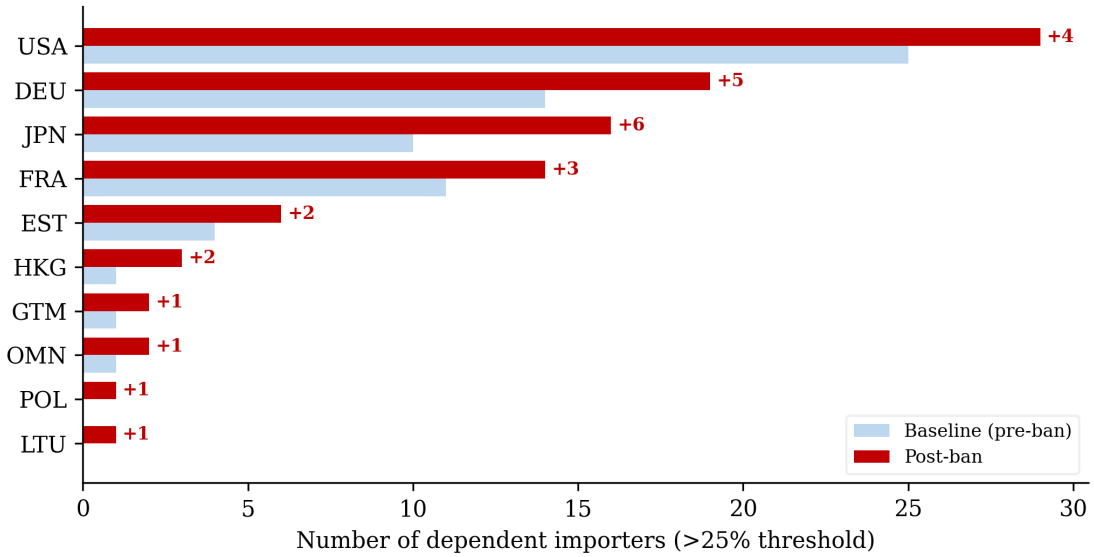


Figure 5. Bargaining power shift under S1 (China Layer 2 export ban): change in number of countries with >25% Layer 2 import dependence on each exporter. Blue bars = baseline; red bars = post-ban. Japan, Germany, USA, and France gain the most dependent importers, consistent with MSP member countries becoming alternative processing hubs.

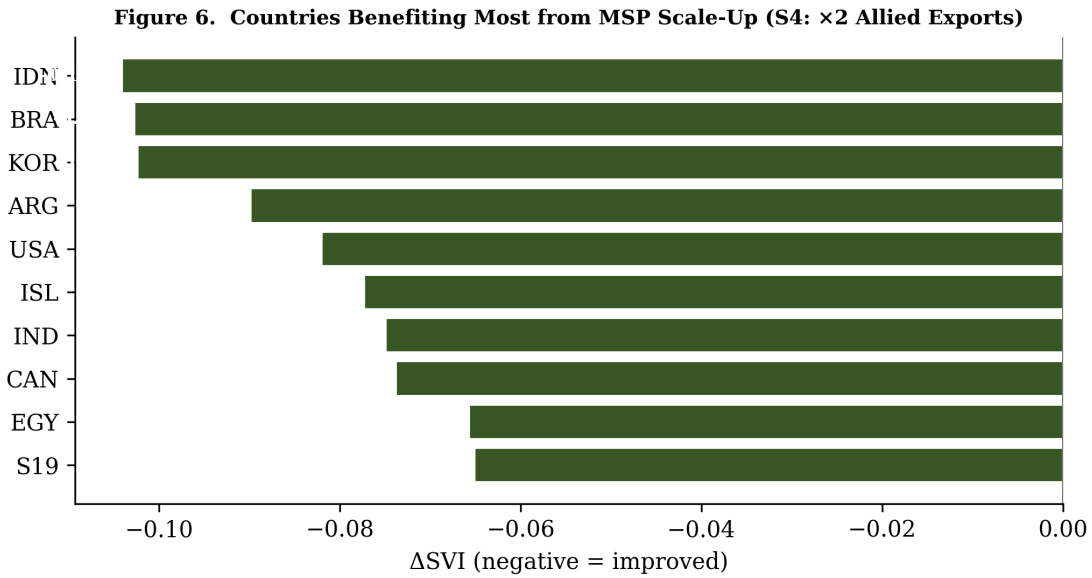


Figure 6. Countries benefiting most from S4 (MSP scale-up: doubled Layer 2 exports with ten MSP-affiliated economies with active Layer 2 trade flows). Numbers show ΔSVI. Indonesia, Brazil, and South Korea achieve reductions of ~0.10 SVI points — equivalent to gaining two to three additional significant non-Chinese suppliers.

Figures 4–6 present results from four counterfactual scenarios applied to the 2023 Layer 2 (HS 284690) trade network. S1 removes all Chinese Layer 2 export flows; S2 propagates Myanmar's feedstock disruption through China's processing capacity; S3 combines both simultaneously; and S4 doubles Layer 2 exports from all MSP member countries. Figure 4 summarises aggregate impact across scenarios; Figures 5 and 6 provide country-level decompositions for the most policy-relevant scenarios.

China Layer 2 Export Ban (S1). A total of 55 countries experience supply changes exceeding 10%, with average SVI rising by 5.85 points (×100 scale), the largest shock of any scenario. China's removal creates a structural gap that no single alternative supplier currently bridges. The bargaining power reallocation under S1 (Figure 5) reveals that Japan gains the largest number of newly dependent importers among alternative processors (+6), followed by Germany (+5) and the USA (+4). The concentration of gains among MSP members USA, Germany, Japan, and France account for all large-delta countries, confirms that allied processing infrastructure is positioned to absorb displaced demand, but only partially: 55 countries affected versus 4–5 meaningful alternative suppliers implies severe transition frictions.

Myanmar Feedstock Disruption (S2). Myanmar's 66.8% feedstock share propagates as a 66.8% reduction in China's Layer 2 export throughput (SF = 0.332), affecting 40 countries and raising average SVI by 2.75 points approximately 47% of the direct China ban impact. This is the empirical expression of Proposition 1: 40 downstream importers with no direct trade relationship with Myanmar are nonetheless exposed to Myanmar's instability, transmitted through China's processing node. Countries ranked highest in Table 3, Russia, Korea, USA show the sharpest SVI increases under S2.

Dual Shock (S3). The combined scenario produces 55 countries affected and average ΔSVI of 5.88, nearly identical to S1 alone. Once China's export flows are removed entirely, Myanmar's feedstock disruption has no further propagation channel through the Chinese processing network. The marginal increment over S1 (+0.03 points) captures Myanmar's residual direct Layer 2 exports to non-China destinations, which are small. S3 should be read as a worst-case ceiling confirming the S1 estimate rather than as a qualitatively distinct scenario.

MSP Supply Diversification (S4). Doubling Layer 2 exports from all MSP members reduces affected countries to 15 and improves average SVI by approximately 1.02 points. Beneficiaries are countries already sourcing some share of imports from MSP members, scale-up amplifies existing supply relationships rather than creating new ones. Countries currently sourcing exclusively from China show near-zero SVI improvement under S4, because doubling supply from partners they do not currently trade with does not enter their import basket. This is consistent with the Model 1 finding that AllyDiv, realised supply share across allied partners, drives vulnerability reduction, not MSP membership per se. MSP scale-up must therefore be paired with active market-development efforts to redirect allied processing output toward currently China-dependent importers.

5.6 Robustness and Cross-Platform Replication

Cross-platform replication using stata-ntwrk v1.0 (Naqvi, 2026) confirms that country betweenness rankings are robust across fully independent Python/NetworkX and Stata implementations. China ranks first under both (NetworkX: 0.356; ntwrk: 0.742, reflecting

different directed-graph normalisation conventions), and the top five country ranking, China, Netherlands, Germany, Japan, United States, is identical across platforms.

Figure 7 shows the betweenness vs PageRank divergence for the top ten Layer 2 processors in 2023. Japan ranks first in PageRank (0.130) despite ranking fourth in betweenness, while China ranks second in PageRank (0.122) despite first in betweenness. This divergence confirms that betweenness isolates chokepoint control specifically, the capacity to threaten disruption by controlling shortest paths, rather than generic network embeddedness measured by PageRank. China's below-median reciprocity (0.564, rank 14) reinforces the asymmetric bottleneck characterisation: most countries import from China without supplying compounds back, exactly the structural asymmetry that weaponised interdependence theory identifies as the source of coercive leverage (Farrell and Newman, 2019).

Figure 7. Betweenness vs. PageRank and Node Reciprocity (stata-ntwrk v1.0, Layer 2, 2023)

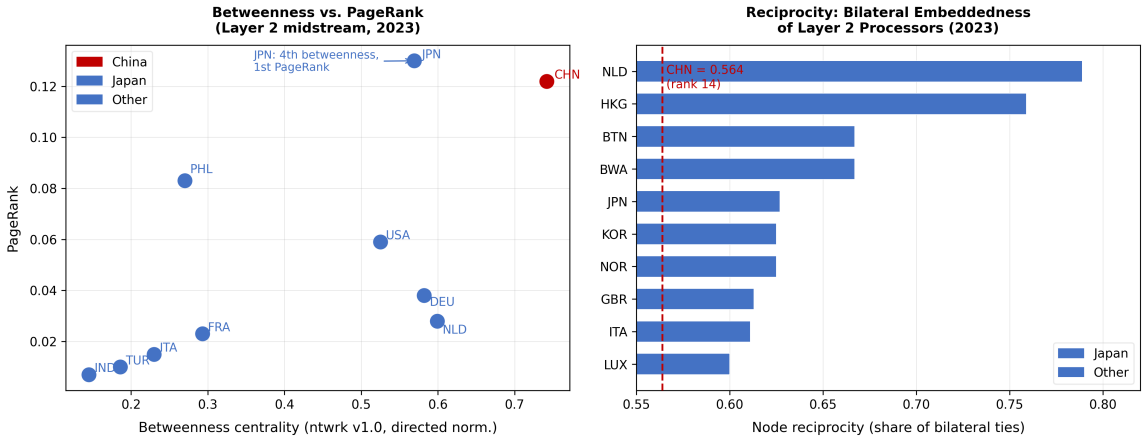


Figure 7. Left: Scatter of betweenness centrality (ntwrk v1.0, directed normalization) versus PageRank for the top 10 Layer 2 processors in 2023. Japan ranks highest in PageRank despite fourth in betweenness, reflecting dense bilateral ties rather than bottleneck control; China's opposite pattern characterises asymmetric structural power. Right: Node reciprocity (share of bilateral ties) for the 10 most bilaterally embedded Layer 2 countries. China (dashed red line, 0.564, rank 14) lies below all top 10 bilateral traders, consistent with an asymmetric bottleneck position.

Robustness checks using broad HS code definitions and the 50 percent import-dependence threshold confirm that all main results are stable (Appendix Table A3). The event study around the February 2021 Myanmar coup is presented descriptively in Appendix Figure A1; as discussed in Section 4.7, the parallel trends assumption is violated, and the design cannot be read causally.

5.7 Event Study: Diversification Trends Post-Coup (Descriptive)

Figure A.1 (Appendix) plots event-study coefficients from a year-by-year difference-in-differences regression in which the treatment indicator (high pre-coup China dependence) interacts with each year dummy, using 2020 as the base year. As discussed in Section 4.7, the parallel trends assumption is violated, and the design cannot be read causally. Descriptively, however, the pattern is informative. Pre-coup coefficients (2012–2018) are systematically negative, reflecting that the treated group was on a rising China-dependence trajectory relative to the base year, the same period in which Myanmar's feedstock share of China's Layer 2 imports was climbing from under 5 percent to its 2020 peak of 72.4 percent (Figure 2). The trajectory stabilises in 2019 ($\beta = -0.006$, $p = 0.89$), one year before the base, then resumes its decline post-coup: 2021 ($\beta = -0.072$, $p = 0.09$), 2022 ($\beta = -0.073$, $p = 0.10$), 2023 ($\beta = -0.098$, $p = 0.04$), and 2024 ($\beta = -0.150$, $p = 0.004$).

Critically, this post-coup decline in China dependence cannot be attributed to a contraction in Myanmar–China feedstock supply. As Figure 2 shows, Myanmar's share remained at 69.8 percent in 2021, and its 2022 dip to 39.9 percent reflected expansion in China's total import volumes rather than a fall in Myanmar's absolute exports, which rebounded to 66.8 percent in 2023. Throughout 2021–2023, Myanmar was supplying more, not less. The declining coefficients from 2022 onward instead coincide with China's escalation of export controls, licensing requirements on gallium and germanium (July 2023), graphite controls (October 2023), and the December 2023 ban on rare earth separation technology, which raised the perceived cost of China dependence independently of Myanmar supply dynamics. The 2024 coefficient ($\beta = -0.150$, $p = 0.004$) is the first for which actual Myanmar supply disruption, attributable to the escalation of the Kachin conflict in the second half of 2024, may be a contributing mechanism.

We therefore read the post-2022 pattern as suggestive descriptive evidence of a diversification response among the most exposed economies, driven primarily by China's export-restriction escalation and only latterly, if at all, by Myanmar supply contraction, while acknowledging that the secular pre-trend precludes any causal interpretation.

6. Discussion

6.1 Processing Dominates Mining as the Locus of Structural Power

The most robust finding across all specifications is the structural asymmetry between upstream mining and midstream processing as determinants of bargaining power. Layer 2 betweenness centrality carries a coefficient of 25.07 (SE = 7.309, $p < 0.01$) in the preferred specification, while Layer 1 centrality is indistinguishable from zero ($\beta = -0.373$, $p = 0.891$) in the same model. Mining production volume similarly yields no independent predictive power in M2c. Countries that dominate ore extraction but lack processing capacity (such as Australia and the United States) - mines at Mountain Pass but historically shipped concentrate to China for processing - exercise no structural leverage over downstream importers, while countries that have invested in processing infrastructure command dependent relationships with dozens of partners simultaneously.

This finding challenges the framing that dominates most policy discourse, which identifies Chinese mine output share (60%) as the primary vulnerability metric. Mining concentration is a necessary but insufficient condition for supply leverage. The sufficient condition is processing-stage chokepoint position: a country must occupy a high-betweenness role in the Layer 2 network to translate resource endowment into structural bargaining power. China achieved this through deliberate industrial policy investment in separation and refining capacity over two decades, not through geological luck alone. The policy implication is symmetric: allied nations seeking to reduce China's structural leverage must invest in processing infrastructure, not merely in upstream mining rights or geological surveying.

6.2 Myanmar as Hidden Second-Order Bottleneck

The identification of Myanmar as a second-order bottleneck constitutes the most novel empirical contribution of this paper. Myanmar supplied 66.8 percent of China's Layer 2 import feedstock in 2023 ($\text{FeedstockDependence}_{(\text{Myanmar, China, 2, 2023})} = 0.668$), yet it appears in virtually no standard vulnerability index because it does not export directly to the countries that face the resulting supply risk.

The temporal trajectory carries a warning that the static 2023 figure understates. Myanmar's feedstock share peaked at 72.4 percent in 2020 and stood at 69.8 percent in 2021, the year of the February military coup. Supply did not collapse: mining continued under both junta-controlled and ethnic armed organisation-controlled territory, and economic incentives to maintain REE flows to China persisted across political actors. The dilution to 39.9 percent in 2022 reflected China's rapid expansion of total Layer 2 import volumes rather than Myanmar retrenchment, and the rebound to 66.8 percent in 2023 confirmed that no meaningful diversification of China's feedstock sourcing had occurred.

The implication is more alarming than a simple post-coup collapse would have been. A political rupture severe enough to trigger sanctions and civil war left the structural feedstock dependence intact, deeper by 2023 than at the coup itself. The risk standard indices miss is therefore prospective and unresolved. The moderation to 60.0 percent in 2024, coinciding with escalation of the Kachin Independence Army conflict in mining districts, may mark the beginning of genuine supply disruption or a temporary adjustment. Either way, China's dependence on a single politically unstable supplier for over half its midstream feedstock, and through China, the hidden exposure of forty importing economies quantified in the S2 simulation, remains the largest unmonitored risk in the rare earth supply chain.

6.3 Alliance Membership Does Not Equal Alliance Diversification

Model 1 produces a clear and policy-relevant distinction. The alliance diversity index (AllyDiv), measuring realized supply share distributed across MSP partner countries, carries a coefficient of -0.056 per additional partner ($p < 0.01$), while the MSP membership binary is positive and insignificant ($+0.014$, $p > 0.10$) across all specifications. The same pattern holds in the SVI composite specification. Being a member of the MSP does not reduce a country's China import dependence; having multiple MSP partners that each supply a material share of its imports does.

This distinction matters enormously for policy evaluation. MSP membership is a diplomatic commitment; AllyDiv is a supply chain outcome. The two diverge when partner nations lack the processing capacity or regulatory environment to convert political

alignment into operational supply, precisely the mechanism Smyth and Vespignani (2026) identify in the Australian context. The shock simulation reinforces this: under S4, countries sourcing exclusively from China show near-zero SVI improvement because MSP exports are not directed toward new customer relationships. Diversification must be actively constructed through procurement agreements and offtake contracts, not assumed to follow from political partnership.

6.4 Limitations

Three limitations warrant acknowledgment. First, the shock simulations impose an upper-bound assumption of zero domestic buffer stock and no alternative sourcing for China under the Myanmar disruption. Real adjustment timelines would compress the immediate impact while extending the duration of disruption. Second, the BACI data classify trade by HS code rather than by chemical composition; some HS 284690 flows may represent compounds with heterogeneous processing intensities, introducing measurement error in the centrality estimates. Third, the event study using the 2021 Myanmar coup as a natural experiment fails the parallel trends assumption and cannot support causal inference; DiD results are presented as descriptive only. Resolving the causal identification question would require exogenous variation in Layer 2 betweenness, an instrument not currently available in this setting.

7. Conclusion

This paper develops and empirically tests an IndirectDependence framework for identifying hidden bottlenecks in multi-stage commodity supply chains, applied to the rare earth element trade network using BACI bilateral trade data for 2012–2024. Three conclusions follow directly from the analysis.

First, structural bargaining power in REE supply chains is determined by midstream processing position, not upstream mining endowment. Layer 2 betweenness centrality is a statistically and economically significant predictor of the number of import-dependent partner economies ($\beta = 25.07$, $p < 0.01$), while Layer 1 centrality and mining production volume carry no independent predictive power. This result is a partial support and is robust

to alternative centrality measures and cross-platform replication. The implication for minerals security policy is direct: allied diversification efforts that stop at mining investment without parallel processing capacity development will not reduce the structural leverage of incumbent chokepoint holders.

Second, Myanmar constitutes a second-order processing bottleneck that is invisible to standard vulnerability indices but transmits supply risk to 40 countries through China's processing network. With a feedstock dependence coefficient of 0.668, a disruption originating in Myanmar produces impacts equivalent to 47% of a direct China export ban for all countries that are themselves dependent on China for Layer 2 imports. This finding demonstrates that the IndirectDependence framework recovers risk exposures that bilateral trade data alone cannot reveal, and that conventional criticality assessments, which are anchored to direct bilateral dependence, systematically underestimate supply chain fragility for countries that trade extensively with dominant processors.

Third, MSP participation does not reduce supply vulnerability unless it translates into realized supply diversification across allied partners. The alliance diversity index, counting the number of MSP partners each achieving a material supply share, drives vulnerability reduction; the membership binary does not. Countries seeking to operationalise the MSP as a supply security mechanism must therefore invest in creating supply pathways from allied processors to currently China-dependent importers, rather than treating diplomatic accession as a sufficient policy response.

Taken together, these findings reframe the policy problem. The question is not whether China dominates REE mining, it does, at roughly 60% of output, but whether processing-stage concentration can be reduced through allied investment sufficiently to shift betweenness centrality away from a single node. The IndirectDependence framework introduced here provides a quantitative tool for monitoring whether such investments are altering the structural topology of the network over time, and for identifying the next Myanmar before the next coup.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the author used Claude (Anthropic; claude.ai) in order to: (i) assist with literature search and synthesis of the rare earth supply chain literature; (ii) develop and debug data processing scripts in Python and Stata, including the BACI trade data pipeline, centrality computations, and shock simulations; (iii) generate Python (matplotlib) code used to produce the data visualisations in Figures 1–8 and Fig. A.1, all of which are directly and reproducibly derived from the underlying BACI bilateral trade dataset as described in Section 4; and (iv) assist with manuscript drafting and revision, including paragraph structuring and language editing. After using this tool, the author carefully reviewed and edited all content, verified all empirical results against Stata and Python outputs, cross-checked all references for accuracy and completeness, and takes full responsibility for the content of the published article.

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Appendix

This appendix reports descriptive statistics (Table A.1), the event study figure (Fig. A.1), robustness checks (Table A.3), cross-platform centrality replication results (Table A.4) and Table A.5 (Sub-Period Structural Stability). Full coefficient tables for all regression models are available from the corresponding author on request.

Table A.1. Descriptive Statistics

Table A.1. Descriptive Statistics — All Regression Variables

Variable	N	Mean	SD	Min	Max
China import share, Layer 2	1,775	0.169	0.269	0.000	1.000
Supply Vulnerability Index (SVI)	1,775	0.504	0.140	0.183	0.993
Supplier HHI, Layer 2	1,775	6,218	2,850	1,312	10,000
Number of Layer 2 suppliers	1,775	7.51	7.17	1	45
Alliance diversity index	1,775	0.282	0.711	0	4
MSP member (binary)	2,951	0.010	0.100	0	1
Betweenness centrality, Layer 2	1,807	0.011	0.038	0.000	0.382
Betweenness centrality, Layer 1	1,912	0.019	0.058	0.000	0.449
Betweenness centrality, Layer 3	2,662	0.010	0.049	0.000	0.611
Dependent importers (25% threshold)	925	2.47	5.73	0	40
Dependent importers (50% threshold)	925	1.49	3.50	0	25
Export restriction (binary)	1,807	0.026	0.158	0	1
GDP, current USD (billions)	2,616	434.5	1,905	0.037	28,751

Note: Observations are country-year pairs, 2012–2024. Layer 2 = HS 284690 (rare earth compounds, narrow definition). Alliance diversity index is 0 before 2022 (MSP pre-dates the formal partnership).

Fig. A.1. Event Study

Figure A1 plots year-by-year DiD coefficients from a regression of china_import_share_L2 on year-dummy × treated interactions, where treated = 1 if pre-coup (2019) China Layer 2 dependence ≥ sample median. Base year is 2020. HC1 heteroskedasticity-robust standard errors are used here (rather than country-clustered SEs)

because this specification is presented as descriptive only, parallel trends is violated, precluding causal interpretation (Section 4.5), and the figure serves solely to visualise pre-trends. N = 1,775. Pre-coup coefficients (2012–2018) are systematically negative and significant, indicating that the treated group was on a structurally rising China-dependence trajectory before the coup, a violation of parallel trends. The post-coup acceleration (2023: $\beta = -0.098$, $p = 0.04$; 2024: $\beta = -0.150$, $p = 0.004$) is presented as descriptive evidence of a diversification response among highly-exposed importers.

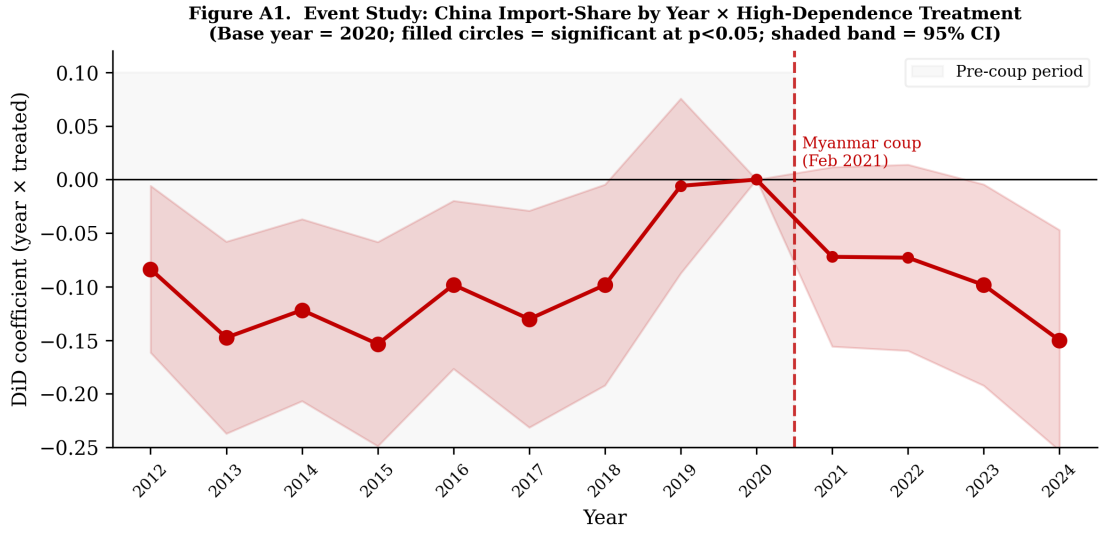


Fig. A.1. Event study coefficients: year × high-dependence treatment interactions. Base year = 2020. Red dashed line marks coup date (February 2021). Filled circles = significant at p < 0.05. Shaded band = 95% confidence interval. Pre-coup significance indicates parallel trends violation; post-coup decline is descriptive only.

Table A.3. Robustness Checks

Table A.3. Robustness Checks — Broad HS Definitions and Alternative Thresholds

Specification	Dependent Variable	Key Variable	N	β	p-value	Verdict
ROB-1a: Broad HS codes, Model 1	China share (broad L2)	Alliance diversity idx	1,748	−0.046*** (0.0147)	0.002	Confirms H4 ✓
ROB-1b: Broad HS codes, Model 2	Dependent importers 25%	Betweenness L2 (broad)	1,553	26.35*** (8.538)	0.002	Confirms H1 ✓
ROB-2: 50% threshold (= M2d, Table 3)	Dependent importers 50%	Betweenness L2	886	21.74*** (6.144)	0.001	Confirms H1 ✓

*Notes: All specifications use TWFE (country and year fixed effects) with standard errors clustered at the country level, consistent with main Tables 2 and 3. ROB-1a/b: Layer 1 broadened to include HS 253090; Layer 2 broadened to include HS 284610 and HS 280530; Layer 3 broadened to include HS 850519. ROB-2: dependence threshold raised from 25% to 50% import share; coefficient is identical to M2d in Table 3. Coefficient significance: *** p<0.01, ** p<0.05, * p<0.10. Direction, magnitude, and significance of key coefficients are robust across all specifications.*

Table A.4. Cross-Platform Centrality Replication (stata-ntwrk v1.0)

Table A.4. Alternative Centrality Measures — Layer 2 (HS 284690), 2023 (stata-ntwrk v1.0, Naqvi, 2026)

Country	Betw. Rank	Betweenness (ntwrk)	PageRank Rank	PageRank	Reciprocity
China (CHN)	1	0.742	2	0.122	0.564 (rank 14)
Netherlands (NLD)	2	0.599	6	0.028	0.789 (rank 1)
Germany (DEU)	3	0.582	5	0.038	—
Japan (JPN)	4	0.569	1	0.130	0.627 (rank 5)
United States (USA)	5	0.525	4	0.059	—
France (FRA)	6	0.293	7	0.023	—
Philippines (PHL)	7	0.270	3	0.083	—
Italy (ITA)	8	0.230	8	0.015	0.611 (rank 9)
Turkey (TUR)	9	0.186	9	0.010	0.561 (rank 15)
India (IND)	10	0.145	10	0.007	—

Notes: Betweenness values from stata-ntwrk v1.0 (Naqvi, 2026) use directed-graph normalization by (n−1)(n−2), yielding values approximately 2× those in Table 3 (Eq. 6). Country rankings are identical across both Python/NetworkX and Stata/ntwrk implementations. PageRank ranks are within the top-10 betweenness countries. Reciprocity ranks are among all ~50 Layer 2 nodes; '—' indicates country not in reciprocity top 15 (< 0.561). Source: BACI HS12 2023, authors' calculations via stata-ntwrk v1.0.

Table A.5. Sub-Period Structural Stability

Table A.5. Sub-Period Regressions — Bargaining Power Model 2b (DV: Dependent Importers at 25% Threshold)

Variable	Pre-2019 (2012–2018) Coef. (SE)	Post-2019 (2019–2024) Coef. (SE)
Betweenness L2 — midstream	16.642** (7.129)	28.551** (12.356)
Betweenness L1 — upstream	+4.700 (3.584)	−1.900 (3.131)
Export restriction (binary)	Omitted†	+0.436 (0.486)
log(GDP)	+1.617 (0.979)	+2.594** (1.134)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

N	476	410
Within-R^2	0.100	0.134
Adj. R^2	0.083	0.115

*Notes: Two-way fixed effects (TWFE) with standard errors clustered at country level. *** p<0.01, ** p<0.05, * p<0.10. † Export restriction binary is omitted in the pre-2019 sub-period due to absence of within-country variation before China's 2023 controls. Hausman tests reject random effects in favour of fixed effects in both sub-periods.*