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How Do Supply Chain Disruptions Affect the Prices of Critical Minerals?[‡]

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Abstract

This paper estimates the dynamic price effects of supply chain shortage shocks on 31 critical minerals over the period June 2009 to January 2026. We identify exogenous shortage shocks for each mineral and estimate their cumulative effect on prices over a 36-month horizon. Critical mineral prices exhibit pronounced rockets-and-feathers dynamics: a worsening of shortage conditions produces a rapid and persistent price increase, while an easing of equal magnitude generates essentially no downward price adjustment. Furthermore, supply concentration amplifies the price response, with minerals whose production is dominated by a few countries exhibiting substantially larger cumulative price gains than those with diversified supply structures, and a continuous interaction specification confirms that the amplification scales smoothly with the Herfindahl–Hirschman Index. Additionally, the effect is heterogeneous across end-use categories, with electric-vehicle and battery minerals showing the strongest sensitivity. The paper also translates these findings into a country-level implied cost-push channel for the GCC economies, documenting meaningful heterogeneity in exposure that is shaped primarily by the compositional mix of each country’s mineral-import basket.

Keywords: Critical minerals, Supply chain disruptions, Local projections, Asymmetric price transmission, Supply concentration

JEL Codes: Q31, Q37, C32, E31, F14

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1 Introduction

The global economy’s dependence on critical minerals has intensified rapidly over the past decade, driven by the accelerating deployment of clean energy technologies, the expansion of digital infrastructure, and the growing strategic importance of these materials for defense and advanced manufacturing. Minerals such as lithium, cobalt, rare earth elements, and gallium are essential inputs for electric vehicle batteries, wind turbines, solar panels, and semiconductor devices, and demand for them is projected to grow several-fold under net-zero emissions scenarios (Boer et al., 2024). At the same time, the supply chains for these minerals are characterized by extreme geographic concentration, long development lead times, and limited short-run substitutability, making them uniquely vulnerable to disruptions. Since 2023, this vulnerability has been underscored by a series of export controls imposed by China on gallium, germanium, antimony, tungsten, and heavy rare earth elements, as well as by the Democratic Republic of Congo’s suspension of cobalt exports in early 2025¹. These developments have elevated critical mineral supply chain resilience to the top of the economic and national security agenda for governments worldwide.

In this paper, we examine how supply chain shortage shocks propagate into the prices of 31 critical minerals over the period June 2009 to January 2026. We adopt a two-stage empirical strategy. In the first stage, we identify exogenous shortage shocks from structural vector autoregression (SVAR) models using a recursive (Cholesky) ordering of the shortage index, trade policy uncertainty, global economic conditions, global consumer prices, and mineral prices. In the second stage, we use the identified structural shortage shocks as impulse variables in a panel local projections (LP) framework following Jordà (2005) to estimate the cumulative responses of mineral prices to shortage shocks over a 36-month horizon. Thus, throughout the empirical analysis, the reported impulse re-

¹MOFCOM and General Administration of Customs Announcement No. 18 of 2025, issued on April 4, 2025, imposed dual-use export-licensing requirements on seven medium and heavy rare earth elements, samarium, gadolinium, terbium, dysprosium, lutetium, scandium, and yttrium, along with their metals, alloys, oxides, compounds, mixtures, and related permanent magnet materials; this measure built on a sequence of earlier Chinese controls covering gallium and germanium (August 2023), antimony (September 2024), and tungsten, tellurium, bismuth, molybdenum, and indium (February 2025). See https://english.mofcom.gov.cn/Policies/AnnouncementsOrders/art/2025/art_0dd87cbee7b045bf93fabe6ab2faceee.html. The Democratic Republic of the Congo, which accounts for roughly three-quarters of global mined cobalt supply, suspended all cobalt exports on February 22, 2025 by decree of the Authority for the Regulation and Control of Strategic Mineral Substances’ Markets (ARECOMS), citing market oversupply and a sharp decline in prices; the initial four-month ban was subsequently extended and then replaced in October 2025 by a volume-based export quota system. See <https://www.iea.org/policies/28969-temporary-suspension-of-cobalt-export-from-the-democratic-republic-of-congo>.

sponses refer to cumulative changes in mineral prices following a one-standard-deviation shortage shock. This two-step approach separates shock identification from the estimation of dynamic responses, providing a flexible framework that does not impose the same dynamic structure at all horizons. We estimate the model for the full panel and then separately for four economically meaningful mineral groups: electric-vehicle and battery minerals, rare minerals, refractory minerals, and industrial minerals. We extend the baseline analysis in three directions. First, we test for sign asymmetry by decomposing shortage shocks into positive (worsening shortage conditions) and negative (easing shortage conditions) components to examine whether the price transmission exhibits rockets-and-feathers dynamics. Second, we construct a Herfindahl–Hirschman Index (HHI) of production concentration for each mineral using country-level data from the U.S. Geological Survey Mineral Commodity Summaries 2025² and test whether minerals with more concentrated supply chains amplify shortage-driven price pressures, using both a median-split specification and a continuous interaction specification that lets the shock response scale smoothly with concentration. Third, to connect the mineral-price results to a concrete regional application, we construct a mineral-import exposure index for GCC economies. The index combines the composition of each country’s critical-mineral import basket, measured from UN Comtrade at the HS-6 level, with the group-level peak price responses estimated in the paper to quantify the direct first-round increase in the mineral import bill implied by a global shortage shock. This exercise is intentionally illustrative rather than structural: it is designed to measure relative exposure across countries, not to estimate full pass-through to aggregate inflation or output. In this way, the GCC extension shows how differences in basket composition and in the size of mineral imports relative to total imports and GDP shape country-level exposure to shortage-driven price pressures.

A growing literature connects supply chain disruptions directly to commodity prices and inflation. Benigno et al. (2022) developed the Global Supply Chain Pressure Index (GSCPI), demonstrating that GSCPI shocks explain a substantial share of pandemic-era inflationary pressures. Caldara et al. (2025) constructed the text-based shortage index, showing that shortage episodes are associated with persistently high inflation and lower economic activity. Finck and Tillmann (2023) use narrative sign restrictions to identify supply chain disruptions in a SVAR for the euro area, finding that a global supply chain shock explains about 30 percent of inflation dynamics over a one-year horizon. Känzig and Rüth (2025) construct shipping cost surprises around maritime chokepoint disruptions, documenting stagflationary effects, while Burriel et al. (2024) develop a text-

²For the full report, see <https://pubs.usgs.gov/periodicals/mcs2025/mcs2025.pdf>

based Supply Bottlenecks Index and show that bottleneck increases function as cost-push shocks.

The intersection of critical minerals with the energy transition has generated a rapidly expanding literature. [Boer et al. \(2024\)](#) identify metal-specific demand shocks and estimate supply elasticities for copper, nickel, cobalt, and lithium, finding that under net-zero scenarios metal prices would reach historical peaks for an unprecedented sustained period. [Considine et al. \(2023\)](#) develop a Global VAR model showing that critical mineral price shocks are beginning to have macro-level impacts similar to oil price shocks. [Attílio \(2025\)](#) confirms this result across 34 economies, while [Miranda-Pinto et al. \(2024\)](#) use local projections to demonstrate significant pass-through of metals prices to both headline and core inflation across 39 countries. [Olivetti et al. \(2017\)](#) identify lithium and cobalt as facing short-term scaling challenges for battery production, and [Sovacool et al. \(2020\)](#) document sustainability challenges in mining minerals for clean energy technologies. [Zeng et al. \(2024\)](#) establish a company-level database showing that 47 percent of lithium and 71 percent of cobalt mined in 2019 were under foreign direct investment, proposing supply risk indices that account for investor nationality.

The measurement of supply concentration and its relationship to price vulnerability is central to our analysis. [Graedel et al. \(2012\)](#) established the foundational methodology for metal criticality assessment using the HHI for geographic production concentration. [Graedel et al. \(2015\)](#) applied this framework to 62 metals, finding that rare earth elements and technology metals have the highest supply risk scores. [Nassar et al. \(2020\)](#) developed a comprehensive risk framework identifying 23 commodities as posing the greatest supply risk to U.S. manufacturing. [Gulley et al. \(2018\)](#) documented competition between China and the United States for 42 nonfuel minerals, while [Habib et al. \(2016\)](#) showed that China's share of global metals production grew from 23 to 44 percent between 1994 and 2013. Most recently, [Bucciarelli et al. \(2025\)](#) investigated HHI validity as a supply risk indicator for 33 strategic metals, finding that HHI variation has more impact on metal prices at lower concentration levels, questioning conventional thresholds. Despite this extensive work on measuring concentration, the link between supply concentration and the dynamic price response to shortage shocks has not been empirically tested.

This paper contributes to the literature along several dimensions. First, we extend structural shock identification to a broad panel of 31 minerals commonly classified as critical, covering electric-vehicle and battery minerals, rare minerals, refractory materials, and industrial minerals. This extension is important because critical-mineral markets are not homogeneous: they differ sharply in end use, geographic production concentra-

tion, short-run substitutability, inventory practices, and exposure to policy-driven demand. Focusing only on base metals, or a small set of battery metals would therefore miss the cross-mineral heterogeneity that is central to understanding supply-chain vulnerability and resilience. The broader panel allows us to estimate an average mineral-price response to shortage shocks while also comparing responses across economically meaningful mineral categories. Second, we document rockets-and-feathers dynamics in critical mineral markets, showing that prices spike rapidly when shortage conditions worsen but adjust downward only slowly when conditions ease. Third, we quantify the role of supply concentration using a Herfindahl–Hirschman Index, combining a median-split design with a continuous interaction specification to show that minerals with above-median concentration exhibit larger cumulative price responses than diversified minerals, with the amplification scaling smoothly in HHI. Fourth, we document substantial heterogeneity in shortage sensitivity across mineral categories, with battery-EV minerals showing the largest and most persistent response, consistent with their concentrated refining capacity and exposure to policy-driven demand growth. These findings also carry policy implications for supply chain resilience, strategic stockpiling, and the management of import exposure, which we discuss in the conclusion and in the GCC application.

The key findings can be summarized as follows. The baseline results show that a one-standard-deviation shortage shock generates a positive, hump-shaped, and persistent price response across all 31 critical minerals, peaking at about 2.9 percent around eleven months before gradually reverting. Heterogeneity across mineral categories is substantial: the electric-vehicle and battery group exhibits the strongest response, peaking at 4.9 percent at about nineteen months, consistent with the concentrated refining capacity and policy-driven demand growth that characterize this segment. The asymmetric analysis reveals pronounced rockets-and-feathers dynamics: a one-standard-deviation tightening shock produces a cumulative price increase of 3.8 percent at six months and 5.5 percent at one year, whereas an easing shock of equal magnitude produces essentially no price decline over the same horizons, and the null of symmetric adjustment is rejected at the one-percent level over the medium run. The supply-concentration analysis shows that minerals with HHI above the sample median exhibit a one-year response of 3.2 percent compared with 2.1 percent for diversified minerals, and that the continuous interaction specification delivers the same amplification pattern: raising HHI from 0.15 to 0.85 increases the implied one-year shock response by roughly 1.7 percentage points. All baseline results are robust to alternative lag specifications and to replacing the shortage index with the Global Supply Chain Pressure Index.

The paper is organized as follows. Section 2 describes the data. Section 3 presents

the estimation strategy. Section 4 reports the empirical findings, including baseline results, asymmetric effects, supply concentration analysis, and mineral category heterogeneity. Section 5 presents additional analyses. Section 6 discusses the implications for GCC economies through a country-level mineral import exposure analysis. Section 7 concludes.

2 Data

The dataset spans the period from June 2009 to January 2026. The monthly frequency is well suited to the paper’s identification strategy because it captures the relatively fast transmission of supply-side disturbances into commodity prices while remaining consistent with the availability of the macro-financial controls. The availability of data determines time period. Some critical minerals prices data do not extend further back than June 2009.

The dependent variables are the prices of 31 critical minerals compiled from Bloomberg.³ These series constitute the outcome variable in all panel local projections specifications. Following the strategic-minerals literature (Graedel et al., 2015; Nassar et al., 2020), we organize the 31 minerals into four economically meaningful groups that reflect their dominant end-use, market structure, and exposure to the energy transition: (i) electric-vehicle and battery minerals (cobalt, electrolytic manganese, lithium carbonate, nickel plate, silicon, tellurium, and vanadium pentoxide); (ii) rare minerals (antimony, gallium, germanium, neodymium oxide, silver, strontium, tantalum, and terbium); (iii) refractory minerals (chromium, mercury, molybdenum, niobium, titanium dioxide, tungsten, and zircon sand); and (iv) industrial minerals (aluminum, copper, copper alloy, enameled wire, lead, magnesium, magnesium ingot, tin, and zinc). Descriptive statistics of monthly returns for each mineral and each group are reported in Table A.1 of the appendix.

This grouping is useful for several reasons. The electric-vehicle and battery panel isolates minerals most directly tied to electrification and energy storage, where demand growth is policy-driven and short-run substitution is limited. The rare-mineral panel captures thin-market technology metals whose supply is frequently concentrated at the refining rather than the mining stage. The refractory panel covers processing-intensive specialty materials with narrower end-use applications, while the industrial panel con-

³We use the term “critical minerals” to refer to minerals that are economically or strategically important and are also exposed to supply chain disruptions. The term does not imply that all minerals are inherently critical. Rather, it refers to the mineral commodities in our sample whose combination of supply risk and economic importance makes them particularly relevant for current discussions on the energy transition, technology, and industrial policy.

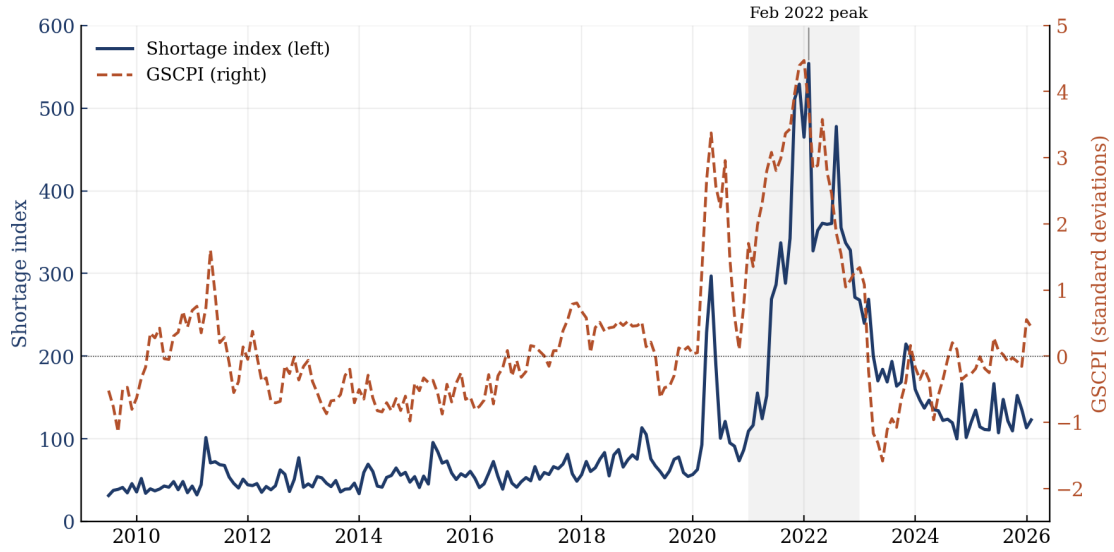
tains broadly traded base metals with deeper and more liquid markets. Estimating the empirical model separately on these four panels, in addition to the pooled sample, therefore allows us to test not only whether shortage shocks matter on average, but also whether their effects are amplified in transition-critical segments of the mineral market.

The key shock variable is the aggregate shortage index developed by [Caldara et al. \(2025\)](#). The index is a text-based indicator constructed from roughly 25 million newspaper articles and is designed to capture shortages across industry, labor, food, and energy markets. Its construction combines shortage-related keywords such as shortage, scarcity, bottleneck, and rationing with economics-related terms such as economy, trade, commerce, market, price, demand, factory, wages, and supply. [Caldara et al. \(2025\)](#) then classify relevant articles into sectoral topics using collocates and topic words, with prominent examples including oil, coal, food, labor, steel, and fuel. A distinctive feature of this measure is that it does not record disruptions in any single commodity market; rather, it captures a broad shortage environment that can propagate into critical mineral prices through extraction bottlenecks, processing constraints, and transportation frictions. We complement this news-based shortage measure with the Global Supply Chain Pressure Index (GSCPI) of [Benigno et al. \(2022\)](#), an indicator-based measure of global supply-chain pressure constructed from transportation costs, supplier delivery times, and manufacturing backlogs. The two measures capture related but distinct dimensions of supply-side stress: the shortage index is closer to shortage and bottleneck narratives, while the GSCPI captures system-wide logistics and production pressures. We therefore use the shortage index as the baseline measure, given the paper’s focus on shortage shocks, and use the GSCPI as a complementary indicator-based exercise to assess whether the results extend beyond the news-based measure.

Figure 1 plots the observed shortage index together with the GSCPI, highlighting the major episodes of supply-chain stress in the sample, especially the sharp run-up during 2020–2022. The figure provides historical context for the shortage environment captured by our measure. In the empirical analysis, however, a one-standard-deviation shortage shock is not a one-unit increase in the raw shortage index shown in the figure. Rather, it is the structurally identified unexpected component of the shortage index, after conditioning on mineral prices, global activity, inflation, trade-policy uncertainty, and lagged dynamics. It should therefore be interpreted as an unanticipated tightening in broad shortage conditions, not as a disruption in any single mineral market. Such shocks may affect mineral prices through several channels, including input bottlenecks, energy and logistics constraints, processing delays, and precautionary inventory accumulation.⁴

⁴China’s imposition of export-licensing requirements on gallium in mid-2023 provides an illustrative

Figure 1: The shortage index and the Global Supply Chain Pressure Index, 2009–2026



Note: The figure plots the monthly shortage index of [Caldara et al. \(2025\)](#) (solid, left axis) and the Global Supply Chain Pressure Index of [Benigno et al. \(2022\)](#) (dashed, right axis, in standard deviations) over June 2009–January 2026. The shaded band marks the 2021–2022 supply-chain crisis. The shortage index peaks at 554 in February 2022, roughly 8.7 times its 2015–2019 average.

The model includes three control variables. The first is the global consumer price index, which absorbs broad inflationary pressures that may co-move with mineral prices for reasons unrelated to shortage shocks. The second is the global economic conditions indicator of [Baumeister et al. \(2022\)](#), a composite measure built to summarize worldwide economic activity and to assess future energy-demand and oil-price pressures. Including this index helps separate shortage-driven price movements from fluctuations associated with the global business cycle. The third control is trade policy uncertainty developed by [Caldara et al. \(2020\)](#), which measures uncertainty about future trade policy using information from newspaper coverage, firms’ earnings calls, and tariff rates. This variable is included because uncertainty surrounding tariffs and trade arrangements can alter input costs, market access, and inventory decisions in mineral markets even in the absence of a physical shortage.

All variables are transformed to ensure comparability and to focus the analysis on dynamic responses rather than common trends. Specifically, we take the logarithmic difference of all series except the global economic conditions indicator. For mineral prices, the log difference converts levels into approximate monthly percentage changes. The log

example of the type of episode reflected in shortage news, an abrupt tightening in the availability of a metal whose refining is highly concentrated, although the empirical shock used below remains the identified innovation to the aggregate shortage index rather than a hand-coded mineral-specific event.

transformation is applied to the shortage, global CPI, and trade policy uncertainty variables so that the estimated responses are driven by changes in shortage conditions, inflation, and policy uncertainty rather than by low-frequency drift. By contrast, the global economic conditions index enters the model in levels, since it is already constructed as a cyclical indicator of worldwide economic conditions. This treatment keeps the empirical design parsimonious and preserves the interpretation of the local-projection coefficients as the response of mineral-price growth to a shock in shortage conditions, conditional on global inflation, global activity, and trade-policy risk.

3 Estimation Strategy

The empirical analysis is conducted in two stages. In the first stage, we identify exogenous shortage shocks from mineral-level structural vector autoregression (SVAR) models. In the second stage, we use the identified structural shortage shocks as the shock variable in a panel local projections framework to estimate the dynamic response of critical mineral prices. This two-step strategy is useful because it separates shock identification from the estimation of impulse responses. The SVAR isolates the shortage innovation after controlling for the interaction between the mineral price, global economic conditions, the global consumer price index, trade policy uncertainty, and the shortage index, while the panel local projections model traces how this identified shock propagates through critical mineral prices over time.

The first-stage SVAR is estimated separately for each mineral i using five monthly variables: the shortage index, trade policy uncertainty, global economic conditions, the global consumer price index, and the mineral's price. Let the vector of endogenous variables be

$$X_t = [s_t, tpu_t, gecon_t, gcpi_t, p_{i,t}]' \quad (1)$$

where s_t is the shortage index, tpu_t is trade policy uncertainty, $gecon_t$ is the global economic conditions indicator, $gcpi_t$ is the global consumer price index, and $p_{i,t}$ denotes the price of mineral i . The structural representation of the model is written as

$$A_0 X_t = c + \sum_{\ell=1}^L A_\ell X_{t-\ell} + \varepsilon_t \quad (2)$$

where A_0 is the contemporaneous impact matrix, c is a vector of constants, A_ℓ denotes the coefficient matrices at lag ℓ , L is the lag length, and ε_t is the vector of mutually orthogonal structural shocks with $E(\varepsilon_t \varepsilon_t') = I$. We identify the structural shocks by imposing

a recursive (Cholesky) restriction on A_0^{-1} , so that A_0^{-1} is lower triangular. Under this scheme, variables ordered earlier in X_t are assumed to be contemporaneously exogenous to variables ordered later, while still being allowed to respond to all variables with a lag.

The ordering in equation (1) reflects a hierarchy from the most exogenous to the most endogenous determinants of critical mineral prices. The shortage index s_t is placed first because the shortage conditions it captures are dominated by physical supply disruptions, geological constraints, strikes, export bans, and other mining-sector frictions that are largely predetermined within the month. Because the index itself is a news-based count that could in principle react within the month to commodity-price movements, contemporaneous exogeneity with respect to the price of any single mineral is an identifying assumption rather than a mechanical property; we verify below that reversing the recursive ordering leaves the identified shocks and impulse responses essentially unchanged. Trade policy uncertainty tpu_t is ordered second, as policy announcements and tariff actions are set by governments in response to broader political considerations and react only sluggishly to short-run movements in prices and global activity, but may plausibly respond within the month to observed shortages. Global economic conditions $gecon_t$ are ordered third, since real activity responds to shortage shocks and policy uncertainty but moves slowly relative to nominal variables and is observed by price-setters before it feeds into inflation; placing it ahead of the price index is also consistent with the Kilian-style view that aggregate demand pressures drive inflationary dynamics rather than the reverse. The global consumer price index $gcpi_t$ comes fourth, capturing inflationary pressures that respond to shortage conditions, policy uncertainty, and real activity, and that adjust faster than real output but more slowly than commodity prices; this placement also acknowledges that headline global CPI contains a substantial pass-through component from commodity prices themselves, making it more endogenous than real activity in the system. Finally, the mineral price $p_{i,t}$ is ordered last, reflecting that commodity prices are the most forward-looking and information-sensitive variable in the system: they incorporate news about shortages, policy, activity, and inflation contemporaneously. This ordering is consistent with the standard practice in the oil-market SVAR literature (e.g., Kilian, 2009), where slow-moving supply and activity variables are ordered ahead of the price variable to isolate exogenous structural shocks.⁵

After estimating the reduced-form VAR, we recover the structural innovations from the reduced-form residuals using the inverse of the contemporaneous matrix. Denoting

⁵We verify that our results are robust to the ordering of variables in X_t . In particular, reversing the ordering of all variables, so that the mineral price is placed first and the shortage index last, yields identified shortage shocks and impulse responses that are quantitatively similar to those reported in the main analysis. This indicates that our findings do not hinge on the specific recursive structure imposed in equation (1).

the reduced-form residuals by u_t , the relationship between reduced-form and structural shocks reads

$$u_t = A_0^{-1} \varepsilon_t, \quad (3)$$

which implies that the structural shocks can be obtained as

$$\varepsilon_t = A_0 u_t. \quad (4)$$

The structural shortage shock $\hat{\varepsilon}_t^{sh}$ is defined as the component of ε_t corresponding to the shortage equation. This procedure yields a shortage shock series that is orthogonal to the other innovations in the system and can therefore be interpreted as an exogenous shortage disturbance (Kilian and Lütkepohl, 2017). In other words, the identified shock captures unexpected changes in shortage conditions after accounting for the joint dynamics of prices, global macroeconomic conditions, inflationary pressures, and trade policy uncertainty.

In the second stage, the identified structural shortage shocks are used in a panel local projections model following Jordà (2005). For each horizon $h = 0, 1, \dots, 36$, we estimate the following specification on the panel of 31 minerals:

$$y_{i,t+h} = \alpha_{i,h} + \beta_h \hat{\varepsilon}_{i,t}^{sh} + \sum_{\ell=1}^L \phi_{h,\ell} \Delta p_{i,t-\ell} + \sum_{\ell=1}^L \gamma_{h,\ell} \hat{\varepsilon}_{i,t-\ell}^{sh} + \sum_{\ell=1}^L \Theta_{h,\ell} W_{t-\ell} + u_{i,t+h} \quad (5)$$

where $y_{i,t+h} = 100 \times (p_{i,t+h} - p_{i,t-1})$ is the cumulative log-price change (in percent) of mineral i between period $t-1$ and period $t+h$, $\hat{\varepsilon}_{i,t}^{sh}$ is the mineral-specific structural shortage shock identified from the SVAR, $\Delta p_{i,t-\ell}$ denotes lags of the first-differenced mineral log price, $W_{t-\ell} = (gecon_{t-\ell}, gcpi_{t-\ell}, tpu_{t-\ell})'$ is the vector of macroeconomic and policy controls, $\alpha_{i,h}$ denotes mineral-specific fixed effects, and L is the lag length. The coefficient of interest is β_h , which measures the response of mineral prices at horizon h to a one-standard-deviation structural shortage shock⁶. Standard errors are clustered by mineral id and month (Cameron et al., 2011).⁷

⁶Including L lags of the structural shortage shock itself in the control set is important for two reasons. First, it absorbs any residual serial dependence in the identified shock series, so that β_h captures the marginal effect of a current shortage innovation after netting out the persistent influence of past ones. Second, it aligns the local projection with the SVAR's own dynamic structure, which loads on lags of all five endogenous variables, including the shortage innovation. Without these terms, the coefficient β_h would conflate the true contemporaneous impulse with the cumulative influence of past shocks that tend to cluster with the current one, biasing the IRF at longer horizons.

⁷This allows for arbitrary within-mineral heteroskedasticity and serial correlation of the local-projection residuals, which is particularly important in our setting because the overlapping-horizon regressions induce an $MA(h)$ autocorrelation structure in $u_{i,t+h}$ by construction.

The baseline specification sets the lag length to $L = 12$ months and the forecast horizon to 36 months. This structure allows the analysis to capture both short-run and medium-run price responses to shortage shocks while keeping the effective sample comparable across horizons. The model is first estimated for the full panel of 31 critical minerals and then re-estimated separately for the four mineral groups considered in the paper: electric-vehicle and battery minerals, rare minerals, refractory minerals, and industrial minerals. This group-wise estimation makes it possible to assess whether the effect of shortage shocks differs systematically across mineral categories.

The main advantage of this approach is that the first-stage SVAR identifies a mineral-specific structural shortage innovation, while the second-stage panel local projections model provides a flexible way to estimate how this innovation affects mineral prices over time. Compared with a panel VAR, local projections are less restrictive because they do not impose the same dynamic structure at all horizons. This is particularly relevant in the present context, where the price response to shortage shocks may be delayed, persistent, and heterogeneous across mineral groups.

We also consider three complementary specification exercises. First, we re-estimate the panel local projections using a shorter lag length of six months. Second, we replace the baseline news-based shortage measure with the indicator-based GSCPI and repeat the same identification and estimation procedure. The second exercise examines whether the mineral-price response is specific to news-based shortage shocks or also arises when supply-side stress is measured using observable logistics and production indicators. Third, we replace the global consumer price index with the global producer price index as the general-price variable, in both the SVAR and the local projection control set, to verify that the results do not depend on the broad price measure used to condition the structural shock.

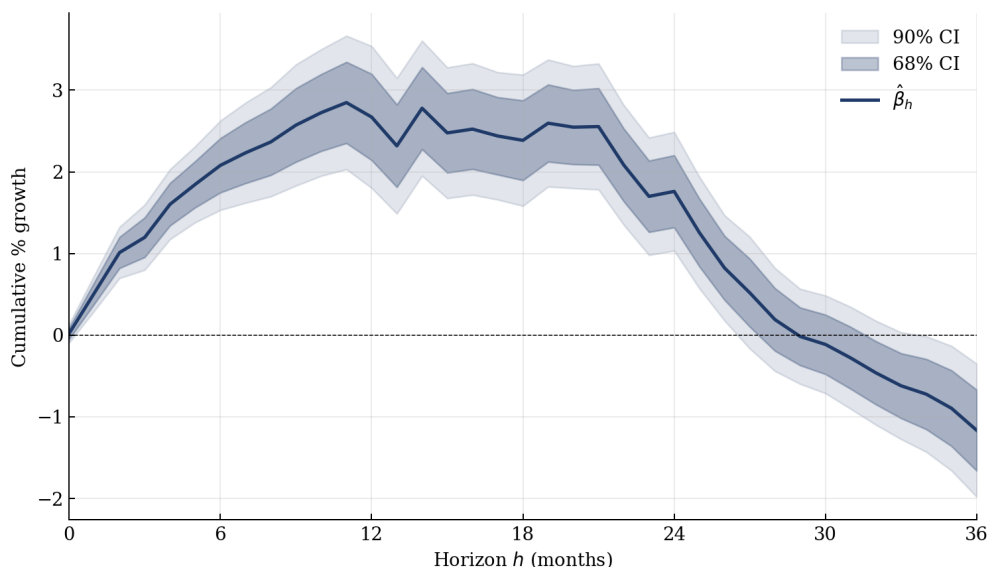
4 Empirical Findings

4.1 Baseline Results

Figure 2 shows that the pooled response across all 31 critical minerals is positive, hump-shaped, and highly persistent. Following a one-standard-deviation shortage shock, the average price response rises quickly in the first year, reaches a peak of about 2.85 percent at around eleven months, and only gradually eases thereafter. This pattern suggests that shortage shocks in critical mineral markets are not fleeting disturbances; rather, they generate durable price pressures consistent with sluggish supply adjustment, long invest-

ment lead times, and rigidities in refining and downstream processing. In that sense, the baseline evidence suggests that broad shortage conditions are associated with durable price pressures in critical-mineral markets, rather than purely transitory fluctuations.

Figure 2: Responses of critical mineral prices to shortage shocks



Note: The figure shows cumulative price responses of all critical minerals to a one-standard-deviation shortage shock, estimated using the panel LP model. The solid line represents point estimates of the responses, and the dark and light shaded regions indicate 68% and 90% confidence intervals based on the robust standard errors clustered at the mineral level and month.

The hump-shaped profile and slow mean reversion documented here are broadly consistent with prior findings on commodity price dynamics, though our estimates reveal important differences in magnitude and persistence. [Stuermer \(2018\)](#) shows that supply shocks affect base metal prices for up to five years using 150 years of data on copper, lead, tin, and zinc, a horizon that aligns closely with the decay pattern observed in our impulse responses. [Boer et al. \(2024\)](#) estimate that the short-run supply elasticities of copper, nickel, cobalt, and lithium are all well below unity, implying that prices must absorb the bulk of any supply-side disturbance in the near term, similar to the mechanism that drives the steep initial rise in our estimates. The persistence we document is also consistent with the findings of [Jacks and Stuermer \(2020\)](#), who show that commodity price booms and busts are predominantly demand-driven but that supply-side shocks generate more protracted adjustments. Relative to the supply chain disruption literature, our peak response of 2.9% is comparable in order of magnitude to the inflationary effects of GSCPI shocks estimated by [Benigno et al. \(2022\)](#) for consumer prices, but notably more persistent, suggesting that critical minerals, with their concentrated supply chains and limited

inventories, amplify and prolong the transmission of shortage conditions relative to the broader economy. The slow mean reversion we observe is also consistent with the long capital gestation periods that characterize mining, which the IEA estimates at over 16 years from discovery to first production on average ([International Energy Agency, 2021](#)).

4.2 Asymmetric Effects

The baseline analysis imposes a linear relationship between shortage shocks and mineral-price responses, and in particular forces positive and negative shortage shocks to have symmetric effects of equal magnitude and opposite sign. This subsection relaxes that assumption and tests formally whether the direction of the shock matters: do positive shortage shocks (worsening shortage conditions) and negative shortage shocks (easing shortage conditions) produce symmetric price responses in critical mineral markets? The question is motivated by the observation that commodity prices often exhibit asymmetric adjustment, with prices rising rapidly in response to adverse supply news but falling sluggishly when conditions improve. This pattern, known in the energy-market literature as "rockets-and-feathers" ([Bacon, 1991](#); [Borenstein et al., 1997](#)), reflects a combination of inventory buffers, long-term contracting, minimum take-or-pay commitments, and downward rigidities in price negotiation. If it is present in critical mineral markets as well, then the linear baseline model understates the average impact of shortage shocks on downstream prices.

To test for sign asymmetry, we decompose the structural shortage shock into its positive and negative components:

$$\hat{\varepsilon}_{i,t}^+ = \max(\hat{\varepsilon}_{i,t}^{sh}, 0), \quad \hat{\varepsilon}_{i,t}^- = \min(\hat{\varepsilon}_{i,t}^{sh}, 0). \quad (6)$$

The two series are mechanically exhaustive, so that $\hat{\varepsilon}_{i,t}^{sh} = \hat{\varepsilon}_{i,t}^+ + \hat{\varepsilon}_{i,t}^-$ at every date. We then estimate the following panel local projection for each horizon $h = 0, 1, \dots, 36$:

$$\begin{aligned} y_{i,t+h} = & \alpha_{i,h} + \beta_h^+ \hat{\varepsilon}_{i,t}^+ + \beta_h^- \hat{\varepsilon}_{i,t}^- \\ & + \sum_{\ell=1}^{12} \phi_{h,\ell} \Delta p_{i,t-\ell} + \sum_{\ell=1}^{12} \gamma_{h,\ell}^+ \hat{\varepsilon}_{i,t-\ell}^+ + \sum_{\ell=1}^{12} \gamma_{h,\ell}^- \hat{\varepsilon}_{i,t-\ell}^- \\ & + \sum_{\ell=1}^{12} \Theta_{h,\ell} W_{t-\ell} + u_{i,t+h}. \end{aligned} \quad (7)$$

The specification is estimated on the full panel of 31 critical minerals and mirrors the baseline model exactly except that the contemporaneous shortage shock and each of its

twelve lags are entered separately as positive and negative components. The asymmetric response is therefore identified after conditioning on a full year of signed shock history.

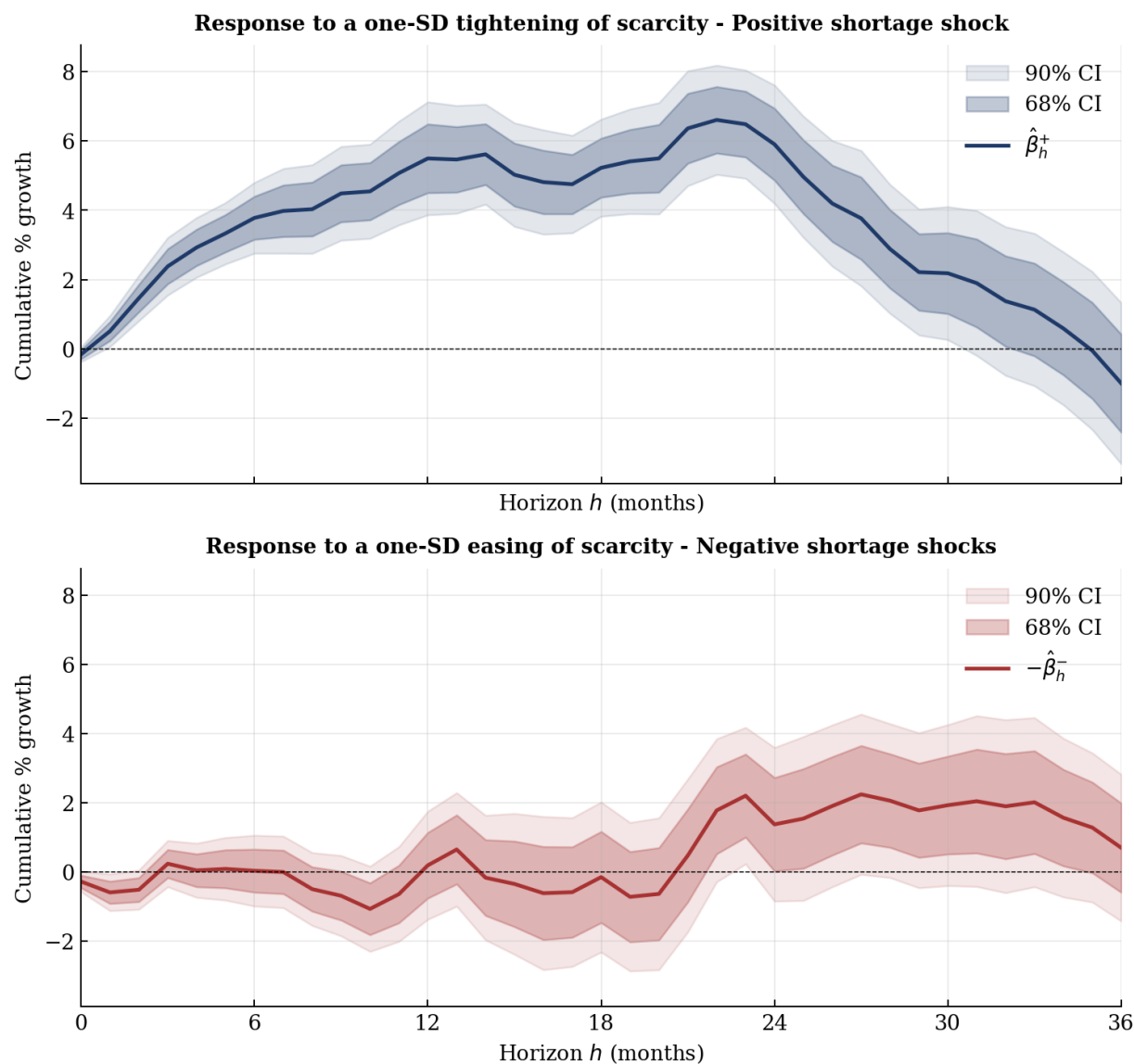
The coefficient β_h^+ captures the cumulative price response to a positive shortage shock, that is, an innovation that tightens shortage conditions. The coefficient β_h^- is the slope on the negative-shock component. Because $\hat{\varepsilon}_{i,t}^- \leq 0$ by construction, the actual price response to a unit easing shock, corresponding to a move in $\hat{\varepsilon}_{i,t}^{sh}$ from zero to -1 , is $-\beta_h^-$. We therefore plot $\hat{\beta}_h^+$ for a one-standard-deviation tightening shock and $-\hat{\beta}_h^-$ for a one-standard-deviation easing shock. These are signed cumulative price responses: positive values indicate cumulative price increases, while negative values indicate cumulative price declines.

Under symmetric adjustment, the response to a positive shock and the response to an equal-sized negative shock should be equal in magnitude and opposite in sign. In terms of the regression coefficients, this null is $H_0 : \beta_h^+ = \beta_h^-$. In terms of the plotted signed impulse responses, where $\text{IRF}_h^+ = \hat{\beta}_h^+$ and $\text{IRF}_h^- = -\hat{\beta}_h^-$, the same null is equivalent to $H_0 : \text{IRF}_h^+ + \text{IRF}_h^- = 0$. Thus, if price adjustment is symmetric, the easing response should be the mirror image of the tightening response around zero. Departures from this mirror-image pattern indicate sign asymmetry in the transmission of shortage shocks to mineral prices.

Figure 3 presents the cumulative impulse responses estimated separately for positive and negative shortage shocks. The results reveal a pronounced sign asymmetry. A positive shortage shock, which corresponds to a tightening of shortage conditions, generates a rapid and persistent increase in mineral prices. The cumulative response rises quickly over the first six months, reaching 3.78% at $h = 6$, and continues to build over the following year. The response reaches 5.91% at $h = 24$, with the monthly profile peaking around the second year, before declining gradually thereafter. Thus, worsening of shortage conditions produces a large, hump-shaped increase in prices that is strongest over the first two years and then gradually dissipates.

The response to negative shortage shocks is markedly different. Since the bottom panel plots $-\hat{\beta}_h^-$, it shows the actual signed price response to a one-standard-deviation easing of shortage conditions. If price adjustment were symmetric, this response should be strongly negative and should approximately mirror the positive response in the top panel. Instead, the estimated easing response is close to zero over the first year and a half. At longer horizons, the point estimate becomes positive rather than negative, reaching 1.92% at $h = 30$. The confidence bands are substantially wider than in the tightening-shock panel, so the positive point estimates at longer horizons should be interpreted cautiously. The central result, however, is clear: easing shocks do not produce an equal and

Figure 3: Asymmetric cumulative responses to positive and negative shortage shocks



Note: The top panel reports $\hat{\beta}_h^+$, the cumulative price response to a one-standard-deviation positive shortage shock, corresponding to a tightening of shortage conditions. The bottom panel reports $-\hat{\beta}_h^-$, the signed cumulative price response to a one-standard-deviation negative shortage shock, corresponding to an easing of shortage conditions. Because the bottom panel is expressed as the actual signed response to an easing shock, negative values indicate price declines and positive values indicate price increases following the easing shock. The dark and light shaded regions indicate 68% and 90% confidence intervals, respectively, based on the robust standard errors clustered at the mineral-id level and month.

opposite decline in prices.

Table 1: Wald tests of sign symmetry for the full panel, $H_0 : \beta_h^+ = \beta_h^-$

Horizon h	$\hat{\beta}_h^+$	$-\hat{\beta}_h^-$	z-statistic	p-value
0	-0.17	-0.28	-1.62	0.105
6	3.78	0.03	3.55	0.000
12	5.50	0.18	3.42	0.001
18	5.23	-0.16	2.61	0.009
24	5.91	1.37	3.30	0.001
30	2.18	1.92	1.65	0.099
36	-1.00	0.69	-0.12	0.903

Note: The table reports Wald tests of the null of symmetric price adjustment, $H_0 : \beta_h^+ = \beta_h^-$, at seven headline horizons for the full panel of 31 critical minerals. The second and third columns report the signed impulse-response values plotted in Figure 3: $\hat{\beta}_h^+$ is the cumulative percentage price response to a one-standard-deviation tightening shock, and $-\hat{\beta}_h^-$ is the cumulative percentage price response to a one-standard-deviation easing shock. Since the third column is the signed easing response, the Wald numerator can equivalently be written as $\hat{\beta}_h^+ - \hat{\beta}_h^- = \widehat{\text{IRF}}_h^+ + \widehat{\text{IRF}}_h^-$. The standard error is obtained from the cluster-robust variance-covariance matrix clustered at the mineral-id level and month. p -values are two-sided.

This pattern is consistent with asymmetric price adjustment in critical mineral markets. Prices respond strongly and quickly when shortage conditions worsen, but they do not fall comparably when conditions ease. In this sense, the evidence points to a “rockets-and-feathers” dynamic: adverse shortage shocks are passed through rapidly into higher prices, while favorable shortage shocks generate much weaker downward price adjustment.

Table 1 formally confirms the visual evidence of asymmetry. The null of symmetric adjustment is rejected at conventional significance levels over the short- and medium-run horizons, indicating that tightening shocks generate substantially stronger price responses than easing shocks of comparable size. At longer horizons, the evidence weakens as the tightening response fades and the confidence bands around the easing response widen. Overall, the Wald tests show that the asymmetry is concentrated in the statistically significant part of the response profile: prices rise sharply when shortage conditions tighten, but they do not fall symmetrically when shortage conditions ease.

4.3 Supply Concentration and Heterogeneous Responses

This subsection examines whether the sensitivity of critical mineral prices to shortage shocks varies with the degree of supply concentration. The hypothesis is that minerals whose global production is dominated by a small number of countries should ex-

hibit larger and more persistent price responses to shortage disturbances, because concentrated supply structures leave fewer margins for substitution, rerouting, or capacity reallocation when shortages arise.

To quantify supply concentration, we construct a Herfindahl–Hirschman Index (HHI) for each mineral using country-level production data from the U.S. Geological Survey Mineral Commodity Summaries 2025. For each mineral m , the index is defined as

$$HHI_m = \sum_{c=1}^C s_{c,m}^2 \quad (8)$$

where $s_{c,m}$ denotes the share of country c in global production of mineral m and C is the total number of producing countries. The index ranges from values close to zero, indicating a perfectly dispersed production structure, to one, indicating a single-country monopoly. For minerals where mine production shares do not adequately capture supply-chain bottlenecks, such as gallium, germanium, and rare-earth oxides, for which processing and refining are more concentrated than extraction, we use refinery or separation-stage production shares instead.⁸

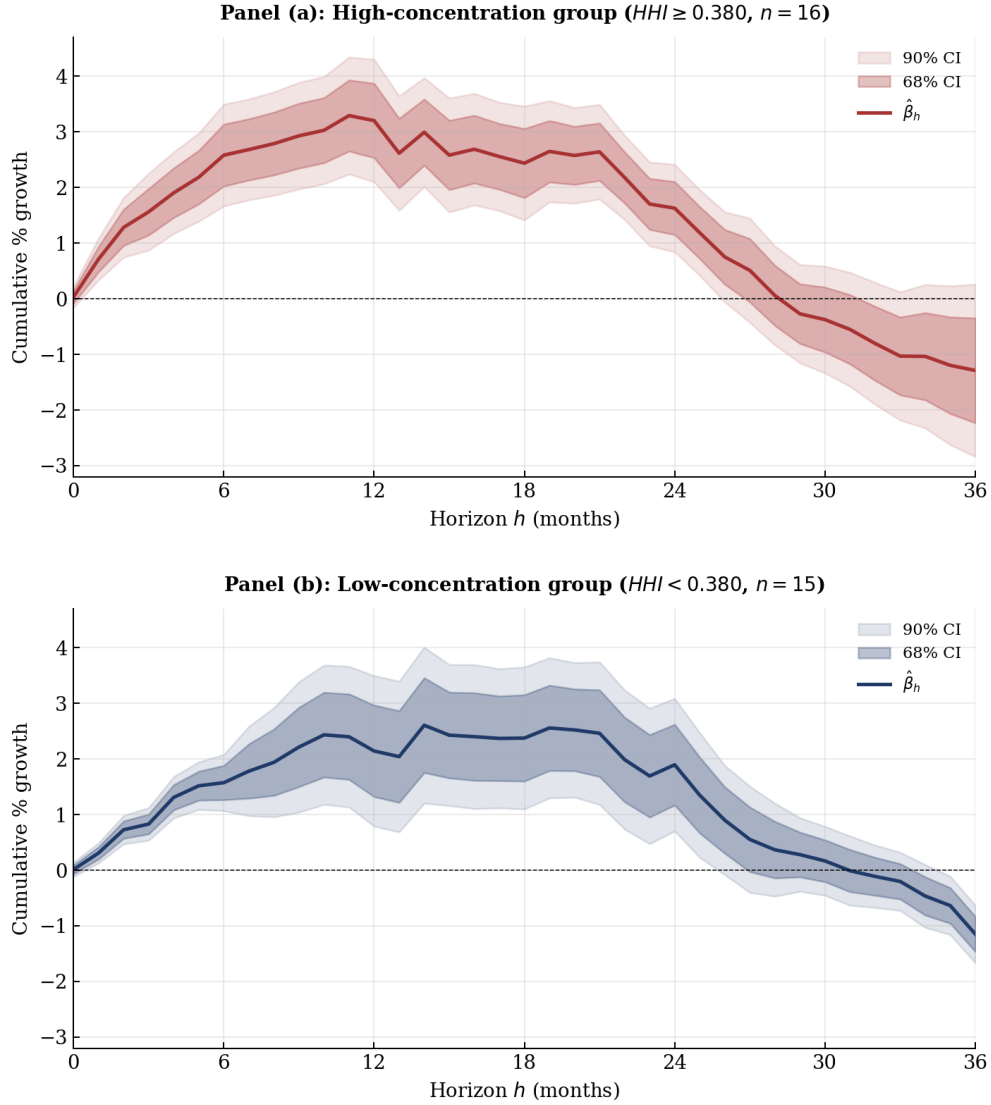
The resulting HHI values reveal substantial cross-mineral heterogeneity. Gallium and magnesium are among the most concentrated markets ($HHI = 0.974$ and 0.904), whereas copper and tin are among the least concentrated ($HHI = 0.132$ and 0.137). The sample median is 0.380 , indicating substantial cross-mineral heterogeneity in supply structure. To evaluate our hypothesis, we use two complementary designs. We begin with a median-split specification that compares the impulse responses of high- and low-concentration minerals. We then estimate a continuous interaction specification, which uses the full cross-mineral variation in HHI and checks that the result is not driven by the choice of cutoff.

4.3.1 Group-Split Specification

We partition the 31 minerals into two groups at the median HHI and re-estimate the baseline panel local projection separately on each subsample. This discrete specification imposes no functional form on how concentration shapes the response and allows the two subsamples to have arbitrarily different dynamics. The high-concentration group contains 16 minerals with $HHI_m \geq 0.380$, while the low-concentration group contains

⁸Even though the HHI is constructed from the most recent available report, supply-structure characteristics such as geographic concentration are highly persistent over time, reflecting geological endowments, long-lived production infrastructure, and slow-moving policy and investment decisions. We therefore treat the index as time-invariant throughout the empirical analysis.

Figure 4: Cumulative price responses of critical minerals to shortage shocks by supply concentration



Panel (a) shows the cumulative price response for the high-concentration group ($HHI \geq 0.380$, $n = 16$ minerals) to a one-standard-deviation shortage shock; panel (b) shows the corresponding cumulative price response of the low-concentration group ($HHI < 0.380$, $n = 15$ minerals). The two panels share a common vertical scale. The solid line is the point estimate, the darker band is the 68% confidence interval, and the lighter band is the 90% confidence interval. Standard errors are clustered at the mineral-id level and month.

the remaining 15 minerals. For each group $g \in \{H, L\}$ and each horizon $h = 0, 1, \dots, 36$, we implement the following specification:

$$\begin{aligned}
y_{i,t+h}^g = & \alpha_{i,h}^g + \beta_h^g \varepsilon_{i,t}^{sh} \\
& + \sum_{\ell=1}^{12} \phi_{h,\ell}^g \Delta p_{i,t-\ell} + \sum_{\ell=1}^{12} \gamma_{h,\ell}^g \varepsilon_{i,t-\ell}^{sh} \\
& + \sum_{\ell=1}^{12} \Theta_{h,\ell}^g W_{t-\ell} + u_{i,t+h}^g.
\end{aligned} \tag{9}$$

Every parameter is free to differ across groups, so that the two subsamples are allowed to have distinct dynamic responses, distinct shock-history adjustment, and distinct control-variable loadings. The coefficient β_h^g measures the group-specific response to a one-standard-deviation shortage shock at horizon h . All other estimation choices match those of the baseline specification in Section 3.

Figure 4 displays the group-specific impulse responses. The high-concentration group, shown in panel (a), exhibits a rapid and pronounced price response, reaching 2.58% at horizon 6 and peaking at 3.20% at horizon 12. The low-concentration group in panel (b) responds more gradually, reaching 1.57% at horizon 6 and 2.14% at horizon 12. The peak response for the high-concentration group is thus roughly 1.1 percentage points higher than for the low-concentration group, consistent with the concentration-amplification hypothesis.

At longer horizons both groups exhibit mean reversion and drift into negative territory, with cumulative responses of approximately -1.3% at $h = 36$ for both groups. This long-run convergence pattern is consistent with commodity markets in which the initial price spike is eventually corrected through demand adjustment, inventory de-stocking, or the activation of higher-cost capacity, and the correction occurs at a similar pace regardless of the underlying supply structure.

4.3.2 HHI-Shock Interaction

To verify that the concentration-amplification pattern is not an artifact of the median-split cutoff, we re-estimate the model using the full continuous variation in HHI. Specifically, we add an interaction term between the contemporaneous shock and each mineral's HHI to the baseline panel local projection. For each horizon $h = 0, 1, \dots, 36$, we estimate the following specification:

$$\begin{aligned}
y_{i,t+h} = & \alpha_{i,h} + \beta_h^{shk} \hat{\varepsilon}_{i,t}^{sh} + \beta_h^{int} (\hat{\varepsilon}_{i,t}^{sh} \cdot HHI_i) \\
& + \sum_{\ell=1}^{12} \phi_{h,\ell} \Delta p_{i,t-\ell} + \sum_{\ell=1}^{12} \gamma_{h,\ell} \hat{\varepsilon}_{i,t-\ell}^{sh} \\
& + \sum_{\ell=1}^{12} \Theta_{h,\ell} W_{t-\ell} + u_{i,t+h}.
\end{aligned} \tag{10}$$

The coefficient β_h^{shk} captures the price response at horizon h at a hypothetical baseline concentration of $HHI_i = 0$, and β_h^{int} captures how the shock response scales with concentration. A standalone HHI level term is omitted because HHI is time-invariant within mineral and is therefore absorbed by the fixed effect $\alpha_{i,h}$. All other estimation choices follow the baseline specification of Section 3.

The quantity of economic interest is the marginal effect of a unit shortage shock for a mineral with concentration level $\overline{hhi}$:

$$\left. \frac{\partial y_{i,t+h}}{\partial \hat{\varepsilon}_{i,t}^{sh}} \right|_{HHI_i = \overline{hhi}} = \hat{\beta}_h^{shk} + \overline{hhi} \cdot \hat{\beta}_h^{int}, \tag{11}$$

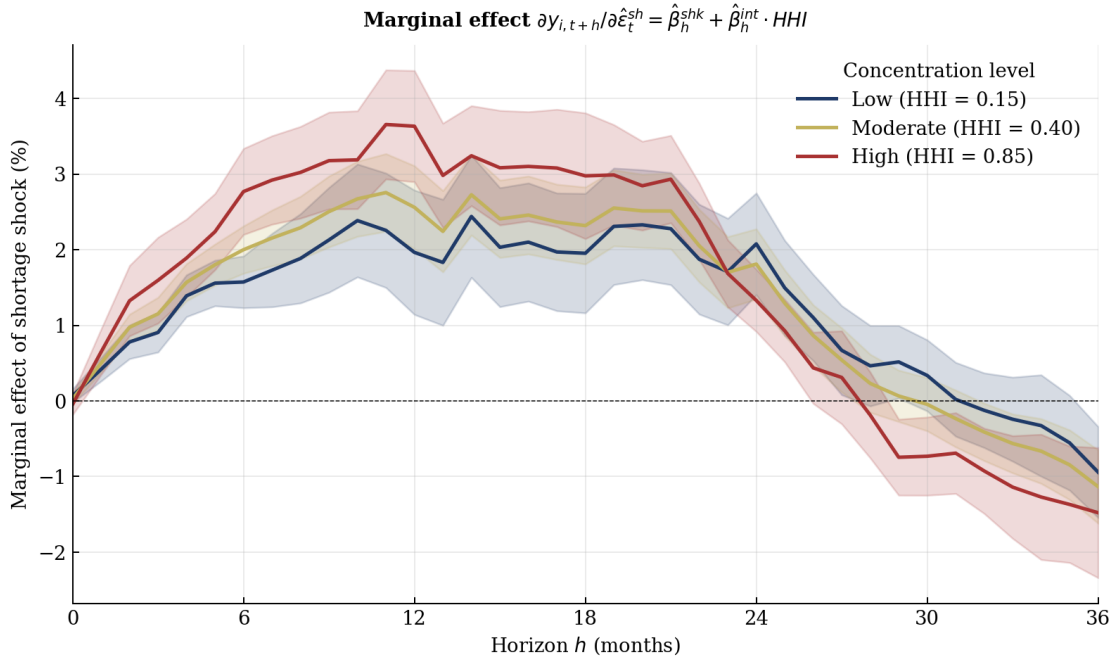
with standard errors obtained via the delta method.⁹

Figure 5 plots the estimated marginal effect at three representative HHI values.¹⁰ The three curves are ordered as the concentration hypothesis predicts: at every horizon from $h = 2$ through $h = 21$, the high-concentration curve ($HHI = 0.85$) lies above the moderate-concentration curve ($HHI = 0.40$), which in turn lies above the low-concentration curve ($HHI = 0.15$). At the one-year horizon the gap is most pronounced: the marginal price response to a one-standard-deviation shortage shock is 1.96% for low-concentration minerals, 2.56% for moderately concentrated minerals, and 3.63% for highly concentrated minerals. An increase in HHI from 0.15 to 0.85 therefore raises the implied one-year shock response by roughly 1.67 percentage points. The interaction coefficient $\hat{\beta}_h^{int}$ is positive and economically large over short and medium horizons, reaching 2.38 at $h = 12$, which quantifies the extent to which supply concentration amplifies the transmission of shortage shocks into prices. All three curves converge around $h = 22$ and drift modestly

⁹The variance is $\text{Var}(\hat{\beta}_h^{shk}) + \overline{hhi}^2 \text{Var}(\hat{\beta}_h^{int}) + 2\overline{hhi} \text{Cov}(\hat{\beta}_h^{shk}, \hat{\beta}_h^{int})$, evaluated using the cluster-robust variance-covariance matrix from the interaction regression.

¹⁰We evaluate the marginal effect at three representative concentration levels chosen to span the empirical distribution of HHI without extrapolating beyond it. The intermediate value, $HHI = 0.40$, coincides with the sample median (0.380) and therefore characterizes the typical mineral. The low value, $HHI = 0.15$, represents the diversified tail occupied by deeply traded base metals such as copper (0.132) and tin (0.137), while the high value, $HHI = 0.85$, represents the concentrated tail occupied by minerals such as magnesium (0.904) and gallium (0.974).

Figure 5: Marginal effect of a one-standard-deviation shortage shock on critical mineral prices, evaluated at three representative HHI values



The figure shows $\hat{\beta}_h^{shk} + HHI \cdot \hat{\beta}_h^{int}$ from Equation 10, evaluated at $HHI \in \{0.15, 0.40, 0.85\}$ corresponding to low-concentration minerals such as copper and zinc ($HHI = 0.15$), moderately concentrated minerals near the sample median such as nickel and aluminum ($HHI = 0.40$), and highly concentrated minerals such as magnesium and gallium ($HHI = 0.85$). Shaded regions indicate 68% confidence intervals based on the delta-method standard errors. Standard errors are cluster-robust at the mineral-id level and month.

negative at the longest horizons, consistent with the mean reversion documented in the baseline results.

Taken together, the two specifications deliver the same economic conclusion: supply concentration amplifies the short- and medium-run transmission of shortage shocks into critical mineral prices, but does not extend their persistence. The group-split evidence in Figure 4 establishes the main result using a clean discrete partition of minerals, and the continuous-treatment evidence in Figure 5 confirms that the amplification scales smoothly with HHI and is not an artifact of the median-split cutoff.¹¹

4.4 Different Categories of Minerals

The baseline results in Section 4.1 establish the average price response across all 31 critical minerals, but this pooled estimate may mask important heterogeneity across mineral groups that differ in their end-use applications, market structure, and exposure to the energy transition. To investigate this possibility, we re-estimate the panel local projections model separately for four economically meaningful categories: electric-vehicle and battery minerals (cobalt, electrolytic manganese, lithium carbonate, nickel plate, silicon, tellurium, and vanadium pentoxide), rare minerals (antimony, gallium, germanium, neodymium oxide, silver, strontium, tantalum, and terbium), refractory minerals (chromium, mercury, molybdenum, niobium, titanium dioxide, tungsten, and zircon sand), and industrial minerals (aluminum, copper, copper alloy, enameled wire, lead, magnesium, magnesium ingot, tin, and zinc). This classification separates minerals according to their dominant technological use and likely sensitivity to supply-chain disruptions: the EV and battery group captures materials most directly tied to electrification, the rare minerals group isolates thin-market technology metals, the refractory group covers processing-intensive specialty materials, and the industrial group contains broadly traded base metals with deeper and more liquid markets. If shortage shocks propagate differently through these distinct market structures, then policies aimed at building supply-chain resilience need to be tailored accordingly.

Figure 6(a) reveals that the strongest response is observed for the electric-vehicle and

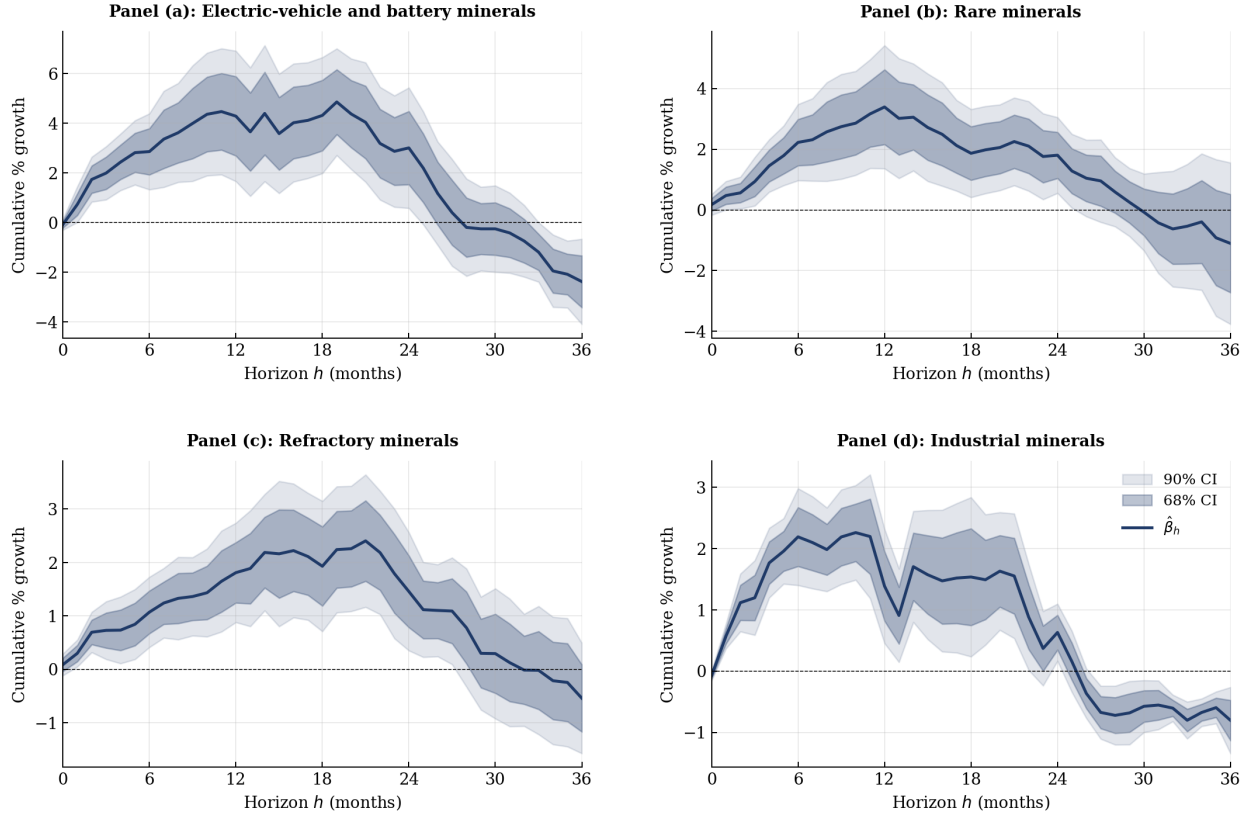
¹¹Because the index uses mine-production shares for some minerals and refining shares for others, a natural question is whether the amplification operates at the mining or the processing stage since the export-control episodes that dominate shortage news (China's restrictions on rare earths, gallium, and germanium) bind at the refining stage. Appendix B examines this directly for the 14 minerals with a country-level distribution at both stages, and finds that over the six- to fifteen-month horizon it is processing concentration that drives the response, while mine concentration does not; the result survives a wild-cluster bootstrap. We treat it as a mechanism check on this subsample rather than a re-estimation of the full panel. It also rationalizes the faster response to the news-based measure relative to the GSCPI in Section 5, since news loads on processing-stage announcements that are priced in quickly.

battery group. For electric-vehicle and battery minerals, the cumulative price response rises rapidly in the first year and peaks at roughly 4.9% at a horizon of about nineteen months. This is approximately 2 percentage points larger than the full-sample peak, consistent with the view that battery-related mineral chains are characterized by concentrated refining capacity, limited short-run substitution, and strong exposure to policy-driven demand growth. A shortage shock therefore appears to be capitalized rapidly into prices and to persist through the first two years while supply chains adjust. Unlike the other groups, however, the response reverses decisively at longer horizons and turns moderately negative by the end of the third year. This mean reversion likely reflects a combination of speculative unwinding, inventory rebuilding, demand destruction at elevated prices, and the eventual ramp-up of new processing capacity, but it does not overturn the central result that this group is by far the most shortage-sensitive over the horizons that matter for investment and policy.

Figure 6(b) illustrates that rare minerals also display a positive and persistent response, though the profile is markedly more uneven than in the battery-EV group. The cumulative price response peaks at about 3.4% around the twelve-month horizon, then drifts down through the second year before eventually crossing into mildly negative territory late in the horizon. This non-monotonic pattern is consistent with thin markets, episodic procurement, and heterogeneous industrial applications across the minerals in this group, and the mid-horizon moderation is consistent with the staggered transmission of recent export-control episodes affecting gallium, germanium, and several rare earth elements. Shortage news is clearly priced in, but the adjustment is less synchronized and the uncertainty bands are visibly wider than for the battery-EV group, particularly at longer horizons. The evidence thus points to meaningful sensitivity of rare-metal prices to shortage conditions, but with stronger cross-mineral heterogeneity than in the other groups.

Figure 6(c) shows that refractory minerals exhibit the slowest-building response among the four categories. Prices increase only gradually during the first year and continue to rise through the middle of the horizon, peaking at about 2.4% around the twenty-first month before easing back toward zero by month thirty and then moving mildly negative thereafter. The delayed peak indicates that refractory minerals absorb shortage shocks through a slow-acting pricing channel rather than reacting to shortage news on impact. The pattern is consistent with processing-intensive production structures, long qualification cycles for specialty end-users, and limited scope for rapid capacity expansion, all of which delay the transmission of shortage conditions into spot prices. Once the short-run bottleneck eases, however, prices revert in line with the other groups, producing a clearly

Figure 6: Responses of critical mineral prices to shortage shocks by category



Note: The figure shows cumulative price responses to a one-standard-deviation shortage shock, estimated separately for four mineral groups using the panel LP model. Panel (a): electric-vehicle and battery minerals. Panel (b): rare minerals. Panel (c): refractory minerals. Panel (d): industrial minerals. The solid line represents point estimates, and the dark and light shaded regions indicate 68% and 90% confidence intervals based on cluster-robust standard errors clustered at the mineral level and month.

hump-shaped profile.

Figure 6(d) shows that industrial minerals display the mildest and most transient response. Prices rise quickly to about 2.3% within the first year, with a noticeable two-stage hump around months six and eighteen, before mean-reverting steadily toward zero by the end of the second year and moving slightly negative thereafter. The peak is the smallest among the four groups and the reversion is the fastest, so that the response becomes statistically insignificant at horizons beyond roughly two years. This weaker and faster-decaying profile is consistent with the central role of industrial metals in global manufacturing and construction networks, where the combination of deep liquidity, active futures markets, more elastic short-run supply responses, and greater scope for substitution and recycling allows initial price spikes to be rapidly arbitrated away. Taken together, the four panels suggest economically meaningful heterogeneity in shortage sensitivity across

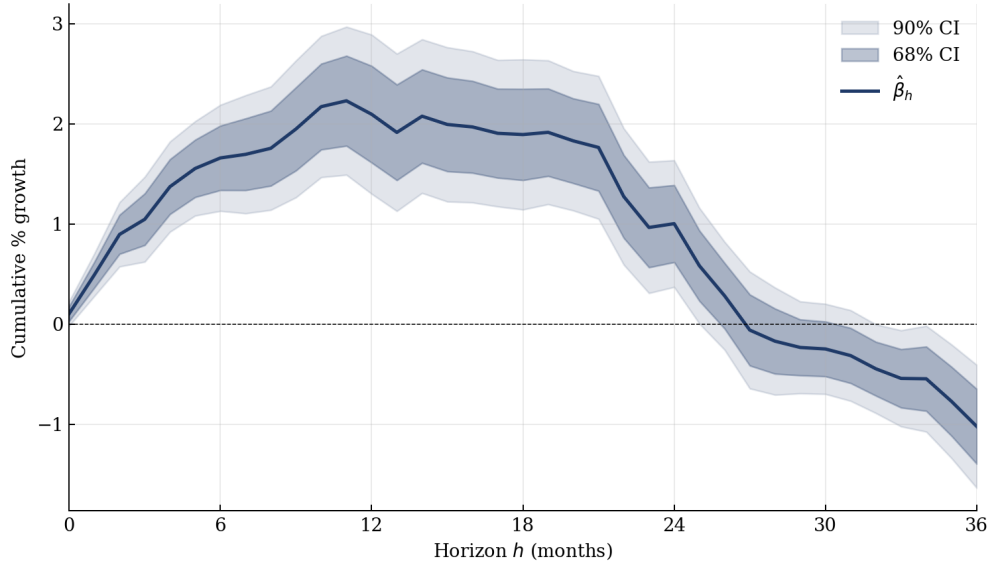
mineral categories. Electric-vehicle and battery minerals display the largest and most persistent response, rare and refractory minerals adjust more slowly, and industrial minerals exhibit the mildest and most transitory response. Therefore, the findings suggest that resilience policies may need to account for differences in market structure, end-use exposure, and adjustment speed across mineral groups.

5 Additional Analyses

The baseline results and their extensions rest on a number of specification choices, most notably the lag length used to control for the dynamic structure of mineral prices and the particular measure employed to capture supply-side disruptions. If the estimated impulse responses were sensitive to these choices, the economic interpretation developed in the preceding sections would be called into question. We address this concern through three additional exercises. First, we re-estimate the full-panel local projections model using six rather than twelve lags for all dynamic components, including the dependent variable, the shock, and the control variables. This check tests whether the baseline results depend on the relatively rich lag structure adopted in the main specification. Second, we replace the text-based shortage index of [Caldara et al. \(2025\)](#) with the Global Supply Chain Pressure Index (GSCPI) developed by the Federal Reserve Bank of New York ([Benigno et al., 2022](#)) and repeat the entire estimation procedure. This check tests whether the results are driven by the particular proxy used to measure supply-side disruptions, or whether they generalize to an independently constructed indicator that captures a different dimension of supply-chain stress, namely, transportation costs, delivery times, and backlogs rather than newspaper-based shortage mentions. Third, we re-estimate the baseline model using the global producer price index in place of the consumer price index as the general-price variable, to verify that the response does not depend on which broad price measure is used to condition the structural shock.

Figure 7 presents the cumulative impulse response when the lag length is reduced from 12 to 6 months. The pooled response for all 31 minerals remains qualitatively unchanged: prices rise following a shortage shock, display a clear positive hump, and gradually normalize at longer horizons. The peak is somewhat smaller and the decay is slightly faster than in the baseline, consistent with the shorter lag structure providing less control for persistent dynamics and thereby attenuating the estimated medium-run response. Crucially, however, the key finding is intact: shortage shocks exert persistent upward pressure on critical mineral prices that remains statistically significant well beyond the one-year horizon. The fact that neither the sign, the shape, nor the statistical

Figure 7: Responses of all critical mineral prices to shortage shocks with a shorter lag specification



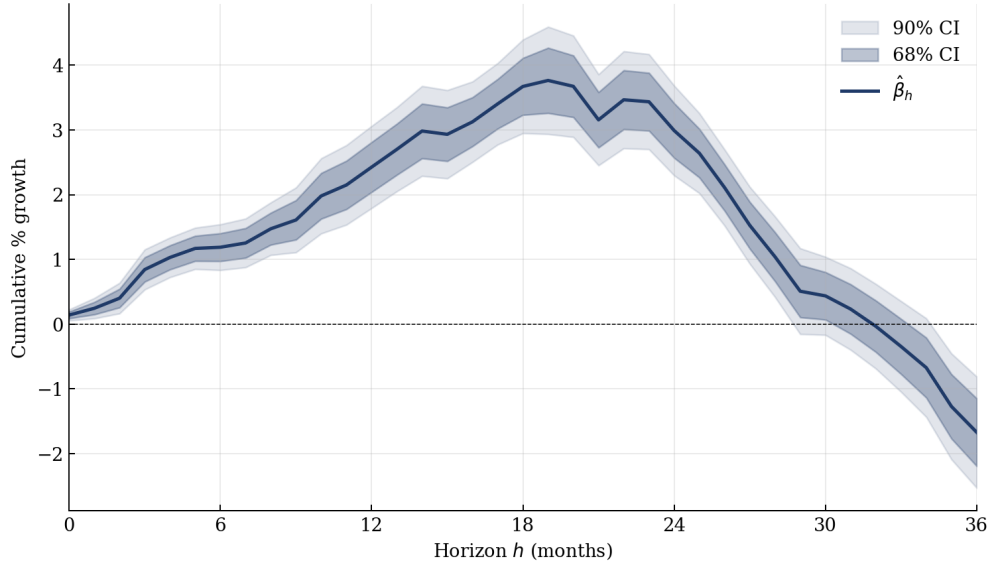
Note: The figure shows cumulative price responses of all critical minerals to a one-standard-deviation shortage shock with six lags, estimated using the panel LP model. The solid line represents point estimates of the responses, and the dark and light shaded regions indicate 68% and 90% confidence intervals, respectively.

significance of the response changes materially when six lags replace twelve indicates that the baseline finding is not an artifact of a relatively rich dynamic specification. The persistence of the result under a narrower lag structure strengthens confidence in the empirical design and suggests that the core price dynamics are captured even with a more parsimonious model.¹²

Figure 8 presents the cumulative impulse response when the shortage index is replaced with the GSCPI. The pooled mineral price response rises gradually and builds over a longer horizon than in the baseline, reaching a peak of 3.77% at $h = 19$ before declining and eventually crossing into slightly negative territory around $h = 30$. Relative to

¹²To be more specific about the sensitivity of the peak response to the lag structure, Table A.2 re-estimates the full-panel response across lag lengths from three to twenty-four months. The peak rises smoothly with L up to the baseline of twelve months and then declines as the specification becomes heavily parameterized. Over the range that brackets the baseline, the peak increases from 2.23% at six lags to 2.85% at twelve, an increase of about 28%, corresponding to an arc elasticity of the peak with respect to the lag length of roughly 0.37. Adding lags up to twelve raises the peak because it more fully absorbs the persistent own-dynamics of mineral prices, attenuating the omitted-lag bias that arises in the overlapping-horizon regression; beyond twelve lags the projection becomes over-parameterized, at twenty-four lags it includes one hundred and twenty right-hand-side terms, and the peak estimate loses precision. Importantly, the horizon of the peak (≈ 11 months) and the sign, shape, and significance of the response are invariant to L ; only the amplitude moves, and modestly.

Figure 8: Responses of all critical mineral prices to shortage shocks with an alternative supply-stress proxy



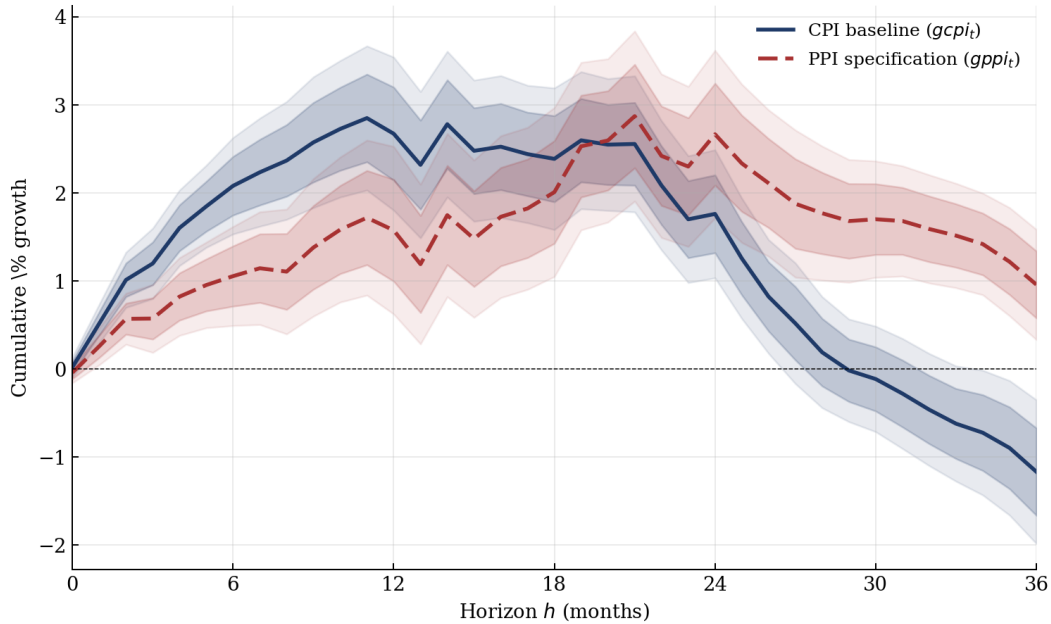
Note: The figure shows cumulative price responses of all critical minerals to a one-standard-deviation global supply chain pressure shock, identified from a per-mineral SVAR with the GSCPI ordered first in place of the shortage index. The solid line represents point estimates of the responses, and the dark and light shaded regions indicate 68% and 90% confidence intervals, respectively.

the baseline specification, the response is both larger in amplitude, peaking roughly 0.9 percentage points higher, and notably more back-loaded, with the peak arriving about eight months later. This timing pattern is economically intuitive. The baseline shortage index is an information-based measure of shortage conditions. It captures shortage narratives, bottleneck concerns, policy news, and precautionary market behavior that can be incorporated rapidly into mineral prices. By contrast, the GSCPI is a hard-data measure of global supply-chain pressure, based on observable logistics and manufacturing constraints such as transportation costs, supplier delivery times, and backlogs. These pressures are less mineral-specific and are likely to pass through more gradually as shipping delays, processing bottlenecks, and downstream production constraints accumulate along the supply chain. This distinction helps explain why the baseline shortage-index response peaks earlier, while the GSCPI response is larger and more back-loaded.

The two proxies therefore identify related but distinct economic mechanisms. Shortage news can affect prices through expectations, precautionary inventory accumulation, and concerns about future availability, especially for minerals exposed to export restrictions or thin spot markets. GSCPI shocks instead capture realized system-wide disruptions in logistics and production networks. The fact that both measures generate pos-

itive, hump-shaped, and persistent price responses strengthens the central conclusion that supply-side stress matters for critical-mineral prices, while the difference in timing suggests that information-based shortage signals and realized supply-chain constraints propagate through mineral markets at different speeds.

Figure 9: Responses of all critical mineral prices to shortage shocks under CPI versus PPI as the general-price variable



Note: The figure overlays the full-panel cumulative price response to a one-standard-deviation shortage shock under the baseline specification, which uses the global consumer price index $gcpi_t$ as the general-price variable (solid, navy), and under the alternative specification that replaces it with the global producer price index $gppi_t$ in both the SVAR ordering and the control set (dashed, red). For each specification the darker and lighter shaded regions denote the 68% and 90% confidence intervals, based on standard errors clustered at the mineral level and month.

Finally, we check that the results are not sensitive to the broad price measure used to condition the structural shock. We replace the global consumer price index with the global producer price index ($gppi_t$) as the general-price variable, both in the SVAR that generates the conditional structural residuals and in the local-projection control set; producer prices are arguably a more natural proxy for the upstream input-cost pressures that co-move with mineral prices. As shown in Figure 9, the peak response is essentially unchanged: it reaches 2.87% under the producer-price specification, against 2.85% in the baseline, and the two identified shock series have a within-mineral correlation of 0.96. The response retains its positive, hump-shaped, and persistent shape, with the only difference being that it builds somewhat more gradually and peaks later. The peak magnitude is therefore robust to using producer rather than consumer prices.

6 Discussion: Implications for GCC Economies

The preceding sections have documented the dynamic price response of critical minerals to shortage shocks and have shown that this response is amplified for minerals with concentrated supply structures. A natural question is how these findings translate into exposure for economies that are not themselves major producers of the minerals in our sample but whose industrial and diversification strategies are increasingly mineral-intensive. The six Gulf Cooperation Council economies, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates, offer a particularly informative setting. Although the region is a major exporter of primary aluminum, it is a net importer of nearly all other minerals in our sample. At the same time, the ongoing industrial-diversification programs across the region, including expanding electric-vehicle manufacturing, renewable-energy infrastructure, and downstream metals processing, are raising the demand for critical minerals as production inputs. This section quantifies the extent to which GCC economies are exposed to the shortage-shock dynamics documented in the preceding analysis through their critical-mineral import structure.

6.1 Mineral Import Exposure Index

We translate the estimated price responses into an illustrative first-round import-exposure measure for each GCC economy. The construction combines two inputs: the composition of each country’s critical-mineral import basket, drawn from UN Comtrade, and the group-level peak responses estimated in Section 4.4. The resulting index is designed to show how a common global shortage shock would mechanically affect the mineral import bill given each country’s trade structure. It should therefore be interpreted as a measure of direct import-cost exposure rather than as a full estimate of pass-through to aggregate inflation or output.

For each of the 31 minerals in our sample, we identify the corresponding six-digit Harmonized System (HS) codes under the 2022 nomenclature maintained by the World Customs Organization and used by the UN Comtrade database. Each code is selected to match the dominant commercially traded form of the mineral, and the full mapping is documented in Table C.1 of the appendix.¹³

For each GCC country c and each year t from 2009 to 2023, we collect annual import

¹³Three HS codes bundle multiple minerals because the internationally binding HS-6 classification does not distinguish between them: code 811292 covers both gallium and germanium in their unwrought forms, code 284690 covers the full set of rare-earth compounds including neodymium and terbium oxides, and code 810411 covers both magnesium and magnesium ingot in our mineral set. For all other minerals, each HS code corresponds uniquely to one sample mineral.

values under each of the HS codes in our mapping from UN Comtrade, annual total merchandise imports from the same database, and nominal gross domestic product in current U.S. dollars from the IMF World Economic Outlook. Letting $\mathcal{H}$ denote the set of unique HS codes in our mineral map and $\text{Imports}_{c,h,t}$ the country’s imports under HS code h in year t , the within-basket weight of HS code h in country c ’s mineral-import basket is

$$w_{c,h,t} = \frac{\text{Imports}_{c,h,t}}{\sum_{h' \in \mathcal{H}} \text{Imports}_{c,h',t}}. \quad (12)$$

We attach to each HS code h a peak price response equal to the simple average of the group-level peak responses estimated in Section 4.4 across the minerals that map to that code,

$$\hat{R}_h = \frac{1}{|\mathcal{M}_h|} \sum_{m \in \mathcal{M}_h} \hat{R}_{g(m)}^{\text{peak}}, \quad (13)$$

where $\mathcal{M}_h$ is the set of minerals mapped to HS code h and $\hat{R}_{g(m)}^{\text{peak}}$ is the peak cumulative response for the group that mineral m belongs to, namely 4.86% for the electric-vehicle and battery group, 3.39% for rare minerals, 2.40% for refractory minerals, and 2.26% for industrial minerals. The country-specific weighted peak response is then

$$\hat{R}_{c,t} = \sum_{h \in \mathcal{H}} w_{c,h,t} \cdot \hat{R}_h. \quad (14)$$

The quantity $\hat{R}_{c,t}$ has a direct economic interpretation: it is the country-specific first-round semi-elasticity of the mineral import bill with respect to a one-standard-deviation global shortage shock, holding import quantities fixed and evaluated at each category’s peak horizon. A country whose import basket is tilted toward mineral categories with larger estimated price responses will exhibit a larger $\hat{R}_{c,t}$, indicating that a given shortage shock translates into a proportionally larger rise in import costs for that country. In this sense, $\hat{R}_{c,t}$ serves as a summary statistic for the implied cost-push channel through which global shortage shocks reach GCC economies via their critical-mineral trade structure. We report country-level averages of this weighted peak response, together with the absolute scale of critical-mineral imports and their share of total imports and GDP, in Table 2, averaged over the 2018–2023 window.¹⁴

¹⁴We chose 2018–2023 because pre-2018 trade patterns predate the electric-vehicle and battery manufacturing build-outs in the GCC, and because 2024–2025 Comtrade data remain incomplete at the time of writing due to reporting lags. The ranking of GCC countries by exposure is robust to alternative windows within the 2013–2023 range.

Table 2: Mineral-import exposure of GCC economies (2018–2023 averages)

Country	Mineral imports (USD bn)	% of total imports	% of GDP	Weighted peak response (%)
Saudi Arabia	1.13	0.69	0.112	2.31
UAE	3.95	1.20	0.881	2.48
Qatar	0.10	0.33	0.052	3.82
Kuwait	0.18	0.36	0.127	2.39
Oman	0.21	0.69	0.226	2.34
Bahrain	0.21	1.26	0.483	2.87

Note: The table reports 2018–2023 averages of country-level mineral-import exposure measures constructed as described in Section 6.1. The first column gives the average annual value of critical-mineral imports across the 28 unique HS-6 codes in the mapping, in billions of U.S. dollars. The second and third columns express this value as a share of total merchandise imports and of nominal GDP, respectively. The fourth column reports the country-specific weighted peak response (Equation 14), computed as the import-share-weighted average of category-level peak responses from Section 4.4. Import data: UN Comtrade. GDP: IMF World Economic Outlook (variable NGDPD).

Table 3: Composition of GCC mineral imports by category (% of mineral imports, 2018–2023 sum)

Country	Industrial	EV/Battery	Rare	Refractory
Saudi Arabia	92.9	0.9	2.3	3.8
UAE	85.1	6.3	5.2	3.4
Qatar	28.6	56.4	9.9	5.2
Kuwait	89.9	0.4	3.9	5.9
Oman	87.0	1.2	3.1	8.7
Bahrain	73.9	23.4	0.8	1.9

Note: The table shows the share of each mineral category in total critical-mineral imports for the six GCC countries, averaged over the 2018–2023 window. Category assignment follows the grouping used in Section 4.4: Industrial (aluminum, copper, copper alloys, enameled wire, lead, magnesium, tin, zinc), EV/Battery (cobalt, electrolytic manganese, lithium carbonate, nickel, silicon, tellurium, vanadium pentoxide), Rare (antimony, gallium, germanium, neodymium oxide, silver, strontium, tantalum, terbium), and Refractory (chromium, mercury, molybdenum, niobium, titanium dioxide, tungsten, zircon sand).

Table 2 reports the weighted peak response alongside three scale measures of mineral-import exposure for the six GCC countries, and reveals substantial heterogeneity in the implied cost-push channel. Qatar exhibits the largest weighted peak response at 3.82%, above the 2.85% full-panel baseline peak documented in Section 4.1, followed by Bahrain at 2.87% and the United Arab Emirates at 2.48%. Saudi Arabia, Oman, and Kuwait cluster at the low end between 2.31% and 2.39%. The cross-country spread of approximately 1.5 percentage points in the implied cost-push elasticity is driven almost entirely by compositional differences across mineral categories: because the four mineral groups have mean-

ingfully different peak responses ranging from 2.26% for industrial minerals to 4.86% for electric-vehicle and battery minerals, a country's weighted peak response is effectively a summary of which categories dominate its import basket.¹⁵

Table 3 documents these compositional differences directly. Qatar's higher weighted peak response is associated with a mineral basket in which electric-vehicle and battery minerals account for 56.4% of imports, while Bahrain also has a relatively elevated share in this category at 23.4%. By contrast, industrial minerals account for between 85% and 93% of mineral imports in Saudi Arabia, the UAE, Kuwait, and Oman, which keeps their weighted peak responses closer to the industrial-group peak. The UAE remains the largest importer in absolute terms, but its basket is dominated by industrial metals and is therefore less sensitive to shortage shocks than the baskets of Qatar and Bahrain.¹⁶

These results should be interpreted as an indicative first-round import-cost channel rather than as a large economy-wide macro shock. The direct exposure of mineral imports remains modest relative to GDP across GCC economies, but the cross-country heterogeneity is still policy-relevant because it identifies where global shortage shocks are more likely to raise input costs for traded-input-intensive sectors and industrial diversification projects. The policy relevance therefore lies less in aggregate GDP arithmetic than in the resilience of manufacturing, metals, logistics, and energy-transition value chains. In country terms, the implications are differentiated. For Saudi Arabia, the results align most naturally with Vision 2030's push to make mining and mineral processing a strategic pillar of diversification.¹⁷ For the UAE, they fit Operation 300Bn and recent moves into selective critical-minerals processing alongside its aluminium base.¹⁸ For Oman, they complement Vision 2040 and current efforts to raise in-country value from

¹⁵Figure A.1 in the appendix plots the weighted peak response by year over 2009–2023. For four of the six economies it is essentially flat—Saudi Arabia, Oman, and Kuwait near 2.3% and the UAE near 2.5%—reflecting persistently industrial-dominated baskets. Qatar is the exception, rising from 2.5–3.3% before 2017 to a stable 3.7–3.9% from 2018 as electric-vehicle and battery minerals come to dominate its imports. The 2018–2023 window therefore characterizes each country's current basket; the cross-country ranking is stable from 2018 onward, so the conclusions are unaffected.

¹⁶To place these regional exposures in global perspective, Appendix Table A.3 reports the GCC's gross import footprint as a share of world exports for the same HS-6 mineral basket. Because import and export data may differ due to valuation, timing, and reporting conventions, and because GCC imports may include re-export activity, especially through regional trading hubs, the measure should be interpreted as a gross import footprint rather than as final domestic consumption. Across all categories, GCC imports account for 1.49% of world exports in 2023. The region is therefore not a dominant global price-setting importer in the aggregate. However, the shares are non-negligible in several categories, including EV/battery minerals (1.33%) and refractory minerals (1.53%). The rare-mineral share is higher at 3.55%.

¹⁷<https://www.vision2030.gov.sa/en/explore/strategies/strategy-for-the-mining-sector>.

¹⁸<https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/industry-science-and-technology/the-uae-industrial-strategy>; see also <https://gulfnews.com/business/markets/uae-and-us-sign-framework-to-secure-critical-minerals-supply> 500434334.

mineral resources.¹⁹ For Bahrain, they reinforce the logic of deepening the aluminium downstream ecosystem.²⁰ For Qatar, the main connection is to manufacturing resilience, strategic stocks, and diversified supply routes rather than to an explicit upstream critical-minerals strategy.²¹ For Kuwait, the most relevant implication is procurement and logistics resilience under New Kuwait 2035.²² Across all cases, diversified sourcing, long-term offtake arrangements, recycling, and efficiency gains are the most defensible tools, while strategic stockpiles are better reserved for low-volume, high-criticality inputs, and any genuine reduction in global concentration risk requires additional mining and refining capacity outside the dominant suppliers.

The remainder of this section turns from these real-sector and industrial-policy implications to the specific question raised by the GCC monetary-policy environment: how would an imported critical-mineral cost shock matter for central banks whose exchange-rate regimes constrain nominal exchange-rate adjustment and whose mandates emphasize financial and currency stability?

6.2 AI-led critical-mineral demand and central-bank policy relevance

The GCC exposure analysis is particularly relevant from a forward-looking perspective. Artificial intelligence and digital transformation have become important components of national diversification strategies across the region, including the UAE Strategy for Artificial Intelligence 2031 and related initiatives in Saudi Arabia, Qatar, Oman, Bahrain, and Kuwait.²³ These strategies support productivity, innovation, and the development of knowledge-based non-hydrocarbon sectors. Their implementation will also require greater investment in data centres, semiconductors, electricity networks, cooling systems, and energy storage, making the region's capital and intermediate-input requirements increasingly mineral-intensive.

AI infrastructure relies on copper, aluminium, silicon, gallium, rare-earth elements, and battery minerals, many of which are examined in this paper. Some of this demand will appear as direct mineral imports, and hence the 2018–2023 exposure estimates

¹⁹<https://www.spf.gov.om/wp-content/uploads/2025/08/OmanVision2040Report.pdf>.

²⁰<https://www.gdnonline.com/Details/1339438>.

²¹<https://qatar-smartmanufacturing.com/qatar-national-manufacturing-strategy>.

²²<https://www.mofa.gov.kw/en/pages/kuwait-vision-2035>.

²³See, for UAE, <https://u.ae/en/about-the-uae/digital-uae/digital-technology/artificial-intelligence/artificial-intelligence-in-government-policies>; for Saudi Arabia, <https://www.pif.gov.sa/en/news-and-insights/press-releases/2025/hrh-crown-prince-launches-humain-as-global-ai-powerhouse/>; for Qatar, <https://www.mcit.gov.qa/en/news/mcit-teams-up-with-microsoft-to-expand-cloud-data-centers-for-ai-innovation>; for Oman, <https://mtcit.gov.om/media-4/news-announcements-11/news-85/oman-ai-digital-future-program-20242026-171>.

should therefore be viewed as a baseline rather than as a fixed measure of future exposure. As AI-related investment expands, the scale of mineral-intensive imports may rise relative to total imports and GDP. The basket may also shift toward rare and battery minerals, which display comparatively large and persistent price responses in our estimates. Both developments would make critical-mineral supply shocks more economically important than suggested by current import shares.

A larger mineral-intensive import share would increase the relevance of pass-through to domestic inflation. Shortage shocks would initially raise import prices, capital-equipment costs, producer prices, and the cost of constructing and operating digital infrastructure. With robust non-hydrocarbon growth and sustained diversification-related investment, demand for these inputs may remain relatively firm, limiting adjustment through lower quantities or postponed projects. Firms may therefore pass a greater proportion of the cost increase into downstream prices. Under these conditions, an initially narrow relative-price shock may translate into a broader absolute increase in the domestic price level. The asymmetric responses documented in this paper strengthen this channel because mineral prices increase rapidly when shortages intensify but decline only gradually when supply conditions improve. Repeated shocks could consequently generate more persistent inflation pressures. The present analysis does not estimate this downstream pass-through, however, and these implications should be interpreted as forward-looking channels for inflation dynamics rather than as quantified effects on GCC inflation.

The GCC exchange-rate regimes shape the available central-bank response. Five GCC currencies are pegged to the U.S. dollar, while Kuwait maintains a peg to an undisclosed currency basket. These arrangements provide a credible nominal anchor but limit the scope for an independent monetary-policy response under open capital accounts.²⁴ For dollar-invoiced mineral imports, the bilateral nominal exchange rate cannot adjust independently to cushion the increase in international prices, while domestic policy rates must remain broadly consistent with the exchange-rate anchor. The monetary response would therefore be concentrated primarily on effective liquidity management and the preservation of strong reserve buffers. Liquidity operations can maintain orderly money-market conditions, keep short-term rates aligned with the prevailing policy stance, and prevent temporary funding pressures from being amplified through the banking system.

The financial-stability implications would also become more relevant as AI-related and mineral-intensive investment expands. Persistent input-cost increases could raise

²⁴International Monetary Fund, *Strengthening Liquidity Management Frameworks in Support of Stability and Growth in the GCC*, 2017, <https://www.imf.org/en/publications/policy-papers/issues/2017/12/14/pp121417gcc-liquidity-management-frameworks>.

project costs and working-capital requirements, compress corporate cash flows, and affect the debt-servicing capacity of firms in data-centre construction, electricity infrastructure, advanced manufacturing, and related sectors. Incorporating mineral-price scenarios into inflation forecasting, macro-financial surveillance, and stress-testing frameworks would therefore support the early identification of potential vulnerabilities.

In the absence of independent nominal exchange-rate adjustment, more of the medium-term adjustment would occur through domestic prices, margins, productivity, and quantities. If mineral-related cost increases pass through to domestic prices more strongly than in trading-partner economies, the resulting inflation differential might place upward pressure on the real effective exchange rate. Given sustained domestic investment momentum, real appreciation may therefore become a more important adjustment channel. This adjustment can be supported by complementary structural and industrial measures, including diversified sourcing, long-term offtake arrangements, regional procurement cooperation, targeted inventories of highly critical inputs, and selective investment in domestic or partner-country processing capacity. Integrating these considerations into the implementation of AI and diversification strategies would strengthen supply-chain resilience.

7 Conclusion

This paper examines how supply chain shortage shocks propagate into the prices of 31 critical minerals over the period June 2009 to January 2026, using a two-stage empirical strategy that combines mineral-level structural vector autoregressions with panel local projections. The baseline results establish that a one-standard-deviation shortage shock generates a positive, hump-shaped, and persistent cumulative price response, peaking at approximately 2.9 percent around eleven months before gradually reverting toward zero. Heterogeneity across mineral categories is substantial: electric-vehicle and battery minerals exhibit the largest peak response, while industrial minerals display the mildest and most transient reaction. The analysis uncovers pronounced rockets-and-feathers dynamics: positive shortage shocks produce a rapid, large, and durable price increase that reaches 3.8 percent at six months and continues building to 5.9 percent by two years, whereas negative shocks of equal magnitude produce no measurable price decline over the same horizons, and the null of symmetric adjustment is rejected at conventional levels over the short and medium run. The supply-concentration analysis shows that minerals with above-median Herfindahl–Hirschman Index values exhibit a one-year cumulative response of 3.2 percent, compared with 2.1 percent for diversified minerals, and a con-

tinuous interaction specification confirms that raising HHI from 0.15 to 0.85 increases the implied one-year response by roughly 1.7 percentage points, establishing that geographic production concentration amplifies vulnerability to shortage-induced price pressures. All baseline findings are robust to halving the lag length and to replacing the text-based shortage index with the Global Supply Chain Pressure Index.

The GCC application provides a complementary interpretation of the main results. The exercise reveals meaningful heterogeneity across the region: some economies have mineral-import baskets dominated by industrial metals and thus transmit shortage shocks close to the full-panel baseline, while others have baskets tilted toward electric-vehicle and battery minerals and therefore absorb shocks through the most shock-sensitive category in our estimates. Direct exposure remains modest relative to GDP in every GCC economy, but the cross-country variation is policy-relevant because it identifies where shortage shocks are more likely to raise input costs for traded-input-intensive sectors and for industrial diversification projects that are increasingly mineral-intensive. The pattern of recent GCC upstream mineral investments, downstream processing capacity additions, and bilateral and multilateral partnerships on critical-mineral security is broadly consistent with the channels the exposure measure highlights, which suggests that the region's accelerating mineral strategy might moderate the cost-push channel documented in this paper.

The findings carry several policy implications. First, the persistent and asymmetric nature of shortage-driven price increases suggests that reactive policy responses, such as emergency stockpile releases or ad hoc export negotiations, are unlikely to be sufficient on their own, because prices rise faster and more sharply than they fall when conditions ease. Policymakers seeking to stabilize input costs for the energy transition should therefore prioritize structural measures that reduce the probability and severity of shortage episodes in the first place, including diversification of refining capacity, long-term offtake agreements with multiple supplier countries, and investment in recycling and secondary recovery infrastructure. Second, the finding that supply concentration amplifies the price response to shortage shocks provides empirical support for ongoing international efforts to develop more diversified and resilient critical-mineral supply chains. The results suggest that reducing geographic concentration could lower vulnerability to shortage-induced price pressures, although the quantitative effect of specific diversification policies would require a separate structural analysis.

Several avenues for future research emerge from this study. First, the analysis could be extended to incorporate downstream transmission channels by linking mineral price responses to manufacturing input costs, consumer price indices, and equity valuations

of mineral-intensive industries, which would quantify the broader macroeconomic footprint of shortage shocks. Second, the current framework treats all shortage shocks as homogeneous in origin; future work could decompose the shortage index into sector-specific components, such as energy, logistics, and labor shortages, to identify which type of disruption is most consequential for critical mineral pricing. Third, as longer time series become available for minerals that have only recently gained strategic importance, such as gallium, germanium, and rare earth oxides, re-estimating the model with an expanded sample would improve the precision of group-specific estimates and allow for richer nonlinear specifications. Finally, incorporating trade policy event studies into the local projections framework would help disentangle the extent to which shortage shocks reflect physical supply constraints export restrictions by major producing countries.

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APPENDIX

A Supplementary Tables and Figures

Table A.1: Descriptive statistics of monthly returns for 31 critical minerals

Mineral	Mean	Std. Dev.	Min	Max	Obs.
<i>Panel A: Electric-vehicle and battery minerals</i>					
Cobalt	0.15	16.32	−96.92	84.41	199
Electrolytic Manganese	0.13	17.34	−102.46	96.19	199
Lithium Carbonate	0.59	25.27	−117.61	143.46	199
Nickel Plate	0.04	11.86	−46.50	53.37	199
Silicon	−0.02	15.28	−63.32	135.84	199
Tellurium	−0.21	16.13	−84.73	115.11	199
Vanadium Pentoxide	−0.13	19.98	−110.82	123.88	199
<i>Panel B: Rare minerals</i>					
Antimony	0.64	13.38	−62.73	57.54	199
Gallium	−0.29	14.53	−64.96	50.34	199
Germanium	0.63	11.14	−59.19	62.02	199
Neodymium Oxide	0.95	21.45	−82.18	126.35	199
Silver 99% Purity	0.83	13.05	−69.91	72.15	199
Strontium	0.08	13.66	−95.40	103.73	199
Tantalum	0.29	10.80	−74.65	55.41	199
Terbium	0.56	23.86	−147.72	158.67	199
<i>Panel C: Refractory minerals</i>					
Chromium	0.06	9.29	−39.95	40.15	199
Mercury	1.12	15.79	−57.70	81.58	199
Molybdenum Concentrate	0.29	13.34	−50.64	61.43	199
Niobium Pentoxide	0.17	10.52	−40.91	47.40	199
Titanium Dioxide	0.02	7.93	−44.81	38.77	199
Tungsten	0.86	14.14	−92.55	64.94	199
Zircon Sand	0.20	12.29	−55.16	57.21	199
<i>Panel D: Industrial minerals</i>					
Aluminum	0.23	7.37	−26.50	40.11	199
Copper	0.36	8.49	−33.72	25.47	199
Copper Alloy	0.37	7.99	−30.92	26.50	199
Enameled Wire	0.33	7.86	−30.36	24.18	199
Lead	0.04	5.63	−29.16	21.62	199
Magnesium	0.03	15.99	−104.93	118.31	199
Magnesium Ingot	−0.04	16.91	−114.75	125.89	199
Tin	0.56	12.26	−69.18	63.72	199
Zinc	0.20	8.89	−40.75	32.71	199
<i>Group-level pooled statistics</i>					
Electric-vehicle and battery	0.08	17.85	−117.61	143.46	1,393
Rare minerals	0.46	15.85	−147.72	158.67	1,592
Refractory minerals	0.39	12.16	−92.55	81.58	1,393
Industrial minerals	0.23	10.80	−114.75	125.89	1,791
Full panel	0.29	14.28	−147.72	158.67	6,169

Note: The table reports descriptive statistics of monthly log-price returns for the 31 critical minerals in the sample, computed as $100 \times \Delta \ln p_{i,t}$ and expressed in percentage points. The sample period runs from June 2009 to January 2026. Panels A–D report per-mineral statistics grouped by category as defined in Section 4.4. Group-level pooled statistics aggregate returns within each category, and the full-panel row aggregates across all 31 minerals. The per-mineral observation count of 199 reflects the 200-month sample with one observation lost to first-differencing. Price data: Bloomberg.

Table A.2: Sensitivity of the peak price response to the local-projection lag length

Lag length L	Peak response (%)	Peak horizon	12-month response (%)	Obs.
3	2.15	11	2.03	5,394
6	2.23	11	2.09	5,301
9	2.68	11	2.55	5,208
12	2.85	11	2.67	5,115
24	2.35	11	2.01	4,743

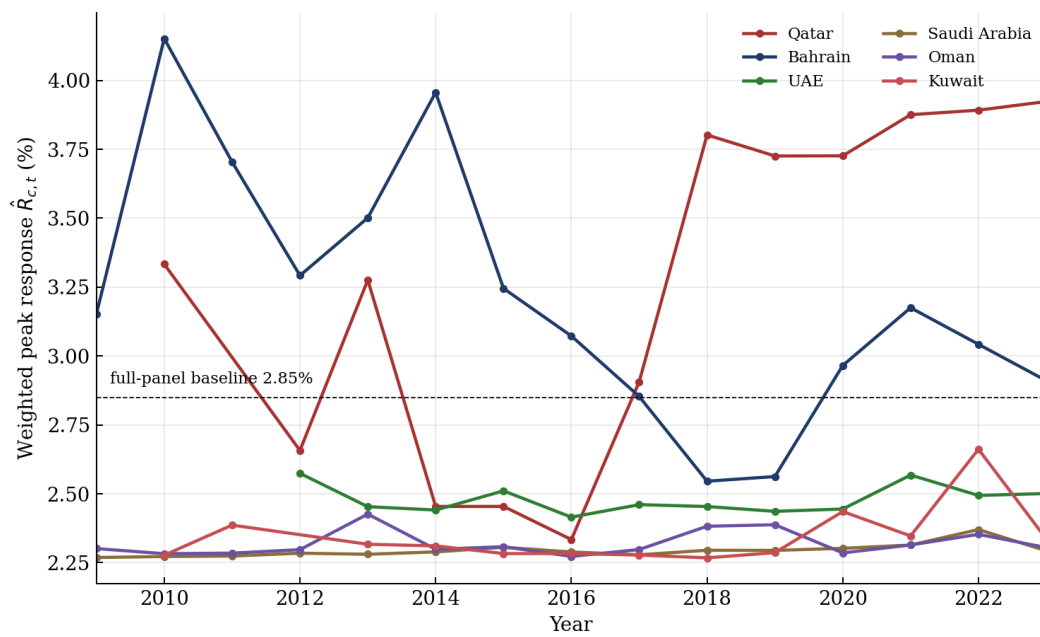
Note: The table reports the sensitivity of the full-panel cumulative price response to a one-standard-deviation shortage shock as the local-projection lag length L varies from three to twenty-four months. Each row re-estimates the baseline specification of equation (5) with L lags of the dependent variable, the shock, and the controls, holding the first-stage SVAR shock fixed. “Peak response” is the maximum cumulative response $\max_h \hat{\beta}_h$ over horizons $h = 0, \dots, 36$; “Peak horizon” is the horizon at which it occurs; “12-month response” is $\hat{\beta}_{12}$. The peak rises with L up to the baseline of twelve months from 2.23% at six lags to 2.85% at twelve, an increase of about 28% (an arc elasticity of the peak with respect to L of roughly 0.37) and declines at longer lag lengths as the specification becomes heavily parameterized, with up to 120 right-hand-side terms at $L = 24$. The horizon of the peak (≈ 11 months) is essentially invariant to L . The observation count falls as L increases because additional initial observations are lost to lagging; the qualitative pattern is unchanged when all specifications are estimated on the common sample available at $L = 24$.

Table A.3: GCC share of global critical-mineral trade by category (2023)

Category	World exports (USD bn)	GCC imports (USD m)	GCC share of world exports (%)
Industrial	114.4	1,113	0.97
EV/Battery	19.8	264	1.33
Rare	29.5	1,048	3.55
Refractory	23.2	355	1.53
All categories	186.9	2,780	1.49

Note: The table reports the GCC’s gross import footprint in global critical-mineral trade in 2023, using the same HS-6 mineral basket and category assignment as in Table C.1. World exports are total reported exports by all reporting economies under the relevant HS-6 codes. GCC imports are the sum of reported imports by Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates under the same HS-6 codes. The GCC share is computed as $100 \times$ GCC imports divided by world exports. HS codes that map to more than one sample mineral are counted once to avoid double-counting. Source: authors’ calculations using UN Comtrade.

Figure A.1: Evolution of GCC mineral-import exposure, 2009–2023



Note: The figure plots the country-specific weighted peak response $\hat{R}_{c,t}$ (Equation 14) by year; the dashed line marks the 2.85% full-panel baseline peak. The United Arab Emirates enters in 2012, and Kuwait and Qatar have occasional missing years, reflecting UN Comtrade reporting gaps. Import data: UN Comtrade.

B Mining versus Processing Concentration

The Herfindahl–Hirschman Index used in Section 4.3 is constructed at the supply-chain stage where availability is actually constrained for each mineral: mine-production shares for minerals whose scarcity is geological, and refining or separation shares for byproduct and processing-dominated metals. A natural question, however, is whether the amplification documented there binds at the mining stage or at the processing stage, because the two need not coincide. Cobalt is mined almost entirely in the Democratic Republic of the Congo but refined in China; rare earths are mined more dispersedly than they are separated; and gallium and germanium are recovered as byproducts of bauxite and zinc processing and therefore have no independent mine stage. This distinction is also of direct economic interest, since the policy episodes that dominate news-based shortage measures, China’s export-licensing actions on rare earths, gallium, and germanium, are constraints at the refining and separation stage rather than at the mine. This appendix separates the two stages, defines the corresponding concentration indices, and identifies which stage drives the dynamic price response.

B.1 Stage-specific concentration indices

For each mineral m we construct two indices that parallel the single index in equation (8) but are computed from stage-specific country shares,

$$HHI_m^{mine} = \sum_{c=1}^C (s_{c,m}^{mine})^2, \quad HHI_m^{proc} = \sum_{c=1}^C (s_{c,m}^{proc})^2, \quad (\text{B.1})$$

where $s_{c,m}^{mine}$ is country c ’s share of global *mine* production of mineral m and $s_{c,m}^{proc}$ is its share of global *processing* output, that is, refining, separation, or smelting. Mine-stage shares are taken from the U.S. Geological Survey Mineral Commodity Summaries 2025; processing-stage shares are taken from U.S. Geological Survey Fact Sheet 2025–3038 and the International Energy Agency *Global Critical Minerals Outlook 2025*. For the two byproduct metals in the subsample (gallium and germanium), which have no independent extraction stage, HHI_m^{mine} is proxied by the mine-stage index of the host ore (bauxite for gallium, zinc for germanium), which inherits the geographic concentration of upstream extraction.

The processing wedge is the difference between the two indices,

$$\Delta_m = HHI_m^{proc} - HHI_m^{mine}, \quad (\text{B.2})$$

which measures the extent to which production becomes more concentrated as a mineral moves downstream from extraction to processing. The mine-stage index in equation (B.1) is available for all 31 minerals, but published processing-stage shares cover only a subset, and the decomposition is informative only for minerals whose mining and processing concentration genuinely diverge. We therefore restrict the analysis to the 14 minerals for which a country-level distribution is available at both stages and treat it as a mechanism check on this subsample rather than a re-estimation of the full panel. The two indices and the underlying Chinese shares for these minerals are reported in Table B.1. The wedge is positive for thirteen of the fourteen minerals, processing is more concentrated than mining, and is largest for the byproduct and rare-earth metals that feature in recent export-control episodes.

Table B.1: Mining- versus processing-stage concentration for the wedge subsample

Mineral	Mine stage		Processing stage	
	HHI_m^{mine}	China sh.	HHI_m^{proc}	China sh.
Gallium	0.170	0.18	0.974	0.99
Magnesium Ingot	0.370	0.59	0.795	0.89
Magnesium	0.370	0.59	0.795	0.89
Terbium	0.502	0.69	0.880	0.95
Neodymium Oxide	0.502	0.69	0.830	0.90
Germanium	0.186	0.33	0.482	0.68
Titanium Dioxide	0.202	0.34	0.490	0.69
Lithium Carbonate	0.223	0.17	0.470	0.65
Aluminum	0.170	0.18	0.385	0.59
Tin	0.137	0.23	0.290	0.50
Copper	0.132	0.08	0.210	0.44
Cobalt	0.591	0.01	0.650	0.80
Zinc	0.186	0.33	0.240	0.48
Nickel Plate	0.380	0.05	0.300	0.35

B.2 Specification

We extend the continuous-interaction local projection of equation (10) to admit both stages simultaneously. For each horizon $h = 0, 1, \dots, 36$ we estimate, on the 14-mineral subsample,

$$\begin{aligned}
y_{i,t+h} = & \alpha_{i,h} + \beta_h^{shk} \varepsilon_{i,t}^{sh} + \beta_h^{mine} \left(\varepsilon_{i,t}^{sh} \cdot HHI_i^{mine} \right) + \beta_h^{proc} \left(\varepsilon_{i,t}^{sh} \cdot HHI_i^{proc} \right) \\
& + \sum_{\ell=1}^{12} \phi_{h,\ell} \Delta p_{i,t-\ell} + \sum_{\ell=1}^{12} \gamma_{h,\ell} \varepsilon_{i,t-\ell}^{sh} + \sum_{\ell=1}^{12} \Theta_{h,\ell} W_{t-\ell} + u_{i,t+h},
\end{aligned} \tag{B.3}$$

where, as in the main text, $y_{i,t+h} = 100 \times (p_{i,t+h} - p_{i,t-1})$ is the cumulative percentage price change, $\hat{\varepsilon}_{i,t}^{sh}$ is the structural shortage shock, $W_{t-\ell} = (gecon_{t-\ell}, gcpi_{t-\ell}, tpu_{t-\ell})'$, and $\alpha_{i,h}$ are mineral fixed effects. The standalone level terms HHI_i^{mine} and HHI_i^{proc} are time-invariant within mineral and are absorbed by $\alpha_{i,h}$. The coefficient β_h^{shk} is the response at a hypothetical mineral with zero concentration at both stages, while β_h^{mine} and β_h^{proc} measure the marginal amplification of the shortage response per unit of mine- and processing-stage concentration, respectively. The marginal effect of a shortage shock for a mineral with concentration $(HHI_i^{mine}, HHI_i^{proc})$ is

$$\frac{\partial y_{i,t+h}}{\partial \hat{\varepsilon}_{i,t}^{sh}} = \hat{\beta}_h^{shk} + \hat{\beta}_h^{mine} HHI_i^{mine} + \hat{\beta}_h^{proc} HHI_i^{proc}. \quad (\text{B.4})$$

Because the two indices are positively correlated across minerals ($\rho = 0.55$), equation (B.3) does not cleanly separate β_h^{mine} from β_h^{proc} , and we therefore also estimate an equivalent reparametrization that isolates the processing contribution. Replacing the processing index with the wedge Δ_i from equation (B.2) gives

$$\begin{aligned} y_{i,t+h} = & \alpha_{i,h} + \beta_h^{shk} \hat{\varepsilon}_{i,t}^{sh} + \tilde{\beta}_h^{mine} (\hat{\varepsilon}_{i,t}^{sh} \cdot HHI_i^{mine}) + \beta_h^{wedge} (\hat{\varepsilon}_{i,t}^{sh} \cdot \Delta_i) \\ & + \sum_{\ell=1}^{12} \phi_{h,\ell} \Delta p_{i,t-\ell} + \sum_{\ell=1}^{12} \gamma_{h,\ell} \hat{\varepsilon}_{i,t-\ell}^{sh} + \sum_{\ell=1}^{12} \Theta_{h,\ell} W_{t-\ell} + u_{i,t+h}. \end{aligned} \quad (\text{B.5})$$

Substituting $\Delta_i = HHI_i^{proc} - HHI_i^{mine}$ into equation (B.5) and collecting terms shows that the two specifications are algebraically equivalent, with

$$\beta_h^{wedge} = \beta_h^{proc}, \quad \tilde{\beta}_h^{mine} = \beta_h^{mine} + \beta_h^{proc}. \quad (\text{B.6})$$

The wedge coefficient β_h^{wedge} therefore equals the processing-stage coefficient from equation (B.3), but it admits a sharper interpretation: it is the additional amplification of the shortage response generated by the concentration that a mineral acquires beyond its mining stage, holding mine concentration fixed. Because Δ_i is, by construction, the component of processing concentration that is orthogonal to the level of mine concentration, equation (B.5) is the better-identified of the two and is the specification we test directly.

B.3 Inference

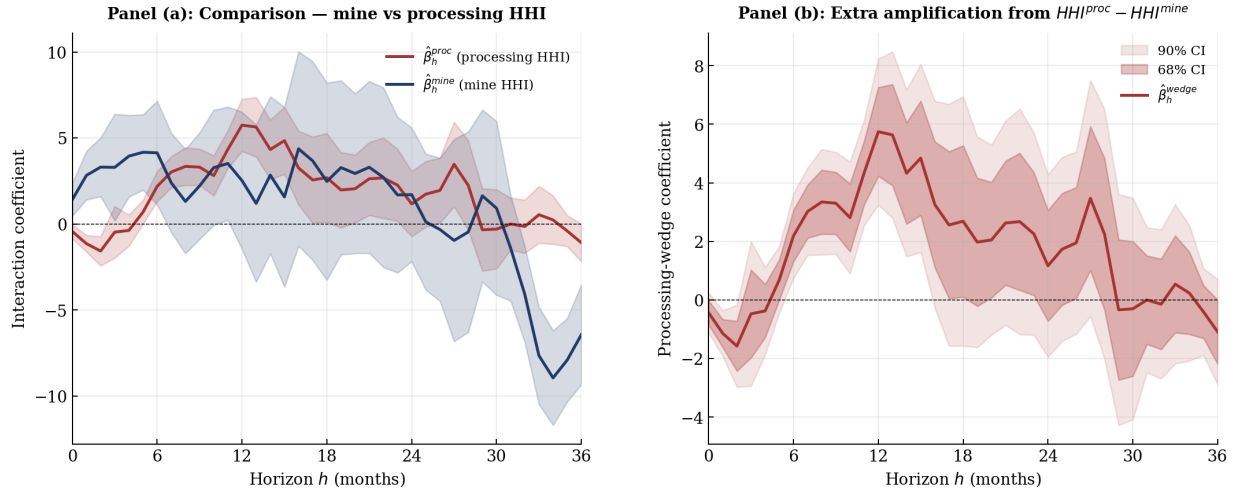
The subsample contains 14 minerals and therefore 14 clusters, a setting in which conventional cluster-robust standard errors are unreliable. We assess the wedge coefficient

β_h^{wedge} using a restricted wild-cluster bootstrap. We first estimate equation (B.5) under the null $H_0 : \beta_h^{wedge} = 0$, that is, omitting the wedge interaction, and retain the restricted residuals $\tilde{u}_{i,t+h}$ and fitted values $\hat{y}_{i,t+h}^0$. For each bootstrap replication $b = 1, \dots, B$ we draw a Rademacher weight $\nu_g^{(b)} \in \{-1, +1\}$ for each mineral (cluster) g , construct the pseudo-outcome $y_{i,t+h}^{*(b)} = \hat{y}_{i,t+h}^0 + \nu_{g(i)}^{(b)} \tilde{u}_{i,t+h}$, re-estimate the unrestricted model, and compute the cluster-robust t -statistic on β_h^{wedge} . The bootstrap p -value is the share of replications for which $|t^{*(b)}| \geq |t^{obs}|$. We use $B = 999$ replications with weights drawn at the mineral level, so that the resampling preserves the within-mineral dependence structure of the local-projection residuals.

B.4 Results

Figure B.1 reports the estimates. Panel (a) plots the two interaction coefficients from equation (B.3). Over horizons of roughly six to fifteen months, the processing-stage coefficient $\hat{\beta}_h^{proc}$ is positive and statistically significant, peaking near 5.7 percentage points per unit of the index at the one-year horizon, whereas the mine-stage coefficient $\hat{\beta}_h^{mine}$ is insignificant throughout this window. Panel (b) plots the processing-wedge coefficient $\hat{\beta}_h^{wedge}$ from equation (B.5): the additional amplification carried by the wedge is positive and significant under the wild-cluster bootstrap, with $p \approx 0.007$ at twelve months and $p \approx 0.04$ at six months, before fading beyond about eighteen months. The mine-stage coefficient attains significance only at the longest horizons, where it turns negative, reflecting the stronger long-run mean reversion of concentrated-supply minerals documented in Section 4.3 rather than contemporaneous amplification. Taken together, the decomposition shows that, for the policy-exposed minerals in this subsample, it is processing concentration rather than mine concentration that drives the dynamic amplification of shortage shocks. This is consistent with the front-loaded response to the news-based shortage measure relative to the more back-loaded response to the Global Supply Chain Pressure Index documented in Section 5, since the news-based measure loads on processing-stage announcements that are priced in rapidly.

Figure B.1: Mining versus processing concentration



Note: Panel (a) plots the mine- and processing-stage interaction coefficients, $\hat{\beta}_h^{mine}$ and $\hat{\beta}_h^{proc}$, from equation (B.3), which enters both $\hat{\varepsilon}_{i,t}^{sh} \cdot HHI_i^{mine}$ and $\hat{\varepsilon}_{i,t}^{sh} \cdot HHI_i^{proc}$. Panel (b) plots the processing-wedge coefficient $\hat{\beta}_h^{wedge}$ on $\hat{\varepsilon}_{i,t}^{sh} \cdot (HHI_i^{proc} - HHI_i^{mine})$ from equation (B.5). Both specifications are estimated on the 14-mineral subsample for which mining- and processing-stage shares are both available, with mineral fixed effects, twelve lags, and standard errors clustered by mineral. The shaded regions indicate 68% and 90% confidence intervals.

C HS Code Mapping for Critical Minerals

Table C.1: Mapping from sample minerals to HS 2022 six-digit codes

Mineral	HS-6 code	Description of the HS-6 code
<i>Panel A: Electric-vehicle and battery minerals (Material)</i>		
Cobalt	810520	Cobalt mattes, unwrought cobalt, cobalt powders
Electrolytic Manganese	811100	Manganese and articles thereof
Lithium Carbonate	283691	Lithium carbonates
Nickel Plate	750210	Nickel, not alloyed, unwrought
Silicon	280469	Silicon, <99.99% purity (metallurgical grade)
Tellurium	280450	Boron and tellurium
Vanadium Pentoxide	282530	Vanadium oxides and hydroxides
<i>Panel B: Rare minerals</i>		
Antimony	811010	Unwrought antimony; antimony powders
Gallium	811292	Unwrought Ga, Ge, Nb, Re, V, Hf, In; powders; waste and scrap
Germanium	811292	Unwrought Ga, Ge, Nb, Re, V, Hf, In; powders; waste and scrap
Neodymium Oxide	284690	Compounds of rare-earth metals, yttrium, or scandium, other
Silver 99% Purity	710691	Silver, unwrought
Strontium	283692	Strontium carbonate
Tantalum	810320	Unwrought tantalum, bars, rods, powders
Terbium	280530	Compounds of rare-earth metals, yttrium, or scandium, other
<i>Panel C: Refractory minerals</i>		
Chromium	720241	Ferrochromium, >4% carbon by weight
Mercury	280540	Mercury
Molybdenum	261310	Molybdenum ores and concentrates, roasted
Niobium Pentoxide	282590	Other metal oxides, hydroxides, and peroxides
Titanium Dioxide	320611	TiO ₂ pigments, ≥80% TiO ₂ content
Tungsten	261100	Tungsten ores and concentrates
Zircon Sand	261510	Zirconium ores and concentrates
<i>Panel D: Industrial minerals</i>		
Aluminum	760110	Aluminium, not alloyed, unwrought
Copper	740311	Refined copper, cathodes and sections
Copper Alloy	740329	Other unwrought copper alloys
Enameled Wire	854411	Insulated winding wire, of copper
Lead	780110	Refined lead, unwrought
Magnesium	810411	Unwrought magnesium, ≥99.8% Mg and other
Magnesium Ingot	810411	Unwrought magnesium, ≥99.8% Mg
Tin	800110	Tin, not alloyed, unwrought
Zinc	790111	Zinc, not alloyed, unwrought, ≥99.99% Zn

Note: The table documents the correspondence between the 31 sample minerals and the HS 2022 six-digit codes used to extract country-level import values from the UN Comtrade database. Category assignments in panel headings follow Section 4.4. Codes are listed at the internationally binding six-digit level; some national schedules further disaggregate at eight or ten digits, but Comtrade reports at HS-6. The mineral-to-HS mapping yields 29 unique HS-6 codes across the 31 minerals, reflecting three cases of HS-level bundling: code 811292 covers both gallium and germanium in unwrought form; code 284690 covers all rare-earth compounds including both neodymium and terbium oxides; and code 810411 covers both “Magnesium” and “Magnesium Ingot” from our mineral set. In these cases the import-value calculation counts each HS code once per country-year to avoid double-counting, while the response assigned to the shared HS code is the simple average of the group-level peak responses for the minerals that share it. Sources: WCO HS 2022 nomenclature; USGS Mineral Commodity Summaries 2025; EU Critical Raw Materials Study 2023 technical appendix.

