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BEYOND THE MARKET: FIRM AND STATE RESPONSES TO CHINA'S CRITICAL MINERAL EXPORT POLICIES

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ABSTRACT

China's export licensing, quotas and targeted restrictions on gallium, germanium, graphite, antimony and rare earths since 2023 create a geoeconomic shock that firms and states must both absorb. This paper asks how do individual firms adjust their investment and innovation behavior, and how do governments respond with policy of their own. It develops firm and state level theoretical frameworks, specifies three testable hypotheses, and reports results from two pilot analyses. The firm level analysis uses a seed panel of four U.S. listed firms positioned differently in mineral dependent supply chains (Tesla, Apple, NVIDIA and MP Materials) over fiscal years 2023-2025, drawing on SEC 10 K data to compute R&D intensity, capital expenditure ratios and return on assets. R&D intensity rose for three of the four firms between fiscal 2024 and 2025 (Tesla +2.11 points, MP Materials +6.22 points, Apple +0.28 points), while NVIDIA's R&D intensity fell 4.34 points as revenue grew 114%. Capital expenditure ratios rose for Apple and NVIDIA but fell for Tesla and MP Materials. The state level analysis reports an exploratory cross-sectional regression across ten countries and blocs, finding a positive and statistically distinguishable association between China origin trade exposure and a coded policy intensity score ($B = 0.24$, HC3 SE = 0.08, $z = 3.02$, $p = 0.003$, $R^2 = 0.62$, $N = 10$). Both analyses are explicitly pilot stage: the firm panel is too small for causal claims, and the state level regression is cross sectional rather than event based. The paper sets out what additional data, mainly patent data and a larger firm and country sample, would be needed to move from these descriptive patterns to defensible causal tests, and closes with a hypothesis-by-hypothesis assessment.

Keywords: Critical Minerals, Firm Strategy, Industrial Policy, Economic Statecraft, Capital Expenditure, Geoeconomics

1 INTRODUCTION

China's export licensing, quotas and targeted restrictions on gallium, germanium, graphite, antimony and rare earths since 2023 are hypothesized to raise input costs and shift trade away from China among the most exposed importers. Market level price and trade effects, however, are only the first stage of adjustment to a shock of this kind. This paper

asks what happens downstream of that market disruption, at two further levels of the causal chain: the firm and the state.

Firms that depend on a restricted mineral can respond by diversifying suppliers, increasing capital expenditure to build alternative capacity, or investing in research and development to substitute away from the constrained input. Governments, in turn, can respond to their exposed industries with subsidies, stockpiling, permitting reform, recycling programs, or alliance-based supply chain cooperation. This paper treats both firm and state behavior as distinct but related transmission stages that follow from the same underlying market shock: the market creates incentives, firms decide how to respond within the constraints of technology, capital and contracts, and states decide whether and how to intervene given fiscal capacity, industrial structure and alliance commitments.

The paper is organized in two halves. Sections 2-8 develop the firm level component: theory, two hypotheses (H1, H2), data, pilot results and a full empirical strategy for a final firm year panel. Sections 9-15 develop the state level component: theory, one hypothesis (H3), data, and an exploratory regression. Sections 16-18 draw the two halves together into a single hypothesis assessment table, a data agenda for future work and a conclusion.

2 FIRM LEVEL THEORETICAL FRAMEWORK: FIRMS AS TRANSMISSION MECHANISMS

Firms coordinate production across technical, contractual and geographical boundaries, and global value chain theory explains why this coordination is rarely a simple spot market exchange: its form depends on the complexity of transactions, how easily specifications can be codified, and supplier capabilities [6]. Critical minerals intensify this problem, since many inputs require technical qualification, performance standards, purity requirements and long approval cycles. A firm may know an alternative supplier exists in a statistical sense while still being unable to use it immediately in a battery, semiconductor, aircraft, motor or defence system.

Production network research adds a second layer. Carvalho et al. [3] show that shocks can propagate both upstream and downstream through direct and indirect supplier customer linkages, although their empirical setting is a natural disaster rather than mineral policy, the propagation mechanism is relevant here because an export licensing rule that delays access to a specialized material can move through downstream sectors much as a physical disruption would, even though the origin and legal form of the shock differ.

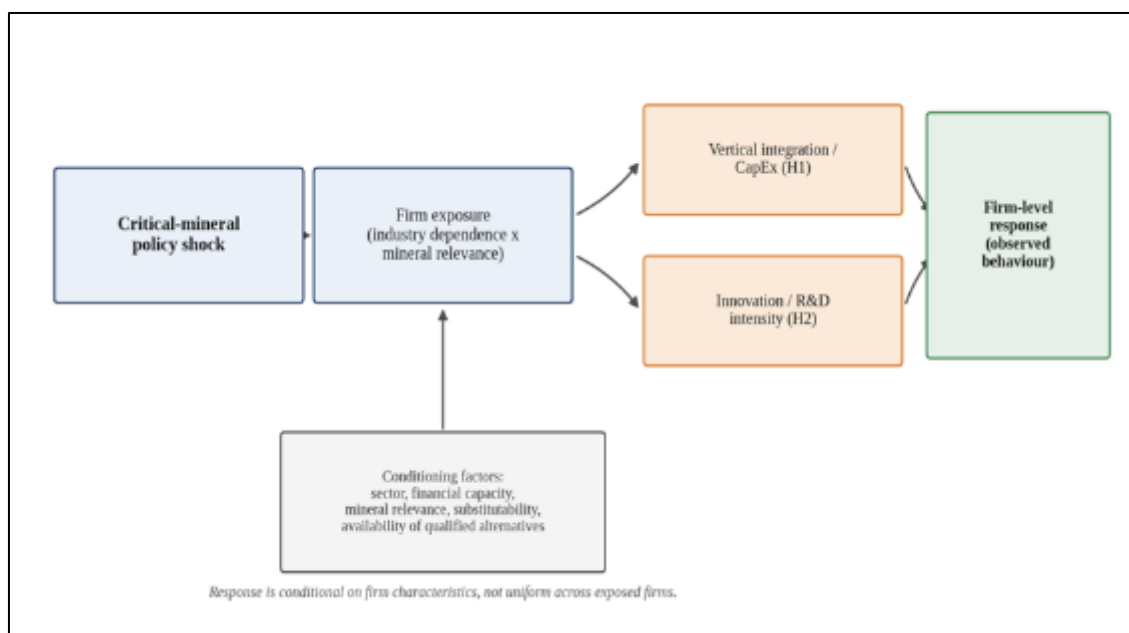


Figure 1: Causal pathway from policy shock to firm level response

Firm response theory is further supported by recent evidence on supply chain risk. Ersahin et al. [4] find that firms with geographically broad supply chains and fewer suppliers face higher supply chain risk, and that exposed firms form new relationships with closer, domestic suppliers. The same study finds that financially unconstrained firms are more likely to pursue vertical mergers and acquisitions after supply chain risk increases, directly relevant to the vertical integration hypothesis (H1) below: risk can generate both procurement adjustments and boundary of the firm responses, and financial capacity conditions which firms can act on the latter.

The innovation channel is conceptually different because it does not require a firm to find a new supplier for the same input. Instead, it asks whether exposure induces firms to reduce the technical need for the restricted input altogether. Alfaro et al. [1] provide directly relevant evidence by showing that China's rare earth restrictions generated directed technological change in rare earth using industries, evidence that a mineral shock can affect both where firms source from and what technologies they choose to develop (the basis for H2).

Taken together, this literature implies that firms are not passive recipients of mineral shocks. They are transmission mechanisms. Policy events alter expectations and constraints, and exposed firms then decide whether to hold inventory, change suppliers, invest upstream, acquire capacity, adjust product design, or intensify research. This paper does not assume that every exposed firm responds identically, firm response is treated as conditional on sector, financial capacity, mineral relevance, substitutability and the availability of qualified alternatives.

3 OPERATIONALIZING FIRM EXPOSURE

The central measurement challenge is that firm exposure cannot be reduced to country exposure. A firm headquartered in the United States may have production facilities, suppliers and customers across several jurisdictions, and it may be exposed even without directly importing a mineral because that mineral is embedded in intermediate inputs such as magnets, battery materials, wafers, optical components or advanced packaging. Firm exposure should therefore be measured at the industry and mineral levels rather than inferred solely from the firm's country of registration:

$$\text{FirmExposure}_{i,m,t-1} = \text{IndustryDependence}_{c,s,m,t-1} \times \text{FirmMineralRelevance}_{i,m}$$

where i denotes the firm, c the country, s the industry, m the mineral and t time. IndustryDependence measures the extent to which the relevant country industry depends on Chinese supply for a given mineral or mineral linked input, while FirmMineralRelevance captures the importance of that mineral to the firm's products, processes or patent portfolio.

In the final dataset, IndustryDependence would be constructed from UN Comtrade and OECD Inter Country Input-Output tables, which can identify imported intermediate inputs across countries and sectors [10, 12]. FirmMineralRelevance can be coded from industry classification, product descriptions, supplier disclosures, patent keywords and annual report discussion.

Exposure should also be distinguished from response. Tesla is exposed to battery minerals and rare-earth magnets; Apple through devices, magnets, semiconductors and supplier networks; NVIDIA through semiconductor supply chains and advanced packaging; and MP Materials through direct rare-earth mining and processing. These firms therefore represent different forms of exposure downstream manufacturing, semiconductor inputs and upstream mineral processing even though all are U.S. listed. This heterogeneity is central to the pilot analysis.

4 FIRM LEVEL LITERATURE REVIEW AND HYPOTHESES

4.1 Vertical Integration, Capital Expenditure and Boundary Decisions (H1)

Firms may respond to critical mineral uncertainty by increasing capital expenditure, investing in upstream or midstream capacity, supporting recycling, entering joint ventures or acquiring suppliers.

4.1.1 H1 (vertical integration hypothesis).

Firms with higher pre-shock exposure increase capital expenditure or upstream/domestic capacity investment after-shocks.

The underlying logic is that greater supply-chain uncertainty may encourage firms with sufficient financial capacity to control more of the supply chain. However, increases in capital expenditure are not necessarily mineral-security responses. CapEx may instead reflect ordinary capacity expansion, data center investment, product cycle timing, manufacturing upgrades or accounting reclassification. CapEx ratio is therefore treated as an observable but imperfect proxy and should be combined with project-level coding of investment announcements, including mines, refineries, recycling plants and magnet facilities.

4.2 Innovation, Substitution and Directed Technological Change (H2)

A second response channel does not require firms to find a new supplier for the same input. Instead, firms may innovate in ways that reduce their technical dependence on the restricted input.

4.2.1 H2 (innovation/substitution hypothesis).

Firms with higher pre-shock exposure increase R&D intensity and substitution-related patenting after-shocks.

R&D intensity provides a broad measure of innovation effort. A more precise measure would identify patents related to mineral substitution, recycling, material efficiency and alternative technologies. This requires patent-level data beyond the present pilot, which the final analysis should add using PatentsView or the USPTO Open Data Portal [13].

Table 1: Firm level hypotheses

Hypothesis	Prediction	Main outcome
H1	Higher pre-shock exposure → higher investment	CapEx ratio; upstream/domestic investment
H2	Higher pre-shock exposure → greater innovation and substitution	R&D intensity; mineral/substitution patents

Note. The hypotheses are designed for a full firm-year panel. The pilot supports descriptive analysis of CapEx ratio and R&D intensity but does not provide definitive hypothesis tests because the panel is small and patent outcomes are not yet coded.

5 FIRM LEVEL DATA AND SAMPLE CONSTRUCTION

The preferred final dataset is a firm-year panel linking firm fundamentals to policy-event timing, mineral exposure and patent outcomes. Compustat Global and Orbis would provide broader international coverage, extending beyond U.S.-listed firms to Japan, Europe, Australia, Canada and Korea, while SEC EDGAR provides a transparent source for U.S.-listed firms through company facts and annual filings [14]. The pilot uses SEC-based public data as a reproducible seed panel, but the publishable analysis should expand the sample substantially.

The full sample should be organized around exposure-relevant sectors rather than convenience. Table 2 identifies candidate firms spanning electric vehicles and batteries, semiconductors and electronics, aerospace and defence, and upstream mining and processing.

Table 2: Candidate firms for the full firm-year panel

Ticker	Firm	Sector	Main exposure	Class
TSLA	Tesla, Inc.	EVs, batteries	Lithium, graphite, nickel, cobalt, rare-earth magnets	High
AAPL	Apple Inc.	Consumer electronics	Rare-earth magnets, gallium/germanium, tungsten	Medium-high
NVDA	NVIDIA Corporation	Semiconductors, AI hardware	Gallium, germanium, rare earths, advanced packaging inputs	Medium-high
MP	MP Materials Corp.	Rare-earth mining/processing	Rare earths, NdPr, magnets	Direct
GM	General Motors Company	Automobiles, EVs	Lithium, graphite, rare-earth magnets, nickel, cobalt	High
F	Ford Motor Company	Automobiles, EVs	Lithium, graphite, rare-earth magnets, nickel, cobalt	High
LMT	Lockheed Martin Corporation	Aerospace and defence	Rare earths, gallium, germanium, antimony, tungsten	High
RTX	RTX Corporation	Aerospace and defence	Rare earths, gallium/germanium, antimony, tungsten	High
INTC	Intel Corporation	Semiconductors	Gallium, germanium, rare earths, tungsten	Medium-high
ON	ON Semiconductor Corp.	Power semiconductors	Gallium, germanium, silicon-carbide-related supply chain	Medium

TM	Toyota Motor Corp.	Automobiles, hybrids/EVs	Rare-earth magnets, batteries	High
PCRFY	Panasonic Holdings Corp.	Batteries/electronics	Lithium, graphite, nickel, cobalt, rare earths	High
LAC	Lithium Americas Corp.	Lithium mining	Lithium	Direct
ALB	Albemarle Corporation	Lithium/specialty chemicals	Lithium, critical mineral processing	Direct
LYC.AX	Lynas Rare Earths Ltd.	Rare-earth mining/processing	Rare earths	Direct
VMM.AX	Viridis Mining and Minerals Ltd.	Rare-earth project development	Rare earths	Direct

Note. These firms are candidate observations for the full panel. The pilot analysis uses only the four firms with populated seed data.

6 VARIABLE CONSTRUCTION

The pilot uses three accounting-based measures:

$$\text{R\&D Intensity}_{i,t} = \frac{\text{R\&D Expense}_{i,t}}{\text{Revenue}_{i,t}}$$

$$\text{CapEx Ratio}_{i,t} = \frac{\text{Capital Expenditure}_{i,t}}{\text{Total Assets}_{i,t}}$$

$$\text{ROA}_{i,t} = \frac{\text{Net Income}_{i,t}}{\text{Total Assets}_{i,t}}$$

The final dataset should additionally include mineral-related patent counts and substitution-related patent shares. R&D intensity measures innovation effort broadly but does not establish that the effort is mineral specific; patent-level classification and text-based coding are therefore needed for the stronger version of H2.

Table 3: Core firm level variables

Variable	Measure	Pilot status
R&D intensity	R&D expense / revenue	Available
CapEx ratio	Capital expenditure / total assets	Available where data are complete
ROA	Net income / total assets	Available where assets are populated
Patent count	Mineral/substitution patents by firm-year	Not yet populated
Firm exposure	Industry dependence × firm mineral relevance	Template only

7 FIRM LEVEL PILOT ANALYSIS

7.1 Data Audit and Completeness

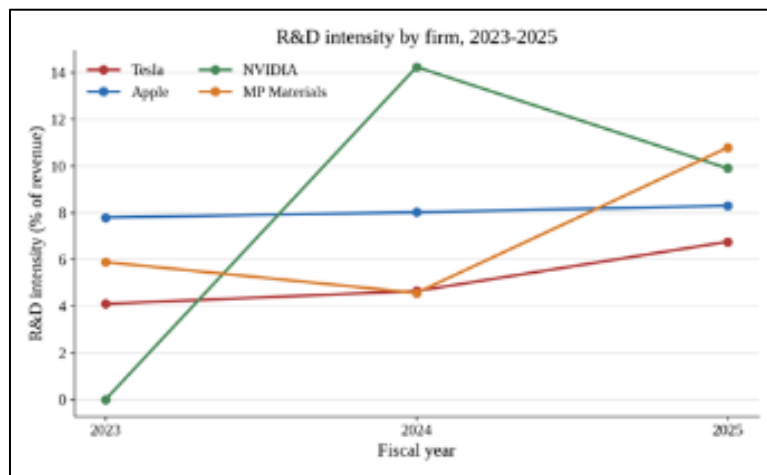
The seed panel contains 12 firm-year observations covering Tesla, Apple, NVIDIA and MP Materials over fiscal years 2023–2025, drawn from SEC 10-K filings. All 12 observations contain revenue and net income, eleven contain R&D expense and CapEx, and eight contain total assets, CapEx ratio and ROA. Missingness is concentrated in fiscal 2023, making the panel more suitable for a 2024–2025 comparison than for analyzing three-year trends. NVIDIA’s zero fiscal-2023 R&D intensity reflects a data gap rather than a true zero and should not be interpreted substantively.

Table 4: Firm-year seed panel

Firm	Year	R&D intensity	CapEx ratio	ROA	Data status
Tesla	2025	6.76%	6.19%	2.75%	Complete
Tesla	2024	4.65%	9.29%	5.81%	Complete
Tesla	2023	4.10%	N/A	N/A	Partial
Apple	2025	8.30%	3.54%	31.18%	Complete
Apple	2024	8.02%	2.59%	25.68%	Complete
Apple	2023	7.80%	N/A	N/A	Partial
NVIDIA	2025	9.90%	2.90%	65.30%	Complete
NVIDIA	2024	14.24%	1.63%	45.28%	Complete
NVIDIA	2023	0.00%*	N/A	N/A	Partial
MP Materials	2025	10.79%	4.46%	−2.22%	Complete
MP Materials	2024	4.57%	7.99%	−2.80%	Complete
MP Materials	2023	5.89%	N/A	N/A	Partial

7.2 R&D Intensity as a Pilot Indicator of Innovation Response

R&D intensity is the most complete response variable in the seed data. Mean R&D intensity across the panel is approximately 7.08% of revenue, but the range is wide. NVIDIA records the highest R&D intensity, at 14.24% in fiscal 2024 and 9.90% in fiscal 2025, consistent with the R&D intensive structure of semiconductor and AI hardware firms. Apple remains relatively stable at 8.02% in 2024 and 8.30% in 2025. Tesla increases from 4.65% to 6.76%, the largest year-over-year increase among the downstream firms. MP Materials increases from 4.57% to 10.79%, the largest proportional increase in the panel, although its measure reflects advanced projects and development spending rather than a conventional R&D line item. This distinction should therefore be retained in the final data dictionary.

**Figure 2: R&D intensity by firm, 2023-2025.**

This pattern is consistent with the innovation channel (H2), but it does not prove it: the sample is small (four firms, three years), the firm exposure variable is not yet populated, and R&D intensity can rise for reasons unrelated to critical minerals. The defensible reading is narrower: R&D intensity is collectable and informative, and the four firms show enough variation to justify a firm level innovation model once exposure and patent data are appended.

7.3 CapEx Ratio as a Pilot Indicator of Investment and Vertical Integration

The CapEx ratio is the closest available financial proxy for H1 in the seed workbook. The 2024–2025 comparison shows divergent patterns: Apple’s CapEx ratio rises from 2.59% to 3.54% of total assets, and NVIDIA from 1.63% to 2.90%, while Tesla’s declines from 9.29% to 6.19% and MP Materials from 7.99% to 4.46%. These changes do not imply that Tesla or MP Materials reduced their strategic commitment to minerals. The CapEx ratio is affected by both its numerator

and denominator and can therefore decline even when investment remains important, particularly for firms whose asset base is also growing.

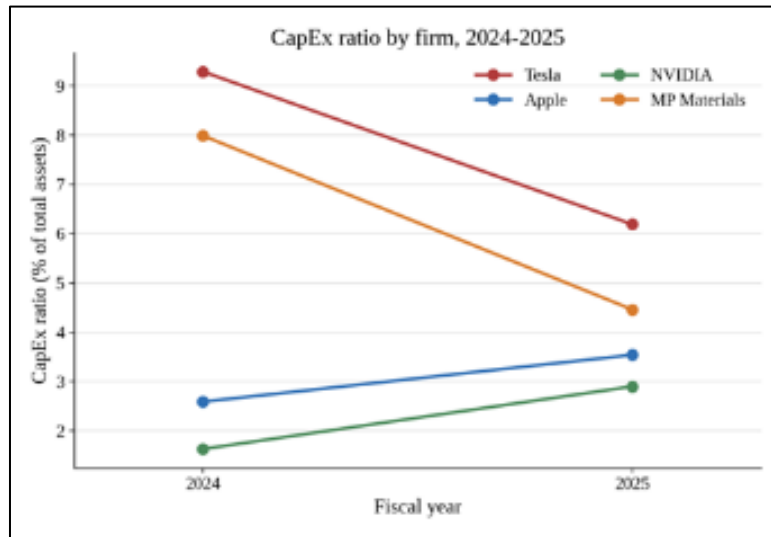


Figure 3: CapEx ratio by firm, 2024-2025.

The more careful interpretation is that the CapEx ratio captures investment intensity rather than the reason for investment and therefore needs to be paired with qualitative project coding. A battery plant, magnet facility, separation facility, or recycling operation should be coded differently from ordinary data-centre or manufacturing expansion. Without this coding, the CapEx ratio remains a useful but imperfect proxy. This is why the final H1 model in Section 8 pairs accounting-based CapEx with an upstream/domestic capacity announcement variable.

7.4 Firm Year Changes, Fiscal 2024-2025

The most reliable pilot comparison is the 2024–2025 change, shown in Table 6. Responses differ sharply. Apple records modest growth on both measures. NVIDIA posts very strong revenue growth (+114.2%) and CapEx growth (+202.7%), but its R&D intensity falls by 4.34 percentage points as revenue outpaces R&D spending. Tesla’s R&D intensity rises by 2.11 percentage points, while its CapEx ratio and ROA both decline by 3.10 and 3.06 percentage points, respectively. MP Materials shows the largest R&D-like increase (+6.22 percentage points), consistent with its position as a direct rare-earth firm, but its CapEx ratio falls by 3.53 percentage points and its ROA remains negative.

Table 6: Firm level changes in selected response variables, fiscal 2024–2025

Firm	Revenue growth (%)	R&D growth (%)	CapEx growth (%)	Δ R&D intensity (pp)	Δ CapEx ratio (pp)	Δ ROA (pp)
AAPL	6.43	10.14	34.59	0.28	0.95	5.50
MP	10.10	160.11	-7.53	6.22	-3.53	0.58
NVDA	114.20	48.86	202.71	-4.34	1.27	20.03
TSLA	-2.93	41.21	-24.78	2.11	-3.10	-3.06

Note. Growth values are percentage changes in the underlying accounting items. Changes in R&D intensity, CapEx ratio, and ROA are percentage-point changes. The table is descriptive and does not constitute a causal estimate.

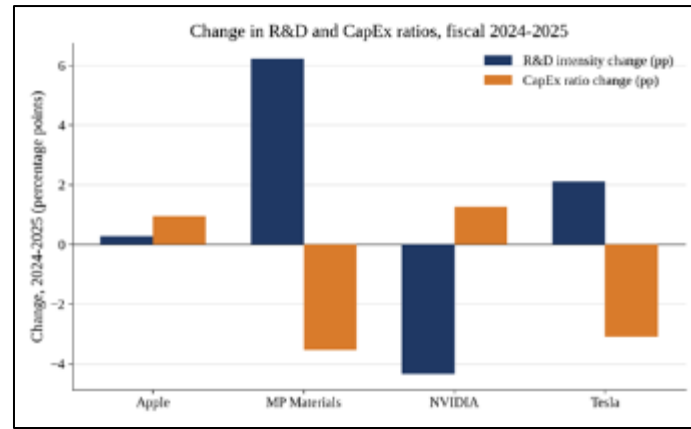


Figure 4: Change in R&D and CapEx ratios, fiscal 2024-2025.

7.5 R&D CapEx Positioning in Fiscal 2025

Positioning firms by fiscal 2025 R&D intensity and CapEx ratio together shows why responses should not be collapsed into a single index. NVIDIA sits high R&D, lower CapEx, an innovation intensive profile. Tesla sits relatively high CapEx, moderate R&D. Apple combines high R&D intensity with a moderate CapEx ratio, and MP Materials shows relatively high R&D like intensity and a moderate CapEx ratio, though its accounting categories are not directly comparable to the downstream technology firms. These differences support treating sourcing, investment and innovation as separate response channels rather than a single resilience index.

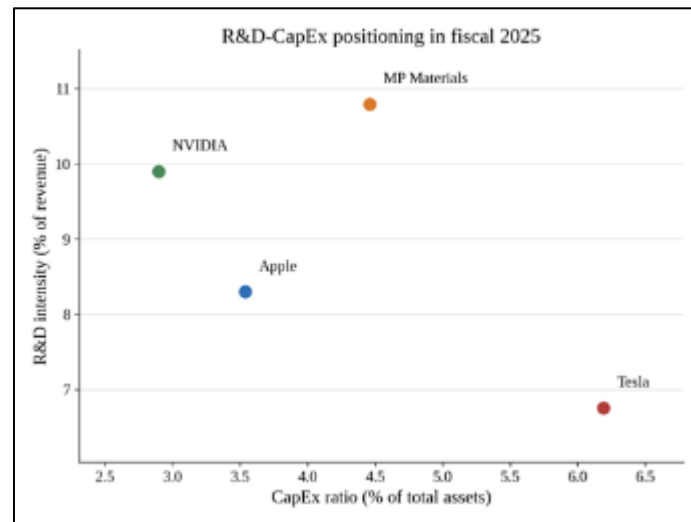


Figure 5: R&D CapEx positioning in fiscal 2025.

8 EMPIRICAL STRATEGY FOR A FULL FIRM LEVEL ANALYSIS

The final analysis should proceed in stages first event-specific and then pooled because the policy events differ in mineral, timing, and affected sector. A 2023 gallium/germanium event is most relevant to semiconductor and electronics exposure, a 2023 graphite event is most relevant to battery and EV exposure, and a 2025 heavy rare-earth event is most relevant to magnets, defence, motors, and direct rare-earth firms. Pooling all events too early could therefore obscure important differences in exposure and response.

The baseline firm-year specification for capital expenditure is:

$$\text{CapExRatio}_{i,t} = \beta_1 \left(\text{PostShock}_t \times \text{FirmExposure}_{i,t-1} \right) + \alpha_i + \lambda_t + X_{i,t-1}\theta + \varepsilon_{i,t}$$

where α_i denotes firm fixed effects, λ_t denotes year fixed effects, and $X_{i,t-1}$ includes lagged controls such as firm size, leverage, and profitability. H1 predicts $\beta_1 > 0$, although this model should be interpreted alongside project-level indicators because changes in CapEx may reflect ordinary business expansion rather than a response to mineral-related

shocks. A stronger specification therefore adds an $\text{UpstreamInvestment}_{i,t}$ or $\text{DomesticCapacity}_{i,t}$ dummy constructed from annual reports, press releases, and project announcements.

Table 7: Empirical model families for the full firm level analysis

Model family	Outcome	Treatment interaction	Expected sign	Interpretation
CapEx ratio	$\text{CapExRatio}_{i,t}$	$\text{PostShock} \times \text{FirmExposure}$	$\beta_1 > 0$	Tests H1 pair with project coding
R&D intensity	$\text{R\&DIntensity}_{i,t}$	$\text{PostShock} \times \text{FirmExposure}$	$\beta_1 > 0$	Partial test of H2
Substitution patents	$\text{PatentCount}_{i,t}$	$\text{PostShock} \times \text{FirmExposure}$	$\beta_1 > 0$	Stronger, mineral-specific test of H2

The innovation model replaces the outcome with $\text{R\&DIntensity}_{i,t}$, while a complementary patent model uses $\text{PatentCount}_{i,t}$ as the outcome. Because patent counts are highly skewed count variables with potentially many zeros, Poisson or negative binomial models, or an inverse hyperbolic sine transformation, may be more appropriate than a linear specification. The final choice should be justified after inspection of the completed patent dataset. Together, these model families provide the empirical framework for testing H1 and H2.

8.1 Mechanisms, Heterogeneity and Robustness

The final analysis should test mechanisms rather than report only average responses. One mechanism is an input-cost channel, reflected in margin pressure arising from more expensive or less reliable inputs and testable using gross or operating margins. A second is an innovation and substitution channel, reflected in R&D or patenting related to mineral saving, recycling, or alternative-material technologies. The latter provides the cleanest test of H2. The pilot analysis cannot yet distinguish these mechanisms because patent data remain a template rather than a populated field. It nevertheless illustrates why mechanism separation matters: Tesla's 2024–2025 data show rising R&D intensity and a falling CapEx ratio, NVIDIA shows the reverse as revenue expanded sharply, and MP Materials shows rising R&D-like intensity alongside a falling CapEx ratio. A single response index would conceal these distinct patterns.

Firm responses should also vary across sectors, minerals, and financial capacity. EV firms are expected to respond most strongly to battery minerals and graphite; semiconductor firms to gallium, germanium, and specialized rare-earth inputs; and defence and aerospace firms to antimony, tungsten, and rare earths. Upstream firms such as MP Materials represent a distinct exposure type of their own. Financial capacity also matters because supplier switching and vertical integration are not costless. Ersahin et al. [4] find that financially unconstrained firms are more likely to pursue vertical mergers and acquisitions when supply-chain risk rises.

The pilot sample already illustrates this heterogeneity: Apple and NVIDIA have high profitability and large asset bases, whereas MP Materials has negative ROA but direct rare-earth relevance. These firms therefore differ not only in exposure but also in their capacity to respond. The main identification risk in the full analysis is that observed firm responses may reflect ordinary business cycles rather than mineral shocks. The final specification should therefore incorporate firm, year, and sector year fixed effects where identifiable, estimate events separately before pooling them, and account for potential anticipation and measurement error in exposure.

8.2 Discussion of Pilot Findings

The pilot evidence supports the feasibility of the firm level design but does not yet provide causal confirmation of H1 or H2. The strongest finding is that firm level financial responses are measurable and heterogeneous: R&D intensity, CapEx ratio, and ROA can be computed from public filings, and the seed panel shows these variables moving in different directions across firms. This supports a multi-channel approach rather than reliance on a single generic response measure.

For H1, the pilot data provide mixed and partial evidence. Apple and NVIDIA increased their CapEx ratios, whereas Tesla and MP Materials reduced theirs. This usefully rules out a simplistic claim that all exposed firms invest more following shocks. For H2, the evidence is suggestive but incomplete. R&D intensity increased for three of the four firms but declined for NVIDIA as revenue growth outpaced R&D growth. This pattern does not contradict the innovation hypothesis, but it demonstrates why R&D intensity should be interpreted alongside absolute R&D spending and, ultimately, patent data.

9 STATE LEVEL THEORETICAL FRAMEWORK: STATES AS POLITICAL TRANSMISSION MECHANISMS

The second half of this paper shifts from firms to states. A market level policy shock does not end when prices move or firms adjust. It can also be converted into domestic industrial policy, strategic stockpiling, subsidy design, permitting reform, recycling programmes, and alliance-based supply chain cooperation. This logic is consistent with the wider literature on economic statecraft and weaponised interdependence, where power is exercised through control over network nodes and chokepoints rather than through direct territorial control alone [2, 5].

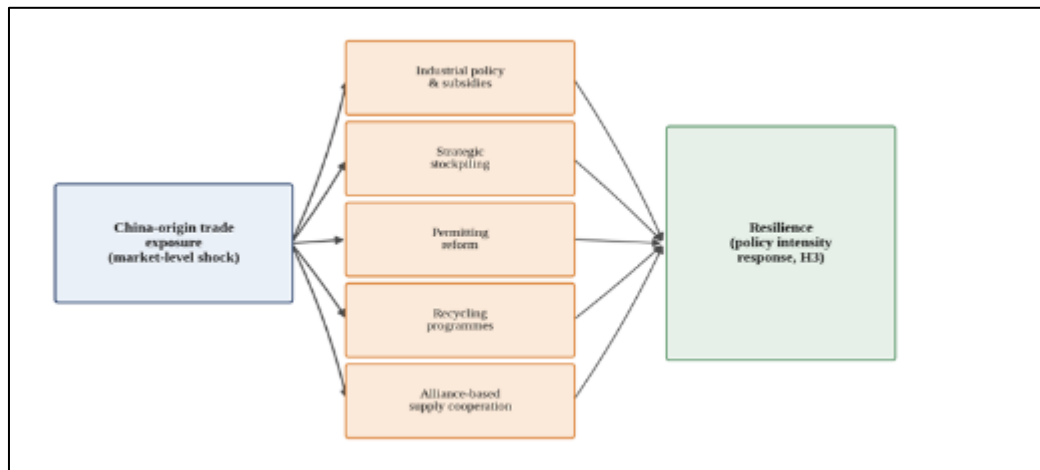


Figure 6: State behaviour as a political transmission mechanism linking market exposure to later resilience or realignment outcomes.

Three related theoretical traditions inform the state level analysis. The first is economic statecraft, which explains how governments use trade, finance, regulation, market access, and industrial support to pursue strategic objectives [2]. The second is the new industrial policy literature, which does not treat industrial policy simply as a return to earlier forms of protectionism but examines how targeted state intervention can address coordination failures, externalities, strategic sectors, and supply-chain vulnerabilities [8, 11].

The third is supply-chain geopolitics, particularly the idea that asymmetric interdependence can create leverage when one actor occupies a central position within a network [5].

In critical minerals, the relevant network is material and industrial rather than financial or informational. A country cannot digitally bypass the absence of battery-grade graphite or magnet feedstock in the way it might reroute a payment or shift a data service. This physical character changes the nature of state responses. Governments respond with more than diplomatic statements: they fund mines, underwrite processing facilities, revise tax-credit rules, create strategic reserves, support recycling, and develop supply-chain alliances. The International Energy Agency's Critical Minerals Policy Tracker classifies critical mineral policies across supply reliability and resilience, exploration, production and innovation, and sustainable practices [7].

At the same time, the paper does not assume that state action automatically produces resilience. A policy document is not equivalent to a mine, refinery, recycling facility, or diversified import base. Critical mineral supply chains are shaped by long project timelines, permitting delays, environmental constraints, metallurgical knowledge, and commercial qualification requirements. A state may therefore respond quickly in policy terms while actual supply-chain reconfiguration proceeds considerably more slowly.

10 STATE LEVEL RESEARCH QUESTIONS AND HYPOTHESES

The state level analysis focuses on one central hypothesis: H3 concerns the industrial policy response to exposure to China linked critical mineral supply chains. The available dataset permits a preliminary test of H3, although the trade data used here contain China as the sole partner. This is treated as an explicit boundary condition of the analysis rather than as a measure of complete import dependence.

Table 8: State level research objectives, questions, and hypothesis

Element	Statement
RO1	Measure whether countries and blocs exposed to China origin critical mineral flows show stronger state policy activity
RO2	Distinguish policy adoption from policy intensity by coding the strength of instruments, including strategies, tax rules, subsidies, stockpiles, and project support
RQ1	Do more exposed countries and blocs adopt more critical mineral industrial policy interventions?
H3	Countries and blocs with greater pre-shock exposure to China linked mineral supply chains show higher policy activity and higher policy intensity after China linked policy shocks

11 STATE LEVEL DATA AND VARIABLE CONSTRUCTION

The empirical material for the state level analysis comes from a two-sheet dataset. The first sheet, State Policies, contains 20 coded policy observations covering countries, blocs, and multilateral groupings: the European Union, the United States, Australia, Canada, Japan, the United Kingdom, India, South Korea, the Minerals Security Partnership, and the G7. The second sheet, Trade_From_China_2024, contains 70 China origin trade observations for selected critical mineral product groups in 2024, structured in a UN Comtrade/WITS style format with reporter, partner, product code, value, quantity, and unit value fields [12].

The dataset is intentionally narrow. It provides a structured state response and China origin exposure dataset rather than a complete global trade panel. This distinction matters because the dataset can support careful descriptive and exploratory analysis, but not a fully specified panel model. Such a model would require imports from all trading partners as well as country mineral year denominators that are not present in the current pilot.

Three variables drive the empirical analysis. Policy counts records the number of critical mineral policy observations for each country or bloc. Total policy intensity sums the coded intensity scores across those policies:

$$\text{TotalPolicyIntensity}_c = \sum_p \text{IntensityScore}_{c,p}$$

This is an additive index across coded policy observations for country or bloc c . It is not a perfect measure of policy effectiveness, but rather a structured indicator of policy activism within the curated sample. A strategy document receives a lower score than a binding regulation, public finance package, stockpiling intervention, or project level support measure.

China origin trade exposure is measured as the total 2024 import value from China for the selected product groups:

$$\text{ChinaTradeExposure}_{c,2024} = \sum_m \text{ImportsFromChina}_{c,m,2024}$$

This is a value-based exposure measure, not a complete import dependence ratio. A true dependence measure would divide imports from China by total imports from all partners for the same mineral group. Because the trade sheet used here includes China as the sole partner, the paper treats China origin exposure explicitly as a proxy rather than claiming that it measures full dependence.

Because this variable is highly skewed, the exploratory regression uses a log transformation:

$$\log_exposure_c = \log\left(1 + \text{ChinaTradeExposure}_{c,2024}\right)$$

The transformation reduces the influence of very large reporters, such as the European Union and the United States, and provides a more tractable measure of exposure for the exploratory regression. The coefficient should nevertheless be interpreted cautiously given the small cross-sectional sample and the proxy nature of the underlying exposure measure.

12 STATE LEVEL DESCRIPTIVE RESULTS

12.1 Policy Activity by Country and Bloc

State responses are not evenly distributed across the sample. The United States records the highest total policy intensity score, followed by South Korea. The European Union, India, and Japan also record high scores. Australia has fewer observations but a relatively high total intensity score because its rare-earth refinery support is coded as a high-intensity public finance intervention. Canada and the United Kingdom have lower total scores because their coded observations are primarily strategy or framework policies rather than large project level finance measures.

Table 9: Critical mineral policy activity by country or bloc

Country/bloc	Policy count	Total intensity	Mean intensity	H3 relevant
United States	3	12	4.00	3
South Korea	3	11	3.67	3
European Union	2	9	4.50	2
India	2	9	4.50	2
Japan	2	9	4.50	2
Australia	2	8	4.00	2
Canada	2	6	3.00	2
United Kingdom	2	6	3.00	2
G7	1	3	3.00	1
Multilateral	1	3	3.00	1

Note. Policy intensity is an author coded ordinal indicator from 1 to 5. Totals indicate relative policy activity within this dataset rather than an exhaustive global ranking of state capacity or policy effectiveness.

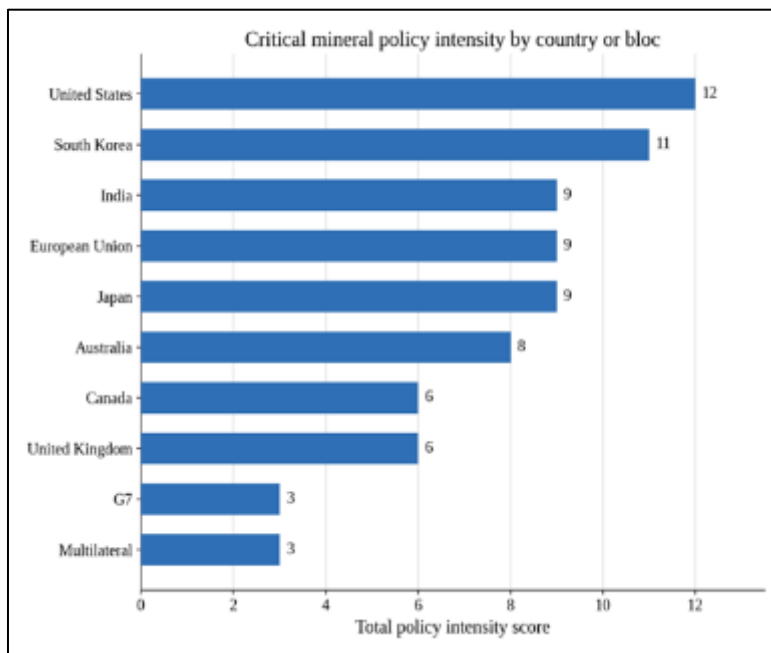


Figure 7: Critical mineral policy intensity by country or bloc.

The year level pattern is also informative: policy activity is concentrated after 2022, with six coded policies in 2023 and six in 2025, and the highest mean intensity appears in 2024 because the coded 2024 observations include binding or materially significant interventions such as the European Critical Raw Materials Act, U.S. clean vehicle credit rules, and project level Australian support (Table 10). This is consistent with a broader shift from general strategy making toward

concrete industrial policy instruments, though it should not be over interpreted as a causal time series result given the curated, small dataset.

Table 10: Critical mineral policy activity by year

Year	Policy count	Total intensity	Mean intensity	H3 relevant
2020	1	4	4.00	1
2022	3	11	3.67	3
2023	6	21	3.50	6
2024	3	15	5.00	3
2025	6	22	3.67	6
2026	1	3	3.00	1

Note. The policy counts reflect the coded dataset rather than a complete universe of all policies worldwide.

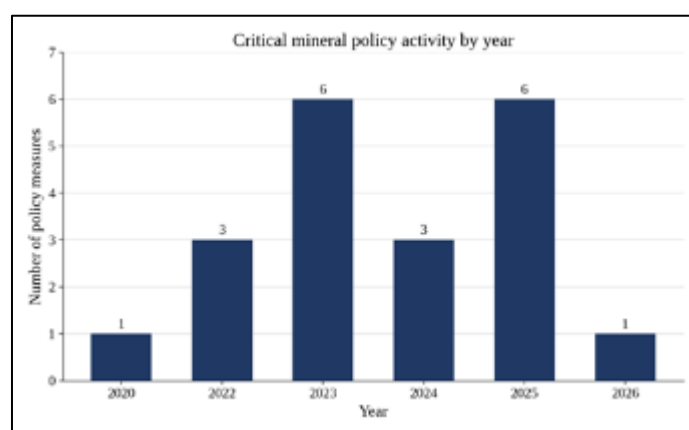


Figure 8: Critical mineral policy activity by year.

12.2 China Origin Trade Exposure by Mineral and Reporter

Trade exposure data show that China origin critical mineral exposure is heavily concentrated in a few product groups. Rare earth magnets dominate trade value in the sample (US\$3,049 million across 10 observations), followed by graphite (US\$1,955 million across 20 observations), rare earths (US\$438 million), a gallium/germanium proxy group (US\$168 million), and antimony (US\$99 million). This is substantively important because rare earth magnets are downstream *industrial* inputs rather than raw ores, supporting the argument that critical mineral dependence extends beyond extraction to processed and component stage goods entering electric motors, defence systems, clean energy technologies and advanced manufacturing.

Table 11: China origin trade exposure by mineral group, 2024

Mineral group	Observations	Trade value (US\$m)	Quantity (million kg)	Mean unit value (US\$/kg)
Rare earth magnets	10	3,048.96	139.59	30.90
Graphite	20	1,954.70	1,088.77	3.17
Rare earths	20	437.93	35.12	37.09
Gallium/germanium proxy group	10	167.66	1.84	142.05
Antimony	10	99.37	5.43	19.40

Note. Values are based on 2024 China origin observations. The gallium/germanium group is a proxy category based on the available HS product grouping, not a mineral pure series.

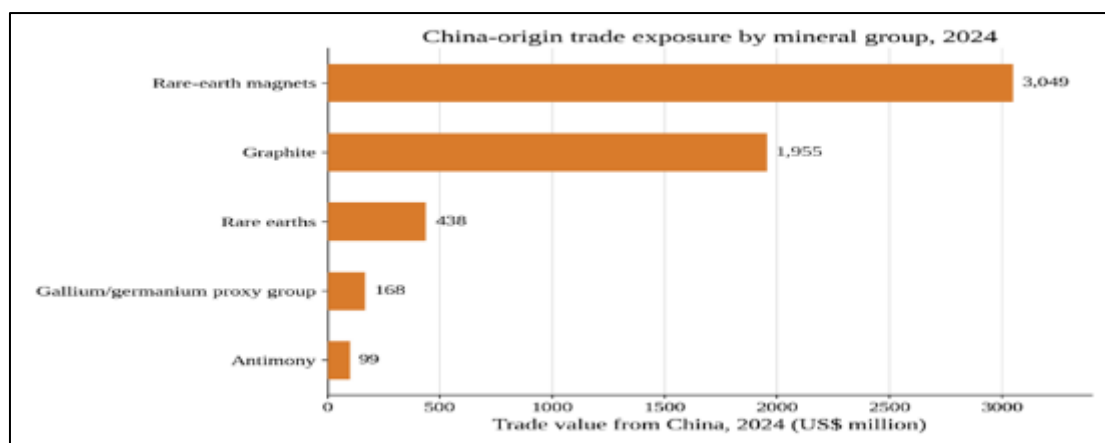


Figure 9: China origin trade exposure by mineral group, 2024.

Reporter level results show that the European Union, the United States, Germany, Japan and South Korea are among the largest importers from China in the selected product groups (Table 12), broadly consistent with the expectation that economies with large clean technology, automotive, electronics, semiconductor or defence manufacturing bases carry the most politically salient exposure to China linked critical mineral supply chains. The data include both the European Union as a bloc and some EU member states as individual reporters, creating possible overlap that must be handled carefully in any final regression panel.

Table 12: Top reporters by China origin trade exposure, 2024

Reporter	Observations	Trade value (US\$m)	Quantity (million kg)	Mean unit value (US\$/kg)
European Union	7	1,580.26	156.55	35.36
United States	7	876.98	128.38	37.13
Germany	6	592.85	42.70	57.76
Japan	7	501.16	101.62	39.09
Korea, Rep.	7	477.05	77.19	43.08
Malaysia	2	397.05	534.97	19.40
Poland	3	282.09	39.64	13.84
Mexico	1	269.54	13.44	20.06
India	5	227.55	113.39	13.35
Hungary	1	158.13	22.67	6.98
France	4	97.48	3.44	22.71
Thailand	2	77.19	4.63	18.88

Note. The reporter list is descriptive. EU level and member state observations should not be pooled without attention to double counting.

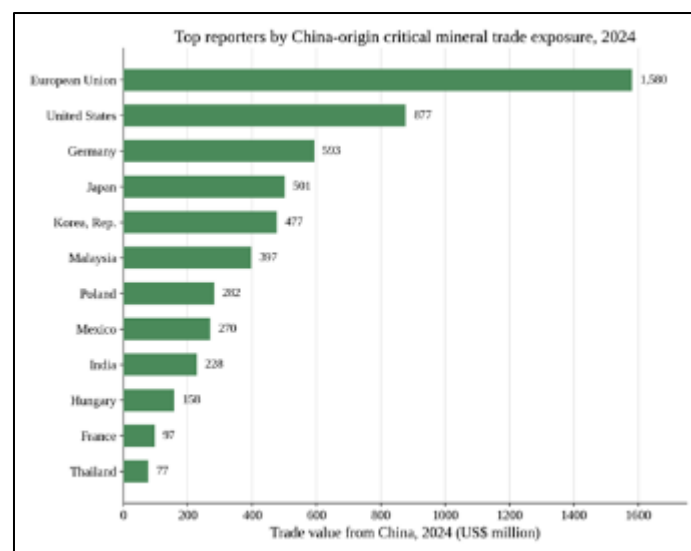


Figure 10: Top reporters by China origin critical mineral trade exposure, 2024.

The leading reporter within each mineral group differs by mineral: Japan leads in antimony, Singapore leads the gallium/germanium proxy group, the European Union leads in graphite and rare earth magnets, and the United States leads in the rare earth rows (Table 13). This variation indicates that exposure is mineral specific (a country may appear highly exposed in one product group but not another) reinforcing the need for country mineral year analysis in any final panel.

Table 13: Largest reporter in each China origin mineral group, 2024

Mineral group	Largest reporter	HS code	Trade value (US\$m)	Unit value (US\$/kg)
Antimony	Japan	811,000	27.21	17.58
Gallium/germanium proxy group	Singapore	811,299	38.80	241.54
Graphite	European Union	380,110	393.10	4.67
Rare earths	Japan	284,690	123.92	20.86
Rare earth magnets	European Union	850,511	1,052.77	30.60

13 EXPLORATORY H3 ANALYSIS: EXPOSURE AND POLICY INTENSITY

The main statistical analysis in this half of the paper is an exploratory test of H3: do countries and blocs with greater China origin trade exposure also have higher critical mineral policy intensity scores? This is a cross-sectional diagnostic, not yet a causal difference in differences model, and should be interpreted as preliminary evidence about the plausibility of H3 rather than as a final estimate of the causal effect of Chinese policy shocks on state behaviour.

$$\text{TotalPolicyIntensity}_c = \beta_0 + \beta_1 \log(1 + \text{ChinaTradeExposure}_{c,2024}) + \varepsilon_c$$

Heteroskedasticity consistent HC3 standard errors are used because the sample is small and error variance is unlikely to be constant across units, following the logic of heteroskedasticity consistent inference developed by White [15] and refined for finite sample settings by MacKinnon and White [9].

Table 14: Exploratory regression of policy intensity on China origin trade exposure

Term	B	SE (HC3)	z	p	95% CI
Intercept	4.83	1.39	3.47	0.001	[2.104, 7.566]
log China origin trade value, 2024	0.24	0.08	3.02	0.003	[0.084, 0.395]

Note. N = 10. $R^2 = 0.623$. Adjusted $R^2 = 0.576$. Standard errors are HC3 robust. The model is exploratory and cross sectional, not a causal panel design.

The coefficient on log China origin trade exposure is positive and statistically distinguishable from zero ($B = 0.239$, $HC3\ SE = 0.079$, $p = 0.003$). Because the explanatory variable is logged, a doubling of exposure corresponds to approximately a 0.166-point increase in the policy intensity score, while a tenfold increase corresponds to approximately a 0.551-point increase. These are modest effects, but their positive direction is consistent with H3. The model's R^2 of 0.623 indicates that this single exposure proxy accounts for approximately 62% of the variation in policy intensity in this small sample. This should not be interpreted as evidence that exposure alone explains state responses, since countries differ in industrial structure, fiscal capacity, defence exposure, domestic reserves, policy traditions, and alliance commitments. More narrowly, the results indicate that higher China origin trade exposure is positively associated with stronger policy activity in the coded sample.

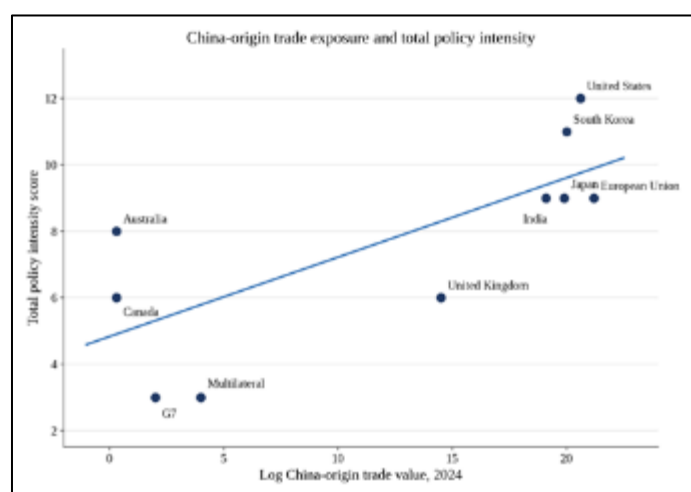


Figure 11: Exploratory relationship between China origin trade exposure and total policy intensity score, with fitted regression line.

The United States and South Korea lie above the fitted line, indicating more policy activity than their exposure alone would predict, while the United Kingdom lies notably below it. Australia and Canada exhibit moderate policy intensity scores despite minimal recorded China origin exposure, consistent with the possibility that policy is driven partly by anticipatory or alliance-based considerations rather than current trade exposure alone.

Several units with no matched trade observations were coded as having zero exposure. This may reflect limitations in the data matching rather than a genuine absence of exposure. The timing problem also remains unresolved: a fuller test would incorporate lagged China import dependence, total imports from all partners, policy-event timing, and country mineral fixed effects.

14 CORRELATION STRUCTURE AND DIAGNOSTIC INTERPRETATION

The correlation matrix provides additional diagnostic information (Table 15). Total policy intensity is strongly correlated with policy count ($r = 0.93$), as expected because total intensity is partly constructed from the number of coded policy observations. More substantively, total policy intensity is positively correlated with China origin trade value ($r = 0.60$) and more strongly correlated with log China origin trade value ($r = 0.79$). The stronger correlation with logged exposure suggests that the relationship between exposure and policy response may be better understood in proportional rather than raw-dollar terms. This is reasonable because a given dollar value of imports may represent very different levels of strategic exposure for economies of different sizes.

Table 15: Selected correlations from the exploratory state level dataset

Relationship	Correlation	Interpretation
Policy counts and total policy intensity	0.93	Strong association. Confirms that the intensity index partly reflects the number of coded measures.
Total policy intensity and China origin trade value	0.60	Moderate positive association between raw exposure and policy intensity.
Total policy intensity and log China origin trade value	0.79	Strong positive association between proportional exposure and policy intensity.

Note. Correlations are descriptive and do not establish timing, causality, or policy effectiveness.

15 ASSESSMENT OF H3

H3 receives preliminary support. Major policy actors with high strategic exposure including the United States, European Union, Japan, South Korea, India, and Australia have adopted multiple policy instruments, and the regression is consistent with H3: China origin trade exposure is positively associated with total policy intensity. The evidence remains exploratory, however, because the model is cross-sectional and does not yet exploit policy-event timing or lagged exposure.

16 INTEGRATED HYPOTHESIS ASSESSMENT AND LIMITATIONS

Table 16 summarizes the firm and state level hypotheses developed in this paper and reports the current evidentiary status of each.

Table 16: Firm and state level hypotheses and their current evidentiary status

Hyp.	Claim	Status with current pilot data
H1	Exposed firms raise CapEx / move toward upstream domestic capacity	Descriptive only: direction is mixed across the four-firm panel
H2	Exposed firms raise R&D intensity and substitution related patenting	Partial: R&D intensity is available, but patents are not yet coded
H3	Higher China origin exposure is associated with greater state policy intensity	Preliminary support: $B = 0.24$, $p = 0.003$, $R^2 = 0.62$ ($N = 10$)

Both analyses are explicitly preliminary. The four-firm panel is far too small to support statistical inference, and CapEx ratio and R&D intensity are broad proxies that can change for reasons unrelated to mineral policy. The state level regression is cross-sectional and therefore cannot establish whether policy activity increased following specific shocks. It shows only that more exposed countries currently exhibit greater policy activity. Moreover, the policy intensity score is an unweighted index that treats a major stockpile or financing programmed differently only insofar as the coding assigns it a higher ordinal score; it does not provide a direct measure of policy effectiveness.

On the firm side, the exposure variable defined in Section 3 remains a template rather than a populated field. The pilot analysis is therefore descriptive rather than conditioned on measured pre-shock exposure. In addition, CapEx ratio is affected by both its numerator and denominator, complicating comparisons across firms of very different scale, such as Apple (US\$416 billion in revenue) and MP Materials (US\$224 million).

17 WHAT WOULD STRENGTHEN THESE RESULTS

For the firm level analysis, two additions are particularly important. First, patent level data from PatentsView or the USPTO Open Data Portal [13] are needed to distinguish substitution relevant innovation from general increases in R&D. Second, the firm panel should be substantially expanded beyond the four seed firms to the sixteen firm universes outlined in Table 2. A larger panel would provide the cross-sectional and temporal variation necessary for more credible firm level inference and make firm fixed effects more informative.

For the state level analysis, the immediate priority is to validate the ordinal policy-intensity coding through sensitivity checks using equal weights, alternative weighting schemes, binary high-intensity indicators, and models based on policy count rather than intensity. This is important because a one-point increase from 2 to 3 may not represent the same substantive change as a one-point increase from 4 to 5. A second priority is to expand the country and bloc sample beyond the ten units used here. A larger sample would improve the precision of the exploratory regression and permit tests of nonlinearity and regional heterogeneity.

18 CONCLUSION

Firm and state level responses represent two downstream stages of the same causal chain that begins with a critical mineral policy shock. The pilot evidence is consistent with heterogeneous, sector specific firm adjustment measurable but not yet causally attributable to mineral policy exposure and with a state level policy response that increases with China origin exposure in a small cross-sectional sample. Neither result, however, should be interpreted as more than suggestive given the current sample sizes, measurement limitations, and identification constraints.

The clearest next steps are to expand the firm level panel with patent data across the sixteen firm universe identified above and to expand the state level country and bloc sample while validating the policyintensity coding. Together, these firm and state level findings establish a falsifiable, multilevel agenda for testing whether China's critical mineral policies function as geoeconomic shocks. They also clarify where the current evidence is relatively strong, where it remains suggestive, and which additional data are needed to close the remaining empirical gaps.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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No conflict of interest to be disclosed.

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