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Constructing and Validating a Critical Minerals Market Conditions Index

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Abstract

Critical minerals are essential inputs into clean energy technologies, advanced manufacturing, and strategic supply chains, yet no widely accepted indicator summarizes aggregate conditions across these markets. This paper constructs and validates a Critical Minerals Market Conditions Index (CMMCI) using monthly prices for sixteen internationally traded critical minerals. Principal Component Analysis (PCA) and a Dynamic Factor Model (DFM) are used to extract the dominant common component of price movements. The resulting indices are highly correlated and identify similar turning points in market conditions. External validation shows that the DFM-based index is most strongly associated with global real economic activity and supply chain pressures, while geopolitical risk and energy-related uncertainty exhibit smaller but economically interpretable relationships. A two-factor DFM indicates that the primary factor remains stable, whereas a second factor captures additional variation concentrated among technology- and energy-transition-sensitive minerals. Indicator Saturation further identifies structural changes corresponding to major commodity-market, pandemic, and geopolitical events. The CMMCI provides a transparent and empirically validated measure of aggregate critical mineral market conditions for economic analysis, policy evaluation, and future real-time monitoring.

Keywords

Critical minerals, Latent factor models, Dynamic factor model, Principal component analysis, Supply chain resilience, Commodity markets.

JEL Classification

C38 (Classification Methods; Cluster Analysis; Factor Models), Q31 (Demand and Supply; Prices).

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1. Introduction

Critical minerals are central to economic security, industrial competitiveness, and geopolitical strategy within the global energy transition (Mustafa et al., 2026). Driven by the expansion of renewable infrastructure, electric vehicles, and advanced manufacturing, the accelerating demand for these commodities highlights their foundational role in modern industrial supply chains. Specifically, lithium, cobalt, nickel, manganese, and aluminum optimize electrochemical performance and structural efficiency in battery technologies, while copper and silver facilitate widespread power distribution. Concurrently, rare earth elements (REE) are required for permanent magnets in wind turbines, while zinc, tin, and molybdenum mitigate environmental corrosion across renewable energy infrastructure. Iron ore, palladium, platinum, vanadium, and uranium likewise remain essential for metallurgy, catalysis, and grid-scale energy storage, reinforcing the strategic importance of critical minerals for contemporary industrial and economic policy.

Unlike conventional energy commodities, these critical minerals occupy strategic positions within complex global supply chains where production, processing, and refining are frequently concentrated in a limited number of countries. As a result, concerns regarding supply disruptions, market concentration, investment adequacy, and geopolitical risk have become integral to discussions of energy security and long-run economic development (Dahl, 2020; International Energy Agency [IEA], 2025; United Nations Conference on Trade and Development [UNCTAD], 2026).

Recent experience has demonstrated that critical mineral markets are subject to substantial volatility arising from technological change, industrial policy, geopolitical tensions, export restrictions, and changing expectations regarding future decarbonization pathways. These forces influence not only individual commodity prices but also the broader functioning of global supply chains that support energy transition technologies. Consequently, policymakers, investors, manufacturers, and researchers increasingly require timely measures capable of monitoring overall market conditions rather than relying exclusively on the behavior of individual mineral prices (IEA, 2025; Dahl, 2020; Resources for the Future [RFF], 2026).

Despite the growing strategic importance of critical minerals, empirical measurement of overall market conditions remains underdeveloped. Existing studies largely examine individual commodities, specific supply-chain characteristics, or isolated geopolitical events. While these approaches have generated important insights, they provide only a partial view of overall market conditions because individual prices reflect both commodity-specific developments and broader economic, technological, and geopolitical forces. Increasing evidence suggests that critical mineral markets exhibit substantial co-movement generated by common demand drivers, integrated production networks, synchronized investment cycles, and shared responses to global shocks (Dahl, 2020; Mammadli et al., 2026; Wang, 2026). Consequently, analyzing individual mineral prices in isolation may obscure important information regarding the underlying evolution of overall market conditions.

The measurement challenge is analogous to those encountered in other areas of economics where researchers seek to summarize complex multidimensional systems through latent indicators. Financial conditions indices, business-cycle indices, and economic activity indices have demonstrated that multiple correlated variables often reflect an underlying common factor that provides a more informative representation of the economic environment than any single series alone (Brave et al., 2019). A similar framework is well suited for critical mineral markets, where numerous commodity prices jointly respond to common macroeconomic conditions, technological developments, supply-chain disruptions, and geopolitical events.

This research develops and validates a Critical Minerals Market Conditions Index (CMMCI) that summarizes the common variation across sixteen major critical mineral price series using latent factor methods. Specifically, the study employs Principal Component Analysis (PCA) and a Dynamic Factor Model (DFM) to extract the underlying common component driving movements across critical mineral markets. The resulting index provides a parsimonious empirical measure of aggregate critical mineral market conditions that can be monitored over time and validated against external indicators.

Beyond constructing the index, the paper evaluates whether the extracted latent factor represents a meaningful measure of critical mineral market conditions. Validation exercises examine the relationship between the index and external indicators of global supply-chain disruptions and broader macroeconomic conditions. The paper also examines the historical evolution of the index, identifies major episodes of market stress, evaluates structural changes in market conditions, and discusses extensions to real-time monitoring and future nowcasting applications.

The paper contributes to the literature in five ways. First, it develops one of the first latent market conditions indices specifically designed for global critical mineral markets. Second, it applies and compares PCA and DFM for measuring common market conditions across critical mineral prices. Third, it validates the extracted latent factor and demonstrates that the index captures meaningful variation in underlying market conditions. Fourth, it characterizes the evolution of critical mineral market conditions over time while identifying major events and structural change. Finally, it provides a parsimonious empirical framework that can support future research related to critical mineral markets.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on critical minerals, supply-chain resilience, latent factor models, and composite indicators. Section 3 describes the data and variable construction while section 4 presents the empirical methodology. Section 5 reports and discusses the empirical results, including latent factor estimation, model validation, comparison of PCA and DFM, robustness analysis, and the historical evolution of critical mineral market conditions. Section 6 concludes with policy implications, limitations, and directions for future research.

2. Literature Review

2.1 Critical Minerals and the Energy Transition

The global transition toward low-carbon energy systems has fundamentally altered the economic and strategic importance of mineral resources. Whereas energy security has typically focused on fossil fuel availability, current research increasingly recognizes that the deployment of renewable electricity, battery storage, electric vehicles, digital infrastructure, and advanced manufacturing depends upon secure access to a relatively small set of critical minerals. For example, lithium, cobalt, nickel, copper, and REE have become indispensable inputs into decarbonization strategies while simultaneously emerging as sources of geopolitical competition, industrial policy, and supply-chain risk (International Energy Agency [IEA], 2023, 2025; International Energy Forum, 2025; UNCTAD, 2026; Dahl, 2020).

Recent studies emphasize that critical minerals should not be viewed as conventional commodity markets. Instead, these markets are shaped by the interaction of geological endowments, extraction technologies, refining capacity, downstream manufacturing, trade policy, environmental regulation, and geopolitical developments. Consequently, prices frequently reflect expectations regarding technology deployment, strategic stockpiling, trade restrictions, investment incentives, and supply-chain resilience rather than contemporaneous supply and demand alone (IEA, 2023, 2025; Jackson & Handler, 2025; Dahl, 2020).

Demand projections consistently indicate that electrification is substantially more mineral-intensive than conventional energy systems. Recent systems-level analysis further demonstrates that constraints in critical mineral availability can materially affect the pace and cost of achieving global decarbonization targets, reinforcing the central role of critical minerals in the energy transition (Shi et al., 2025). Battery technologies, electric transmission networks, wind turbines, photovoltaic systems, and energy storage require substantially larger quantities of copper, lithium, nickel, cobalt, and REE than fossil-fuel technologies. Although technological innovation, recycling, and substitution may partially alleviate future constraints, most assessments conclude that demand growth will remain robust throughout the energy transition, increasing the importance of reliable and diversified supply chains (IEA, 2025; International Energy Forum, 2025; UNCTAD, 2026; Dahl, 2020).

An emerging theme in the literature is that critical minerals constitute an interconnected economic system rather than a collection of isolated commodity markets. Cross-market connections arise through common production networks, shared downstream technologies, synchronized investment cycles, and correlated responses to geopolitical events. This perspective motivates the development of aggregate measures capable of summarizing overall market conditions instead of relying exclusively on individual commodity prices. Such aggregate measures provide a more comprehensive representation of underlying market dynamics and are particularly well suited to empirical analyses that seek to extract and interpret the common factors governing critical mineral market conditions.

2.2 Critical Mineral Prices and Macroeconomic Effects

Critical mineral prices increasingly reflect broader macroeconomic and market conditions because they incorporate information about industrial activity, investment expectations, technological change, supply disruptions, and geopolitical developments. Unlike traditional commodities whose demand is closely tied to current production, critical minerals are influenced simultaneously by expectations regarding electrification, renewable energy deployment, battery manufacturing, defense requirements, and industrial policy. Consequently, price movements often anticipate structural changes in the global economy rather than merely reflecting contemporaneous supply-and-demand conditions (IEA, 2023, 2025; Jackson & Handler, 2025; Dahl, 2020).

Recent research demonstrates that critical mineral price shocks differ fundamentally from conventional oil price shocks. Whereas higher oil prices primarily increase the operating cost of existing capital, increases in critical mineral prices raise the cost of producing new capital embodied in electric vehicles, renewable energy systems, battery storage, and transmission infrastructure. These differences imply distinct adjustment mechanisms affecting investment, capital accumulation, external balances, and long-run economic growth (Concordel et al., 2026).

Growing evidence indicates that critical mineral prices exhibit substantial co-movement arising from common demand drivers, integrated supply chains, synchronized investment cycles, and shared responses to global events. Event-driven analyses demonstrate that major geopolitical developments and policy announcements generate structural changes across mineral markets rather than isolated price responses, suggesting that common latent forces increasingly govern market dynamics (Wang, 2026). This interconnected behavior limits the usefulness of studying individual mineral prices in isolation and instead supports empirical approaches that extract shared variation across multiple commodities.

Price volatility also complicates investment decisions throughout the mining and refining sectors. Although demand projections remain strong, periods of declining prices can discourage exploration, delay project development, and reduce financing despite favorable long-run fundamentals. Institutional assessments therefore emphasize that short-run price weakness should not necessarily be interpreted as evidence of diminishing strategic importance because investment decisions are conditioned by expectations regarding future demand, processing capacity, technological innovation, and policy uncertainty (IEA, 2025; International Energy Forum, 2025).

Taken together, these findings suggest that individual critical mineral prices are observable manifestations of broader underlying market conditions rather than independent economic series. If multiple mineral prices respond to common macroeconomic, technological, and geopolitical forces, latent factor methods provide a natural framework for extracting the common variation that characterizes overall critical mineral market conditions. Such an approach provides a stronger empirical foundation for monitoring market conditions, evaluating structural changes, and supporting real-time assessment than analyses focused on individual commodities alone.

2.3 Supply Chains, Resilience, and Geopolitical Risk

Research on critical minerals has increasingly shifted from questions of resource availability toward the resilience of global supply chains. Although geological scarcity remains important for some minerals, recent studies argue that the principal vulnerabilities arise from the concentration of mining, refining, processing, and transportation networks (Vivoda, 2026). Consequently, supply security depends not only on physical reserves but also on the geographic distribution of production capacity, logistical infrastructure, trade relationships, and institutional stability (IEA, 2023, 2025; International Energy Forum, 2025; UNCTAD, 2026; Dahl, 2020).

Supply-chain concentration represents one of the defining characteristics of contemporary critical mineral markets. Processing and refining activities are heavily concentrated in a small number of countries, creating potential bottlenecks that can propagate rapidly through downstream manufacturing sectors. Recent institutional assessments conclude that diversification of mining alone is insufficient if refining capacity, recycling infrastructure, and intermediate processing remain geographically concentrated. Consistent with these findings, Resources for the Future (RFF, 2026) argues that resilient supply chains require coordinated investments in mining, refining, processing, workforce development, permitting, infrastructure, and technological innovation rather than mining expansion alone. As a result, governments have increasingly incorporated critical minerals into industrial policy, national security planning, and strategic trade initiatives (IEA, 2025; RFF, 2026; UNCTAD, 2026; National Association of Manufacturers, 2026). Recent policy analyses similarly emphasize that expanding domestic mining alone is insufficient unless accompanied by investments in refining capacity, processing infrastructure, permitting reform, workforce development, recycling, and supply-chain diversification (Spiller et al., 2026).

Geopolitical developments further amplify these vulnerabilities. Export controls, sanctions, trade disputes, armed conflict, and strategic resource policies have demonstrated that disruptions need not originate from physical shortages to generate substantial market volatility. Instead, expectations regarding future restrictions often influence investment decisions, inventory accumulation, and commodity prices well before observable supply constraints emerge. Empirical evidence further suggests that geopolitical risk and critical mineral prices jointly influence renewable energy investment and energy-transition outcomes, reinforcing the close relationship between market conditions and policy uncertainty (Lee et al., 2025; Wang, 2026).

Recent empirical evidence directly links global supply chain disruptions to critical mineral prices and price volatility. Kang et al. (2025) apply a macroeconomic-fragility framework to aluminum, copper, nickel, platinum, tin, and zinc using a mixed-frequency structural vector autoregression. They find that global supply chain disruptions and non-technical risk premiums independently increase critical mineral prices and volatility, while the interaction between these forces magnifies and prolongs market responses. Their results indicate that policy, regulatory, geopolitical, and environmental risks can reduce the ability of mining firms to diversify suppliers or expand capacity during disruptions, thereby amplifying supply-chain fragility. The authors also

provide evidence that strategic stockpiling may mitigate these effects by buffering temporary supply shortages and reducing price volatility.

The long investment cycle in mining introduces an additional source of supply-chain risk. Mining projects typically require long development horizons, substantial capital commitments, regulatory approvals, and extensive technical evaluation before production begins. These long lead times reduce the ability of supply to respond quickly to demand shocks, increasing the likelihood of persistent imbalances. Recent theoretical work argues that technical and regulatory uncertainty generates a "back-ended risk premium" that raises financing costs for critical mineral projects, while advances in artificial intelligence may partially reduce these risks by improving exploration, project evaluation, and operational efficiency (Vespignani & Smyth, 2024). Dahl (2020) likewise emphasizes that concentrated production and lengthy mine-development timelines make critical mineral markets inherently vulnerable to persistent supply disruptions.

Viewed collectively, this literature suggests that resilient critical mineral markets are determined by the interaction of prices, production capacity, investment incentives, geopolitical developments, and supply-chain structure. Because these factors evolve jointly and frequently reinforce one another, including through interactions between supply chain disruptions and non-technical risk premiums, monitoring any single commodity or supply indicator provides only a partial view of overall market conditions (Kang et al., 2025). UNCTAD (2026) similarly argues that industrial policies should strengthen backward and forward linkages, promote value-chain diversification, and encourage international cooperation. Likewise, the Trilateral Energy Security Committee (2026) emphasizes coordinated international investment, strategic partnerships, and allied-country cooperation as central components of resilient critical mineral supply chains.

2.4 Measuring Market Conditions: Composite Indicators

As critical mineral markets have become increasingly multidimensional, researchers have recognized the limitations of relying on individual variables to characterize overall market conditions. Mineral prices, production, inventories, investment, trade flows, and supply-chain indicators each capture only one dimension of market performance. Composite indicators provide a systematic and transparent framework for integrating these heterogeneous sources of information into a single quantitative measure that reflects the broader underlying phenomenon while preserving the multidimensional nature of the data (Booyesen, 2002; Nardo et al., 2005; Nardo et al., 2008).

Booyesen (2002) provides one of the earliest comprehensive evaluations of composite indices, arguing that their principal strength lies in their ability to summarize complex, multidimensional phenomena in a form that is both analytically tractable and readily interpretable by researchers and policymakers. At the same time, Booyesen emphasizes that composite indicators are inherently sensitive to decisions regarding variable selection, normalization, weighting, and aggregation. These methodological choices influence the resulting index and require transparency to ensure credibility, reproducibility, and meaningful interpretation.

Composite indices therefore balance competing objectives, including methodological rigor, data availability, flexibility, comparability across time and space, and ease of interpretation, making careful index construction essential rather than merely procedural (Booyesen, 2002).

The composite indicator literature further emphasizes that successful index construction requires a well-defined theoretical framework, careful variable selection, appropriate normalization, transparent weighting, robustness analysis, and sensitivity testing. Rather than serving as arbitrary statistical aggregates, well-designed composite indicators should summarize the common information contained within multiple correlated variables while remaining interpretable and reproducible. Consequently, methodological decisions regarding weighting, aggregation, validation, and uncertainty analysis are central components of index construction rather than purely technical exercises (Booyesen, 2002; Nardo et al., 2005; Nardo et al., 2008).

Recent methodological research has extended traditional composite indicator frameworks to dynamic environments. Instead of producing static rankings, these approaches recognize that complex systems evolve over time and that relationships among constituent variables may also change. Functional data methods, time-varying weighting schemes, and dynamic aggregation procedures have therefore been proposed to improve robustness and interpretability in settings characterized by structural change and evolving market conditions (Łatuszyńska, 2012; Sarra et al., 2024).

Another important methodological development concerns the explicit treatment of uncertainty arising from indicator selection, weighting, normalization, and measurement error. Probabilistic approaches acknowledge that uncertainty propagates throughout the index construction process, improving transparency and facilitating more informative interpretation of composite measures, particularly when the underlying phenomenon is inherently complex (Melo-Aguilar et al., 2022).

Although composite indicators have become common in applications involving competitiveness, sustainability, financial conditions, and economic performance, relatively few studies have developed comparable measures for critical mineral markets. Existing research largely focuses on individual commodities, specific supply-chain characteristics, or institutional scorecards rather than constructing comprehensive latent measures of overall market conditions. This gap provides the methodological foundation for the present study, which develops a CMMCI by integrating composite indicator principles with PCA and DFMing to extract the common variation underlying critical mineral prices. The resulting index provides a transparent and empirically grounded measure of aggregate market conditions suitable for validation and economic interpretation.

2.5 Principal Component Analysis and Dynamic Factor Models

PCA and DFMs have become widely used econometric tools for extracting latent information from large collections of correlated time-series data. Both approaches are founded on the premise that the co-movement observed across numerous variables can be represented by a

relatively small number of unobserved common factors that summarize the underlying state of a complex economic system. By reducing dimensionality while preserving the dominant sources of variation, these methods provide parsimonious and economically interpretable representations of high-dimensional datasets suitable for empirical analysis and policy evaluation (Sargent & Sims, 1977; Bańbura et al., 2010; de Valk et al., 2019).

PCA provides a computationally efficient method for extracting the dominant common variation contained within highly correlated variables. By constructing orthogonal linear combinations that successively maximize explained variance, PCA summarizes the information embedded in multiple indicators using a small number of principal components. Consequently, PCA has become a standard approach for developing composite indicators and latent indices in economics, finance, and related disciplines because it provides an objective, data-driven method for identifying the primary sources of common variation without imposing restrictive structural assumptions.

DFM extend the principal component framework by explicitly incorporating temporal dependence within a state-space representation. Rather than treating the latent factors as static summaries, DFMs model their evolution over time while separating common variation from idiosyncratic disturbances. Estimation through state-space methods provides a flexible framework for capturing persistent dynamics and producing latent factors that reflect the underlying evolution of complex economic systems (Meinhold & Singpurwalla, 1983; Bańbura et al., 2010).

The usefulness of latent factor methods has been demonstrated across a wide range of macroeconomic and financial applications. Central banks, statistical agencies, and researchers routinely employ PCA and DFMs to summarize information contained in large datasets, construct composite indices, characterize financial conditions, and measure business cycle dynamics. Studies comparing alternative empirical approaches consistently find that latent factor methods efficiently exploit cross-sectional information while reducing the influence of idiosyncratic variation, particularly in high-dimensional datasets (Brave & Butters, 2011; de Valk et al., 2019).

Recent methodological advances have further expanded the application of latent factor methods while parallel developments in machine learning have improved commodity price forecasting. Ge et al. (2025) show that transformer-based architectures, particularly the FEDformer model, outperform many conventional econometric and recurrent neural network approaches in forecasting broad commodity indices. Nevertheless, while machine-learning methods often maximize predictive accuracy, latent factor models retain important advantages for economic analysis because they explicitly identify the common factors driving co-movement across observed variables, providing greater interpretability and a direct economic representation of underlying market conditions (Dai et al., 2025; Ge et al., 2025).

These characteristics make PCA and DFMs particularly well suited for analyzing critical mineral markets. Individual mineral prices respond to both commodity-specific developments and broader forces associated with industrial activity, technological change, geopolitical events, and supply-chain disruptions. Because these common influences generate substantial co-movement across mineral prices, latent factor methods provide a more informative representation of

aggregate market conditions than analyses based on individual commodities alone. Building on this literature, the present study first applies PCA to identify the dominant source of common variation across major critical mineral prices and then estimates a DFM to construct a CMMCI. Comparing the PCA- and DFM-based measures provides a robust assessment of the common factors underlying global critical mineral market conditions.

2.6 Research Gap and Contribution

The existing literature establishes the strategic importance of critical minerals, the rapid growth in demand associated with the global energy transition, the increasing complexity of supply chains, and the growing influence of geopolitical developments on market outcomes. Methodological research has likewise established robust frameworks for composite indicators, PCA, DFMing, and latent variable measurement. Despite these advances, these research streams have largely developed independently, leaving an important gap in the empirical analysis of critical mineral markets.

Most studies examine individual dimensions of the market in isolation. Commodity-specific analyses typically focus on the behavior of a single mineral or a narrow group of related commodities, while institutional reports emphasize supply security, investment trends, processing capacity, industrial policy, or geopolitical developments. Although these studies provide valuable insights, they offer only partial representations of a market increasingly characterized by interconnected price dynamics, common macroeconomic drivers, synchronized technological change, and shared responses to geopolitical shocks. Comparatively little attention has been devoted to constructing a comprehensive CMMCI that summarizes the common information embedded across multiple mineral price series and provides an aggregate measure of evolving market conditions.

Similarly, relatively few studies integrate advances in composite indicator methodology with modern latent factor techniques for measuring critical mineral market conditions. Composite indicator research provides rigorous guidance for variable selection, normalization, weighting, aggregation, and validation, while PCA and DFMs have become standard tools for constructing composite measures and extracting latent factors from high-dimensional datasets. However, these complementary methodological literatures have rarely been combined within a unified empirical framework designed specifically for critical mineral markets. Existing research seldom integrates composite indicator methodology, PCA, DFMing, and structural validation within a single coherent framework.

The present study addresses these shortcomings by developing a CMMCI that summarizes common movements across major critical mineral prices using PCA and a DFM. The proposed index is constructed using established composite indicator principles while exploiting latent factor methods to extract the common variation underlying individual mineral prices. The resulting measure provides a parsimonious, transparent, and economically interpretable representation of aggregate market conditions while reducing the influence of commodity-specific fluctuations. The

empirical framework is subsequently evaluated through validation against external indicators, comparison of the PCA- and DFM-based indices, and robustness analysis.

By integrating advances from the literatures on critical minerals, composite indicators, PCA, and DFMing, this study contributes a comprehensive empirical framework for measuring aggregate critical mineral market conditions. Beyond introducing a transparent and empirically validated measure of market conditions, the proposed CMMCI provides a general empirical framework for analyzing market integration, supply-chain resilience, macroeconomic linkages, and geopolitical risk while offering policymakers, industry participants, and researchers a practical tool for measuring and interpreting developments in an increasingly mineral-intensive global economy.

3. Data

This study develops a monthly CMMCI using critical mineral prices. The CMMCI is therefore a price-based measure of aggregate market conditions rather than a comprehensive measure of mineral criticality or supply security. The main objective is to extract the common latent factor underlying critical mineral prices, and to evaluate the resulting index through a series of validation exercises using additional variables that characterize global critical mineral market conditions.

3.1 Critical Mineral Prices

The core variables consist of monthly international prices for the sixteen critical minerals for which consistent price series are available in the International Monetary Fund (IMF) Primary Commodity Prices database over the study period. The IMF reports prices in nominal U.S. dollars which provides internationally comparable measures of market conditions for each commodity. The commodity set includes Aluminum, Iron Ore, Molybdenum, Manganese, Lithium, Cobalt, Palladium, Nickel, Silver, Platinum, Tin, Uranium, Vanadium, Zinc, Copper, and REE. Note that the IMF dataset includes a representative rare-earth price series that reflects market conditions for a benchmark rare-earth product rather than individual rare-earth elements. Although REE comprise a group of chemically distinct minerals, the benchmark series provides a useful indicator of aggregate price movements within this strategically important segment of critical mineral markets. According to the IMF, these commodities are among the most strategically important minerals supporting electrification, battery production, renewable energy technologies, and national supply chain security. Together they represent a broad cross-section of industrial metals and battery minerals whose prices respond to changes in global demand, production capacity, inventories, technological change, and geopolitical events. Accordingly, the mineral basket reflects the availability of consistent historical price series and does not encompass every mineral currently classified as critical or strategically important.

3.2 External Validation Indicators

The analysis includes four external indicators representing global supply chain conditions, geopolitical risk, energy-related uncertainty, and global economic activity. These variables are

used to evaluate whether the estimated CMMCI exhibits economically meaningful relationships with broader market conditions.

The Global Supply Chain Pressure Index (GSCPI), developed by the Federal Reserve Bank of New York, summarizes worldwide transportation costs, delivery delays, manufacturing bottlenecks, and logistics disruptions. Because critical mineral supply chains depend on geographically dispersed mining, processing, refining, and transportation networks, disruptions to these systems may affect both the availability and prices of critical minerals.

Geopolitical conditions are measured using the Geopolitical Risk (GPR) Index, which is constructed from newspaper coverage of military conflict, terrorism, diplomatic disputes, and international crises (<https://www.policyuncertainty.com/gpr.html>). Higher values indicate elevated geopolitical risk that may disrupt mining activity, trade, transportation, investment, or expectations regarding future mineral availability.

Energy-related uncertainty is measured using the GDP-weighted Global Energy-Related Uncertainty Index (GEUI) developed by Dang et al. (2023). The index captures uncertainty associated with global energy markets, energy policy, and related geopolitical developments that may influence critical mineral demand, investment, and supply-chain decisions.

Global economic activity is represented by the Index of Global Real Economic Activity (IGREA), obtained from the Federal Reserve Economic Database (FRED). The index is derived from dollar-denominated global bulk dry cargo shipping rates and provides a measure of activity in global industrial commodity markets. It therefore serves as a proxy for worldwide industrial demand affecting minerals used in batteries, electric vehicles, renewable energy systems, transmission infrastructure, and advanced manufacturing.

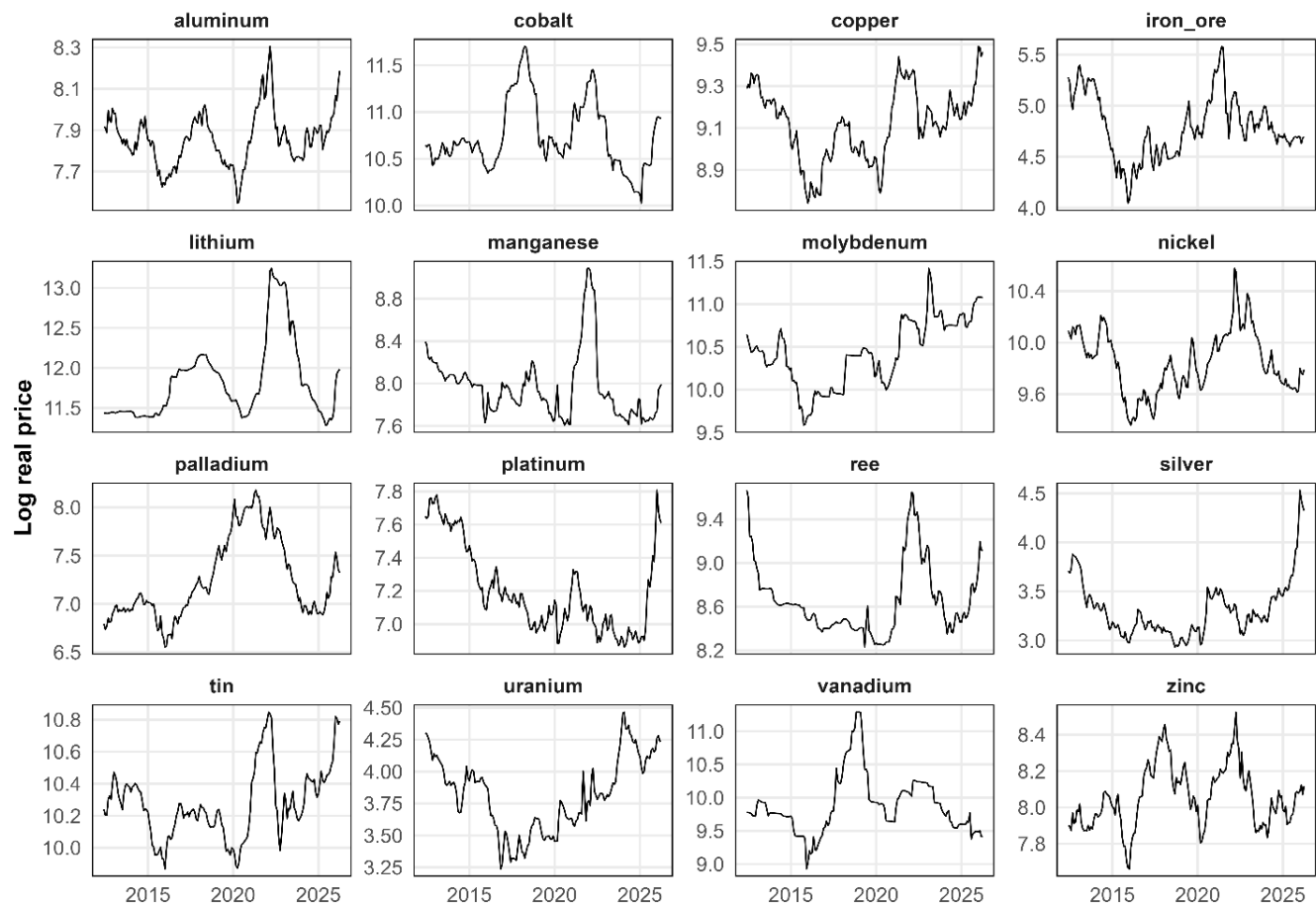
3.3 Data Transformation and Descriptive Statistics

The analysis uses monthly data covering June 2012 through April 2026, corresponding to the longest common sample with complete observations across all variables, except for the Global Energy-Related Uncertainty Index (GEUI), which is available only through November 2023. Commodity prices are converted to real terms using the CPI-U and then transformed to natural logarithms; thus, the values reported in the analysis are log real prices. Variables entering the PCA and DFM are standardized to have zero mean and unit variance, ensuring that differences in measurement units do not disproportionately influence the estimated latent factors. Higher values of the CMMCI indicate stronger broad-based critical mineral prices, while lower values indicate weaker prices. Accordingly, the index measures the direction and intensity of aggregate price-based market conditions and should not be interpreted normatively as indicating more or less favorable conditions for mineral producers or users.

Because the objective is to measure broad market conditions rather than individual commodity behavior, all commodity price series serve as inputs into the latent factor estimation. Figure 1 provides plots of the log real critical mineral price series over the sample period. Although the series exhibit considerable heterogeneity in price levels and volatility, they also display periods

of pronounced co-movement, suggesting the presence of common as well as commodity-specific sources of variation. Together, the plots suggest that critical mineral prices share meaningful common variation while retaining commodity-specific characteristics, providing motivation for the latent factor methods.

Figure 1. Evolution of Critical Mineral Prices



Note: The figure plots the monthly natural logarithms of CPI-adjusted prices for the sixteen critical minerals included in the analysis. The sample covers June 2012 through April 2026.

Table 1 reports descriptive statistics for all variables included in the analysis. The summary statistics indicate substantial variation across both the critical mineral price series and the explanatory variables, reflecting the diversity of market conditions represented in the dataset. Collectively, these variables provide the empirical basis for estimating the CMMCI. The following section describes the latent factor methodologies used to construct and validate the index.

Table 1. Descriptive Statistics

Variable	Mean	SD	Median	Minimum	Maximum	Skewness	Kurtosis
Log Real Aluminum	7.860	0.132	7.856	7.547	8.305	0.503	0.726
Log Real Iron Ore	4.794	0.309	4.743	4.046	5.580	0.257	-0.304
Log Real Molybdenum	10.434	0.392	10.424	9.587	11.418	-0.032	-0.708
Log Real Manganese	7.964	0.307	7.921	7.608	9.086	1.717	3.422
Log Real Lithium	11.822	0.489	11.670	11.286	13.244	1.364	1.161
Log Real Cobalt	10.741	0.364	10.647	10.025	11.700	0.734	-0.145
Log Real Palladium	7.249	0.416	7.107	6.555	8.177	0.619	-0.834
Log Real Nickel	9.848	0.243	9.826	9.361	10.576	0.277	-0.229
Log Real Silver	3.316	0.295	3.254	2.934	4.531	1.585	3.226
Log Real Platinum	7.206	0.264	7.135	6.863	7.807	0.718	-0.735
Log Real REE	8.659	0.330	8.594	8.232	9.666	1.235	0.918
Log Real Tin	10.276	0.221	10.240	9.869	10.847	0.596	0.125
Log Real Uranium	3.819	0.294	3.827	3.239	4.465	0.058	-0.929
Log Real Vanadium	9.882	0.444	9.777	8.929	11.287	1.083	1.527
Log Real Zinc	8.057	0.168	8.048	7.662	8.524	0.345	-0.265
Log Real Copper	9.119	0.173	9.130	8.741	9.489	-0.169	-0.602
Global Supply Chain							
Pressure Index (GSCPI)	0.336	1.247	-0.049	-1.579	4.449	1.442	1.389
Geopolitical Risk Index (GPR)	109.139	39.280	102.190	58.421	326.989	2.468	9.501
Index of Global Real							
Economic Activity (IGREA)	-25.325	47.214	-23.739	-161.382	110.066	-0.036	0.084
Global Energy-Related							
Uncertainty Index (GEUI)	1.290	0.378	1.230	0.660	3.050	1.411	3.641

Note: Commodity prices are expressed as natural logarithms of CPI-adjusted (real) prices. The analysis uses monthly observations from June 2012 through April 2026 ($N = 167$). The Global Energy-Related Uncertainty Index (GEUI) is available only through November 2023 ($N = 138$).

4. Methodology

Two complementary latent factor methods are employed in developing the CMMCI. PCA provides a static measure of the dominant common variation across mineral prices, while a DFM explicitly accounts for the temporal evolution of the latent market conditions factor. The resulting indices are subsequently evaluated using external validation measures representing global supply chain conditions, industrial activity, and related market indicators. Together, these methods provide a comprehensive framework for measuring, validating, and interpreting aggregate critical mineral market conditions.

4.1 Principal Component Analysis

PCA provides a data-reduction technique that transforms a set of correlated variables into a smaller number of orthogonal linear combinations, referred to as principal components (Alexander, 2008). Each principal component is constructed to maximize the proportion of total variation explained, subject to the constraint that successive components remain orthogonal to one another. Because critical mineral prices are expected to respond jointly to common macroeconomic, technological, and geopolitical forces, PCA provides a natural framework for identifying the dominant source of common variation across the sixteen commodity price series.

The first principal component is defined as the linear combination of the standardized critical mineral price series that explains the largest proportion of total variance. Because it captures the dominant source of common variation across the sixteen mineral prices, the first principal component provides a parsimonious measure of underlying critical mineral market conditions. Let $\mathbf{X}$ denote the vector of standardized mineral prices. The first principal component is:

$$PC_1 = w_1X_1 + w_2X_2 + \cdots + w_{16}X_{16}$$

where $\mathbf{w} = (w_1, w_2, \dots, w_{16})'$ is the vector of eigenvector weights determined endogenously to maximize the variance explained by the first principal component, subject to the normalization constraint that $\mathbf{w}'\mathbf{w} = 1$. The extracted first principal component is interpreted as the baseline CMMCI.

As a preliminary assessment of the underlying covariance structure, the pairwise correlations among the sixteen mineral price series are examined using a correlation heatmap. The heatmap provides a visual representation of the strength and direction of correlations across commodities and serves as an initial diagnostic of whether sufficient common variation exists to justify latent factor estimation. Strong positive correlations across a broad set of minerals support the application of PCA and subsequent DFMing.

The number of principal components retained is evaluated using the eigenvalue distribution and scree plot. Because the objective of the study is to construct a single aggregate measure of overall market conditions, the analysis primarily focuses on the first principal component.

Subsequent robustness analysis examines whether additional latent factors provide meaningful incremental information.

4.2 Dynamic Factor Model

Although PCA efficiently summarizes cross-sectional variation, it does not explicitly account for the dynamic evolution of market conditions over time. To address this limitation, the analysis also estimates a DFM, which represents the observed mineral prices as functions of one or more unobserved latent factors evolving according to a state-space system (DeJong & Dave, 2011). The observation equation is given by:

$$X_t = \Lambda F_t + \varepsilon_t$$

where X_t denotes the vector of standardized critical mineral prices at time t , F_t represents the latent market conditions factor, Λ is the vector of factor loadings, and ε_t denotes idiosyncratic disturbances. The latent factor evolves according to the transition equation:

$$F_t = \Phi F_{t-1} + \eta_t$$

where Φ governs the persistence of the latent factor and η_t represents the state disturbance.

The DFM is estimated within a state-space framework using maximum likelihood estimation combined with the Kalman filter and smoother. This approach jointly estimates the latent factor and the corresponding factor loadings while accounting for serial dependence and measurement error. Compared with PCA, the DFM provides a smoother estimate of underlying market conditions by explicitly modeling temporal persistence in the common factor.

The primary analysis estimates a one-factor DFM to construct the CMMCI. A two-factor specification is subsequently estimated as a robustness exercise to evaluate whether additional common variation exists beyond the dominant market conditions factor. Comparing the one-factor and two-factor models provides insight into the dimensionality of critical mineral market dynamics while preserving the one-factor index as the principal measure developed in this study.

4.3 Validation Framework

The usefulness of the proposed CMMCI depends on whether the extracted latent factor represents meaningful variation in underlying market conditions rather than statistical artifacts. Consequently, several complementary validation exercises are conducted. First, the estimated latent factor is compared with external indicators representing global supply chain conditions and worldwide economic activity. Specifically, pairwise correlations are computed between the CMMCI and the Global Supply Chain Pressure Index (GSCPI), the Index of Global Real Economic Activity (IGREA), the Geopolitical Risk (GPR) Index, and the Global Energy-Related Uncertainty Index (GEUI), where data availability permits. Significant relationships with these external

indicators provide evidence that the latent factor captures economically meaningful variation associated with broader market conditions.

Second, regression analysis is used to examine the extent to which external indicators explain variation in the estimated market conditions index. These regressions provide an additional assessment of construct validity by evaluating whether the CMMCI behaves consistently with established economic theory regarding supply chain disruptions, industrial activity, and geopolitical uncertainty.

Third, the estimated market conditions index obtained from PCA is compared directly with the corresponding DFM estimate. A high degree of similarity between the two indices would indicate that the extracted latent factor is robust to alternative estimation methodologies and reflects a stable measure of aggregate market conditions.

4.4 Indicator Saturation

Indicator Saturation (ISAT) is employed to identify statistically significant structural changes and discrete market events affecting the estimated CMMCI. Developed by Hendry et al. (2008) and subsequently extended by Marczak and Proietti (2016) and Pretis et al. (2018), ISAT provides a systematic, data-driven procedure for detecting structural breaks, temporary shocks, persistent level shifts, and outliers without requiring prior knowledge of their timing. Rather than imposing exogenous break dates, the procedure augments the baseline specification with a comprehensive set of impulse and step indicators that capture temporary shocks and persistent shifts in the estimated market conditions index.

The general unrestricted model may be expressed as:

$$y_t = X_t'\beta + \sum_{i=1}^T \delta_i IIS_{i,t} + \sum_{j=1}^T \theta_j SIS_{j,t} + \varepsilon_t$$

where X_t denotes the baseline regressors, IIS represents impulse indicators capturing one-time shocks, and SIS represents step indicators capturing persistent level shifts. A general-to-specific model selection procedure sequentially eliminates statistically insignificant indicators while retaining those representing meaningful departures from parameter constancy. The retained indicators identify statistically significant episodes of market disruption that are subsequently interpreted in the context of major developments affecting global critical mineral markets.

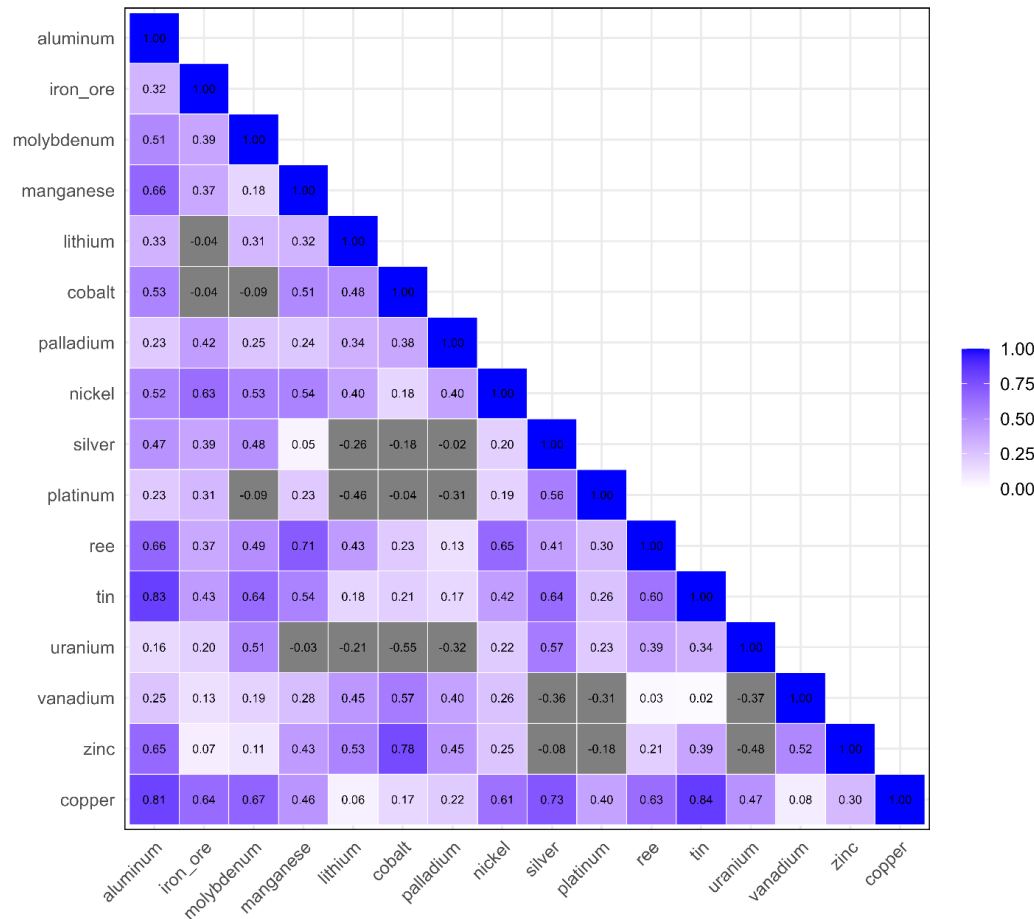
The ISAT analysis complements the external validation exercises by assessing whether the estimated CMMCI captures major historical events reflected in critical mineral markets. Together, the external validation and structural break analyses evaluate the statistical robustness, economic interpretability, and historical relevance of the proposed CMMCI, providing a comprehensive foundation for the empirical results presented in the following section.

5. Results and Discussion

5.1 Correlation Structure of Critical Mineral Prices

The first step in constructing the CMMCI is to examine the degree of co-movement among the sixteen log real critical mineral price series. Because PCA and the DFM seek to extract common latent variation, sufficient cross-sectional dependence among the individual commodity prices is a necessary condition for meaningful factor estimation. Figure 2 presents the correlation heatmap for the standardized log real critical mineral prices and reveals substantial positive correlation across most mineral prices. Many pairwise correlations are moderate to strong, particularly among metals associated with industrial production, electrification, and energy-transition technologies. For example, copper exhibits relatively strong positive correlations with tin (0.84), aluminum (0.81), silver (0.73), molybdenum (0.67), iron ore (0.64), REE (0.63), and nickel (0.61), reflecting their shared sensitivity to global manufacturing activity and investment cycles. Likewise, aluminum and tin (0.83), cobalt and zinc (0.78), and manganese and REE (0.71) display strong positive associations.

Figure 2. Correlation Heatmap of Log Real Critical Mineral Prices



Note: The figure reports pairwise Pearson correlations among the sixteen standardized log real critical mineral price series. Darker shading indicates stronger positive correlation.

Although positive relationships dominate the correlation structure, several mineral pairs exhibit relatively weak or negative correlations. Platinum and lithium (-0.46), uranium and cobalt (-0.55), uranium and zinc (-0.48), uranium and vanadium (-0.37), and silver and vanadium (-0.36) illustrate that certain commodities retain important commodity-specific dynamics associated with distinct end uses, supply conditions, or market fundamentals. These heterogeneous relationships indicate that while a common market component exists, individual mineral prices continue to reflect idiosyncratic influences.

Overall, the correlation structure supports the use of latent factor methods to summarize the common variation across critical mineral markets. The widespread pattern of positive co-movement suggests that a relatively small number of latent factors can capture much of the shared information contained in the sixteen price series, while the remaining variation reflects commodity-specific shocks. These findings provide the empirical motivation for the PCA and DFM estimation.

5.2 Principal Component Analysis Results

The objective of the PCA is to determine whether a relatively small number of latent components summarizes the co-movement observed in the underlying prices and, in particular, whether the first principal component provides a suitable measure of aggregate critical mineral market conditions. Table 2 reports the eigenvalues and proportions of variance explained by the principal components. The first principal component has an eigenvalue of 6.056 and explains 37.85% of the total variation in the sixteen mineral price series. The second principal component explains an additional 23.80% of the total variance, while the third accounts for 9.83%. Collectively, the first three principal components explain 71.48% of the total variation, and the first five account for 85.87%. Although five components have eigenvalues greater than one, the first principal component captures substantially more variation than any subsequent component and provides a parsimonious summary measure of common market conditions.

Table 2. Principal Component Eigenvalues and Variance Explained

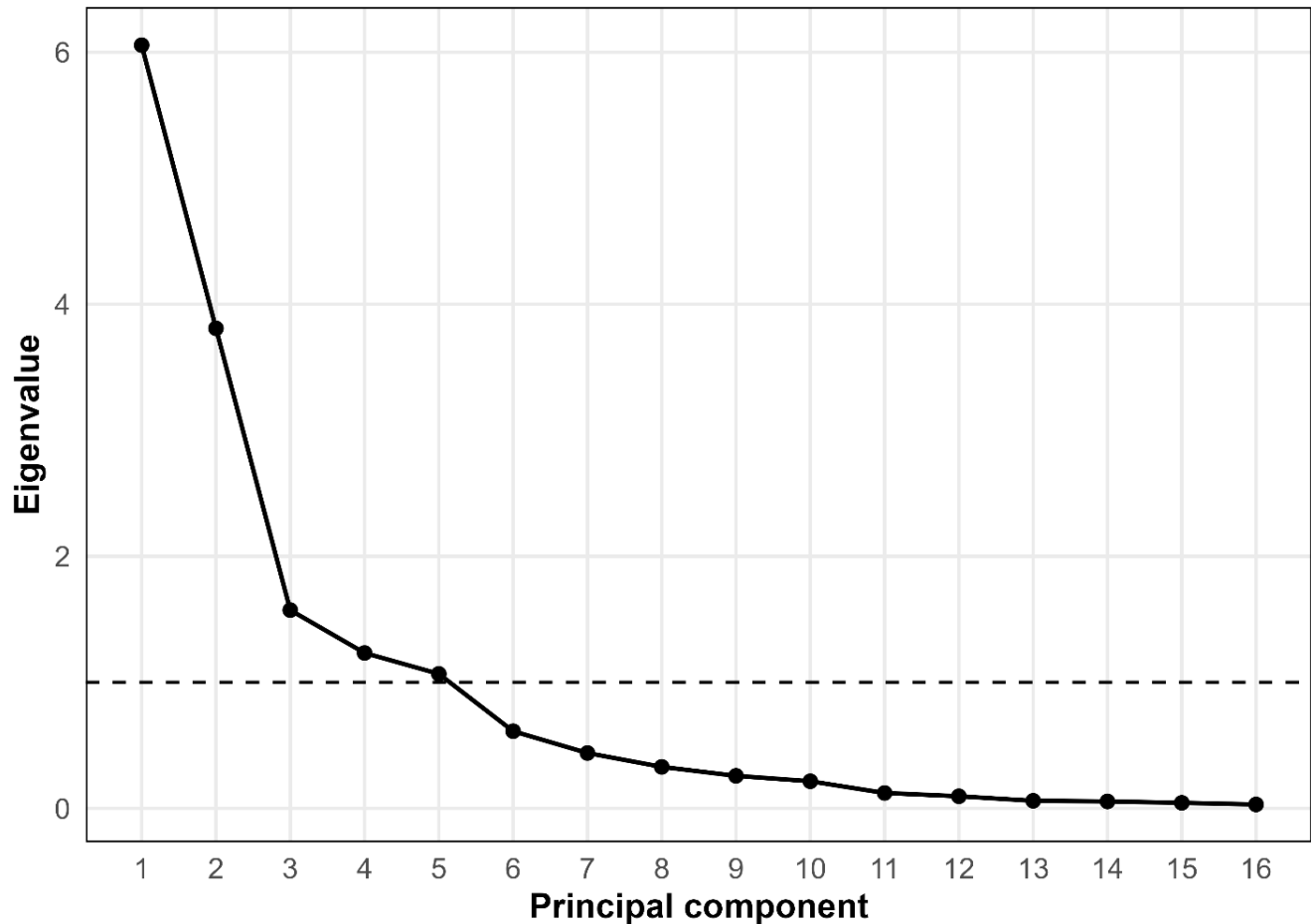
Principal Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	6.056	37.85	37.85
2	3.809	23.80	61.65
3	1.573	9.83	71.48
4	1.233	7.71	79.19
5	1.067	6.67	85.87
6	0.612	3.83	89.69
7	0.439	2.74	92.43
8	0.329	2.06	94.49
9	0.258	1.61	96.11

Principal Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
10	0.215	1.34	97.45
11	0.122	0.76	98.21
12	0.096	0.60	98.81
13	0.060	0.37	99.19
14	0.055	0.34	99.53
15	0.044	0.28	99.81
16	0.031	0.19	100.00

Note: PCA is estimated using the correlation matrix of the sixteen standardized log real critical mineral price series. The first principal component explains 37.85% of the total variance, while the first five principal components collectively explain 85.87% of the total variation.

Figure 3 reinforces this conclusion. The scree plot exhibits a pronounced decline after the first principal component, followed by progressively smaller reductions in successive eigenvalues (Ait-Sahalia and Xu, 2017). This pattern indicates that the dominant source of common variation is concentrated in the first component, with each additional component contributing increasingly limited incremental information. Consistent with the objective of constructing a single CMMCI, the first principal component is retained as the primary latent measure of market conditions. The potential contribution of additional latent factors is examined later through the two-factor DFM robustness analysis.

Figure 3. Scree Plot of Principal Components



Note: The figure reports the eigenvalues obtained from PCA of the sixteen standardized log real critical mineral price series. The dashed horizontal line denotes an eigenvalue of one.

Table 3 reports the PCA factor loadings for the first three principal components. The loadings associated with the first principal component are uniformly negative across all sixteen minerals, indicating that the common factor reflects broad-based movements shared across the critical mineral market rather than the behavior of any individual commodity. Because the sign of a principal component is arbitrary, the uniformly negative loadings have no economic significance; multiplying the component by -1 produces an equivalent index without affecting its statistical properties or interpretation.

Table 3. Principal Component Loadings

Mineral	PC1	PC2	PC3
Log Real Aluminum	-0.364	-0.044	-0.189
Log Real Iron Ore	-0.246	0.107	0.113

Mineral	PC1	PC2	PC3
Log Real Molybdenum	-0.274	0.110	0.455
Log Real Manganese	-0.287	-0.119	-0.242
Log Real Lithium	-0.157	-0.318	0.278
Log Real Cobalt	-0.164	-0.378	-0.332
Log Real Palladium	-0.160	-0.246	0.248
Log Real Nickel	-0.305	-0.016	0.203
Log Real Silver	-0.214	0.349	-0.096
Log Real Platinum	-0.105	0.281	-0.517
Log Real REE	-0.324	0.063	-0.011
Log Real Tin	-0.344	0.103	-0.070
Log Real Uranium	-0.109	0.401	0.253
Log Real Vanadium	-0.112	-0.356	0.134
Log Real Zinc	-0.207	-0.355	-0.180
Log Real Copper	-0.364	0.163	-0.022

Note: Loadings are obtained from PCA estimated using the correlation matrix of the sixteen standardized log real critical mineral price series. PC1, PC2, and PC3 denote the first three principal components. Because the sign of a principal component is arbitrary, multiplying all loadings by -1 yields an equivalent solution without affecting the statistical interpretation of the extracted components.

The largest absolute loadings on the first principal component are observed for aluminum, copper, tin, REE, nickel, manganese, and molybdenum, suggesting that these commodities contribute most strongly to the common market factor. In contrast, platinum, uranium, vanadium, lithium, cobalt, and palladium exhibit comparatively smaller loadings, indicating that a greater proportion of their price variation is driven by commodity-specific factors. Nevertheless, all sixteen minerals contribute to the construction of the latent index, consistent with the objective of measuring broad critical mineral market conditions rather than emphasizing individual commodities.

Figure 4. PCA CMMCI



Note: The figure plots the first principal component obtained from the sixteen standardized log real critical mineral price series. The sign is oriented so that higher values represent stronger critical mineral market conditions.

Figure 4 presents the estimated PCA-based CMMCI. The index exhibits substantial variation over the sample period, reflecting changing conditions in global critical mineral markets. Following relatively strong market conditions during the early portion of the sample, the index declines sharply during 2015–2016 before recovering through 2017 and 2018. A second decline occurs around 2019–2020, followed by a pronounced increase beginning in late 2020 and peaking during 2022. The index subsequently moderates during 2023–2025 before rising again toward the end of the sample. These broad movements correspond closely with major shifts in global industrial activity, supply-chain disruptions, and evolving expectations surrounding the energy transition, suggesting that the first principal component captures economically meaningful changes in aggregate critical mineral market conditions.

Overall, the PCA results provide strong evidence that a single latent factor summarizes a substantial share of the common variation across critical mineral prices. The estimated CMMCI therefore offers a parsimonious measure of aggregate market conditions and provides a useful benchmark against which the DFM is evaluated in the following section.

5.3 Dynamic Factor Model Results

To account for the temporal evolution of common market conditions, a one-factor DFM is estimated using the sixteen standardized log real critical mineral price series. Unlike PCA, which extracts a static linear combination of the observed variables, the DFM explicitly models the latent factor as a dynamic stochastic process within a state-space framework. Consequently, the estimated factor reflects both the cross-sectional co-movement among mineral prices and the persistence of underlying market conditions over time.

Table 4. One-Factor Dynamic Factor Model Loadings

Mineral	Factor Loading
Log Real Copper	0.401
Log Real Tin	0.348
Log Real Aluminum	0.333
Log Real Silver	0.293
Log Real Molybdenum	0.278
Log Real REE	0.270
Log Real Iron Ore	0.256
Log Real Nickel	0.250
Log Real Manganese	0.201
Log Real Uranium	0.190
Log Real Platinum	0.156
Log Real Zinc	0.124
Log Real Palladium	0.093
Log Real Cobalt	0.073
Log Real Lithium	0.037
Log Real Vanadium	0.034

Note: Reported values are estimated factor loadings from the one-factor DFM estimated using the sixteen standardized log real critical mineral price series. Larger factor loadings indicate that the corresponding mineral contributes more strongly to the estimated latent CMMCI. All loadings are positive, implying that increases in the latent factor are associated with broad-based increases in critical mineral prices.

Table 4 reports the estimated factor loadings from the one-factor DFM. All estimated loadings are positive, indicating that increases in the latent factor are associated with broad-based increases in critical mineral prices. The largest loadings are observed for copper (0.401), tin (0.348), aluminum (0.333), silver (0.293), molybdenum (0.278), and REE (0.270), suggesting that these

commodities contribute most strongly to the common market conditions factor. Iron ore (0.256), nickel (0.250), manganese (0.201), and uranium (0.190) also exhibit meaningful associations with the latent factor, whereas palladium (0.093), cobalt (0.073), lithium (0.037), and vanadium (0.034) contribute comparatively less. These results indicate that the common factor is driven primarily by broadly traded industrial and energy-transition minerals while still incorporating information from all sixteen commodities.

The estimated loading pattern closely resembles that obtained from the PCA. Minerals exhibiting relatively large PCA loadings likewise receive the largest DFM loadings, indicating that both methods identify a similar underlying source of common variation despite employing different estimation frameworks. Whereas PCA extracts the dominant contemporaneous component of variation, the DFM additionally incorporates the temporal persistence of the latent factor, producing a market conditions index that evolves smoothly through time while filtering idiosyncratic commodity-specific fluctuations.

Overall, the one-factor DFM provides further evidence that a single latent factor captures the dominant movements shared across critical mineral markets. The similarity between the PCA and DFM loading structures supports the interpretation of the extracted factor as a comprehensive measure of aggregate market conditions.

5.4 Validation Results

The usefulness of the CMMCI depends on whether the extracted latent factor reflects economically meaningful variation in global market conditions rather than statistical artifacts. To evaluate the construct validity of the index, the one-factor DFM is compared with several external indicators representing global supply chain pressures, worldwide economic activity, geopolitical risk, and energy-related uncertainty. Validation is conducted using both correlation analysis and simple regression models.

Table 5. Validation Correlations

Variable	Factor (DFM)	1 PCA Index	GSCPI	GPR	IGREA	GEUI
Factor 1 (DFM)	—					
PCA Index	0.967	—				
Global Supply Chain Pressure Index (GSCPI)	0.446	0.427	—			
Geopolitical Risk Index (GPR)	0.291	0.298	0.291	—		
Index of Global Real Economic Activity (IGREA)	0.617	0.595	0.252	0.147	—	

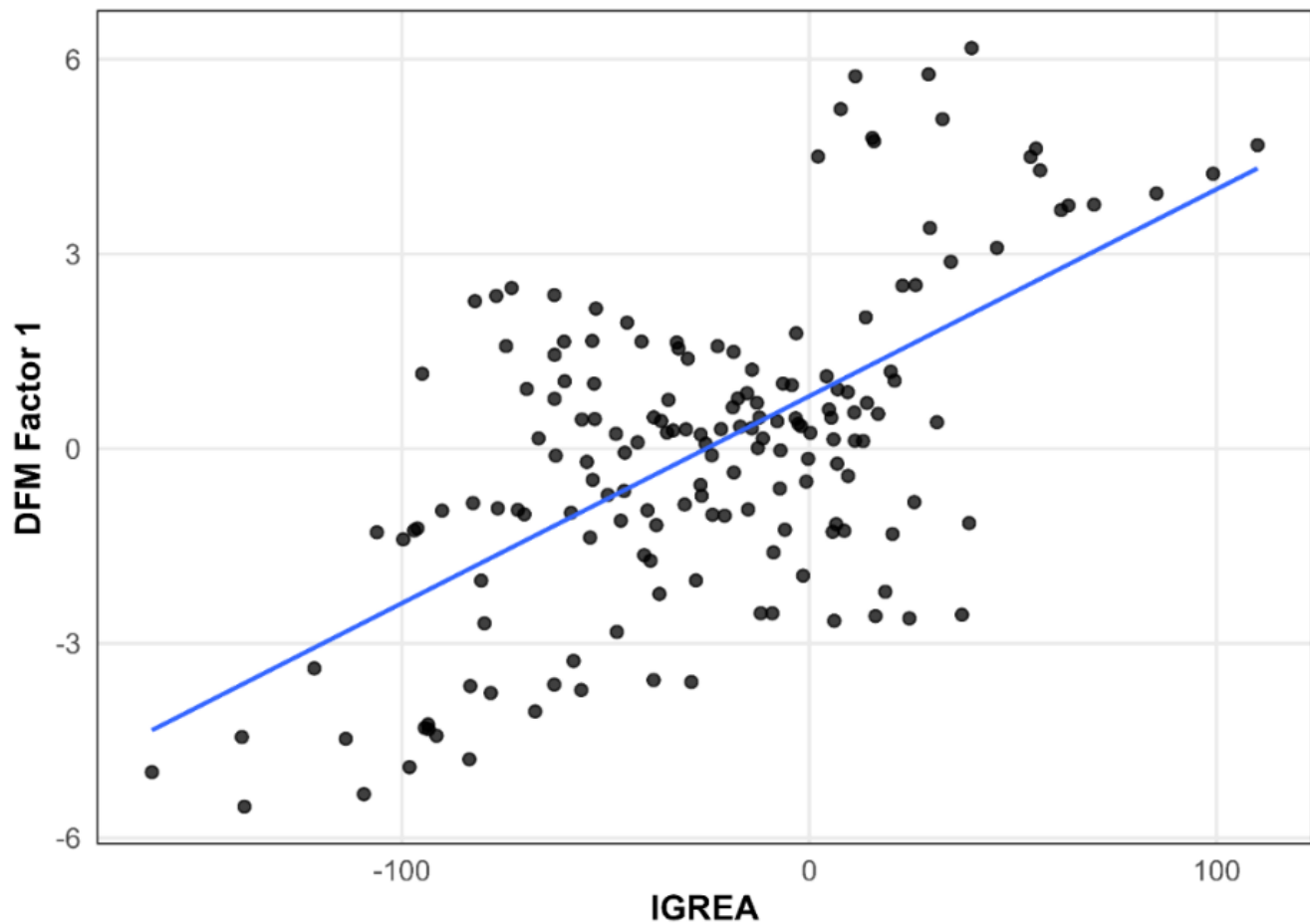
Variable	Factor (DFM)	1 PCA Index	GSCPI	GPR	IGREA	GEUI
Global Energy-Related Uncertainty Index (GEUI)	-0.287	-0.255	-0.060	0.095	-0.158	—

Note: Entries report Pearson correlation coefficients. Factor 1 (DFM) denotes the one-factor DFM estimate of the CMMCI, while the PCA Index denotes the first principal component. GSCPI is the Global Supply Chain Pressure Index; GPR is the Geopolitical Risk Index; IGREA is the Index of Global Real Economic Activity; and GEUI is the Global Energy-Related Uncertainty Index. Correlations involving GEUI are based on the shorter sample available through November 2023. The strong correlation (0.967) between the DFM and PCA indices indicates that both methods recover essentially the same underlying market conditions factor.

Table 5 reports the correlation matrix for the estimated market condition indices and the external validation variables. The one-factor DFM index exhibits a very strong positive correlation with the PCA-based index (0.967), indicating that the two estimation methods recover essentially the same underlying market signal despite employing different statistical frameworks. This high degree of agreement provides strong evidence that the dominant latent factor is robust to the choice of estimation methodology.

Among the external indicators, the one-factor DFM index is most strongly correlated with the Index of Global Real Economic Activity (IGREA) (0.617), followed by the Global Supply Chain Pressure Index (GSCPI) (0.446). Both relationships are consistent with economic intuition, as stronger industrial activity and tighter supply chains are expected to coincide with stronger demand and higher prices for critical minerals. The index also exhibits a modest positive correlation with the Geopolitical Risk (GPR) Index (0.291), suggesting that geopolitical developments contribute to, but do not dominate, aggregate market conditions. In contrast, the correlation with the Global Energy-Related Uncertainty Index (GEUI) is negative (-0.287), indicating that periods of elevated energy uncertainty tend to coincide with weaker overall critical mineral market conditions during the available sample period.

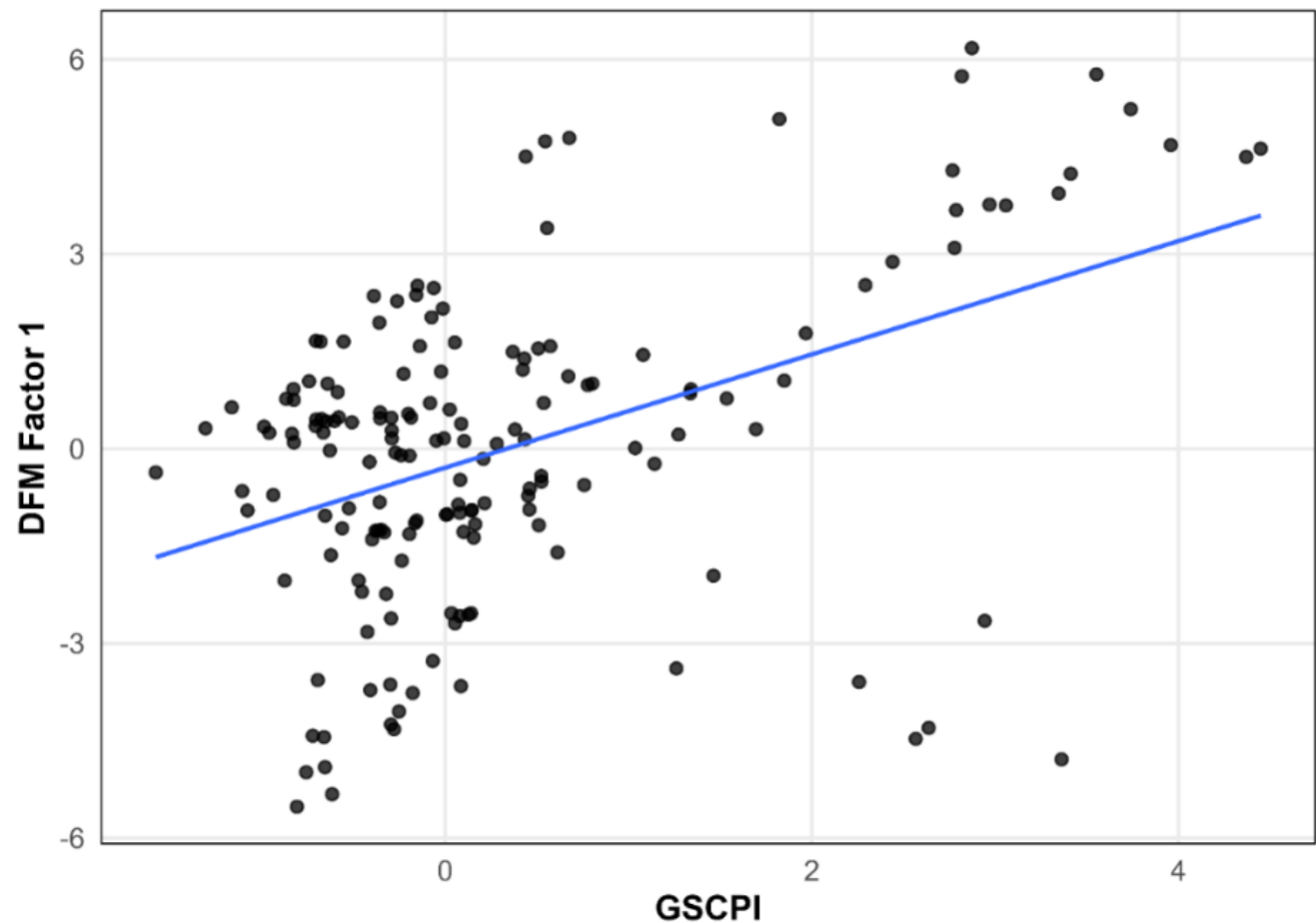
Figure 5. DFM Factor 1 versus Index of Global Real Economic Activity



Note: The figure plots the one-factor DFM estimate of the CMMCI against the Index of Global Real Economic Activity (IGREA). The fitted line is obtained from the bivariate OLS regression reported in Table 6.

Figure 5 plots the one-factor DFM index against the IGREA and includes the fitted line from the corresponding bivariate OLS regression reported in Table 6. The upward-sloping fitted relationship indicates that stronger global industrial activity is associated with more stronger critical mineral market conditions, supporting the interpretation of the estimated latent factor as a measure of broad market demand.

Figure 6. DFM Factor 1 versus Global Supply Chain Pressure Index



Note: The figure plots the one-factor DFM estimate of the CMMCI against the Global Supply Chain Pressure Index (GSCPI). The fitted line is obtained from the bivariate OLS regression reported in Table 6.

Figure 6 plots the one-factor DFM index against the GSCPI and includes the fitted line from the corresponding bivariate OLS regression reported in Table 6. The positive fitted relationship indicates that periods of heightened supply chain pressures are associated with stronger critical mineral market conditions, reflecting the role of production bottlenecks, transportation constraints, and logistics disruptions in critical mineral pricing.

Table 6. Validation Regression Results

Regression Model	<i>N</i>	Coefficient	<i>p</i> -value	Adj.- <i>R</i> ²
Factor 1 ~ IGREA	167	0.032	<0.001	0.381
Factor 1 ~ GSCPI	167	0.873	<0.001	0.199
Factor 1 ~ GPR	167	0.018	<0.001	0.085

Regression Model	<i>N</i>	Coefficient	<i>p</i> -value	Adj.- <i>R</i> ²
Factor 1 ~ GEUI	138	-1.908	<0.001	0.083

Note: Each regression estimates a separate bivariate relationship between the one-factor DFM index and an external validation variable. Factor 1 represents the primary CMMCI. GSCPI is the Global Supply Chain Pressure Index; GPR is the Geopolitical Risk Index; IGREA is the Index of Global Real Economic Activity; and GEUI is the Global Energy-Related Uncertainty Index. Regressions involving GEUI use a shorter sample (*N* = 138) because the series is available only through November 2023.

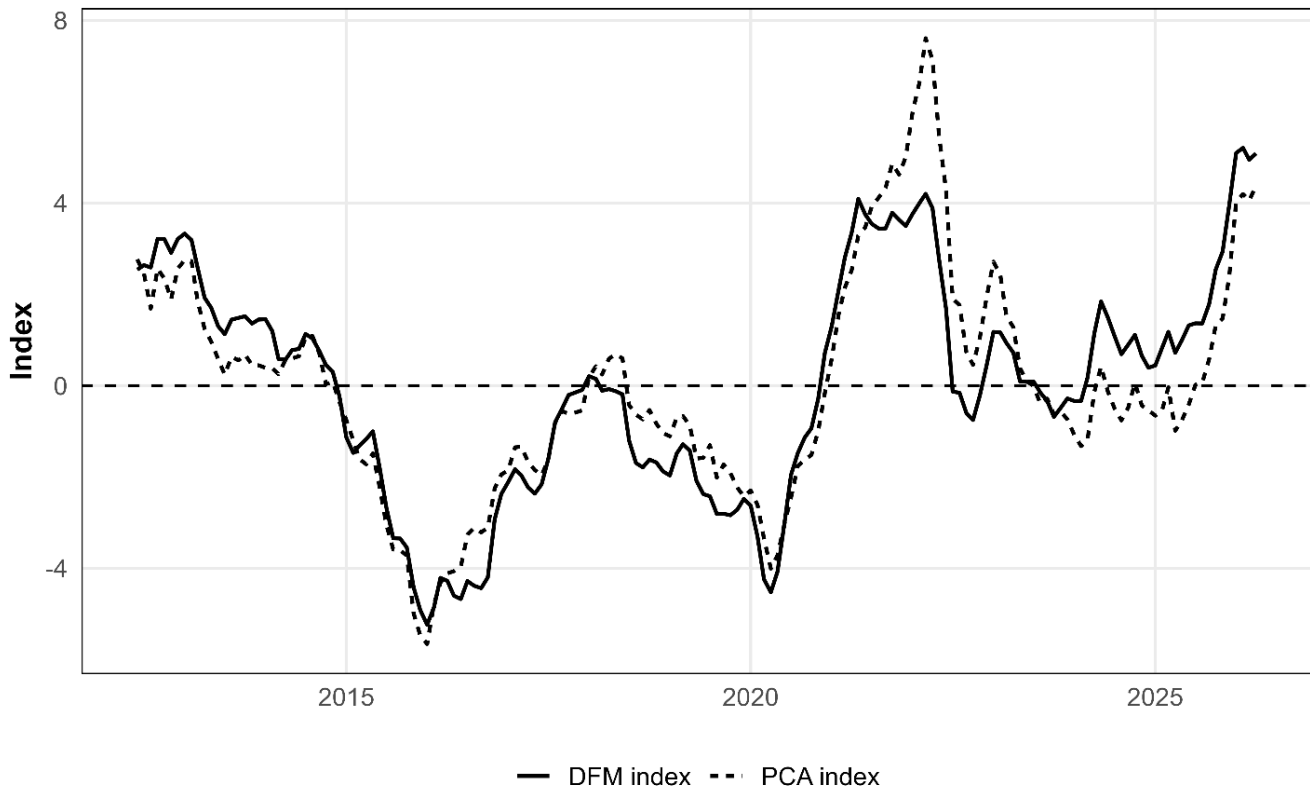
The regression results reported in Table 6 further support these findings. IGREA exhibits the strongest bivariate association with the one-factor DFM index (adjusted $R^2 = 0.381$), followed by GSCPI (adjusted $R^2 = 0.199$), indicating that global economic activity and supply chain conditions account for the largest shares of index variation among the external validation measures considered. Geopolitical risk is positively associated with the estimated index but explains a more modest proportion of its variation (adjusted $R^2 = 0.085$). Although GEUI exhibits a statistically significant negative relationship with the market conditions index, its explanatory power is comparatively limited, reflecting both the shorter sample available for estimation and the distinct economic information captured by energy-related uncertainty.

Overall, the validation exercises indicate that the estimated CMMCI behaves consistently with established measures of global economic activity and supply chain conditions while exhibiting economically plausible relationships with geopolitical risk and energy-related uncertainty. These results provide strong empirical support for interpreting the one-factor DFM as a meaningful measure of aggregate critical mineral market conditions.

5.5 Comparison of the Principal Component Analysis and Dynamic Factor Model Indices

The preceding analyses demonstrate that both the PCA and the DFM identify a dominant source of common variation across critical mineral prices. Although the two methods differ in their underlying statistical frameworks, both are designed to extract the latent component representing aggregate critical mineral market conditions. This section compares the resulting indices to assess the robustness of the estimated CMMCI across alternative latent factor methodologies.

Figure 7. Comparison of the PCA and One-Factor DFM Indices



Note: The figure compares the PCA-based index with the one-factor DFM estimate of the CMMCI over June 2012 through April 2026. Both indices are oriented so that higher values represent stronger critical mineral market conditions.

Figure 7 plots the standardized PCA- and DFM-based market conditions indices over the sample period. The two indices exhibit remarkably similar movements throughout the sample, with both capturing the major turning points in critical mineral market conditions. Periods of declining market conditions during 2015–2016 and 2019–2020, the pronounced increase associated with the post-pandemic recovery and energy transition during 2021–2022, and the subsequent moderation after 2022 are evident in both series. The close correspondence between the indices indicates that the dominant latent factor is highly robust to the choice of estimation methodology.

While the overall movements are nearly identical, the DFM index exhibits a somewhat smoother trajectory than the PCA index. This difference is expected because the DFM explicitly models the temporal evolution of the latent factor through its state-space representation, allowing it to filter short-run idiosyncratic fluctuations while preserving persistent movements in market conditions. In contrast, PCA extracts the dominant contemporaneous component of variation without explicitly accounting for temporal dynamics.

The similarity between the two indices is also reflected in their correlation coefficient of 0.967 reported in Table 5. Such a high correlation indicates that both methods recover essentially

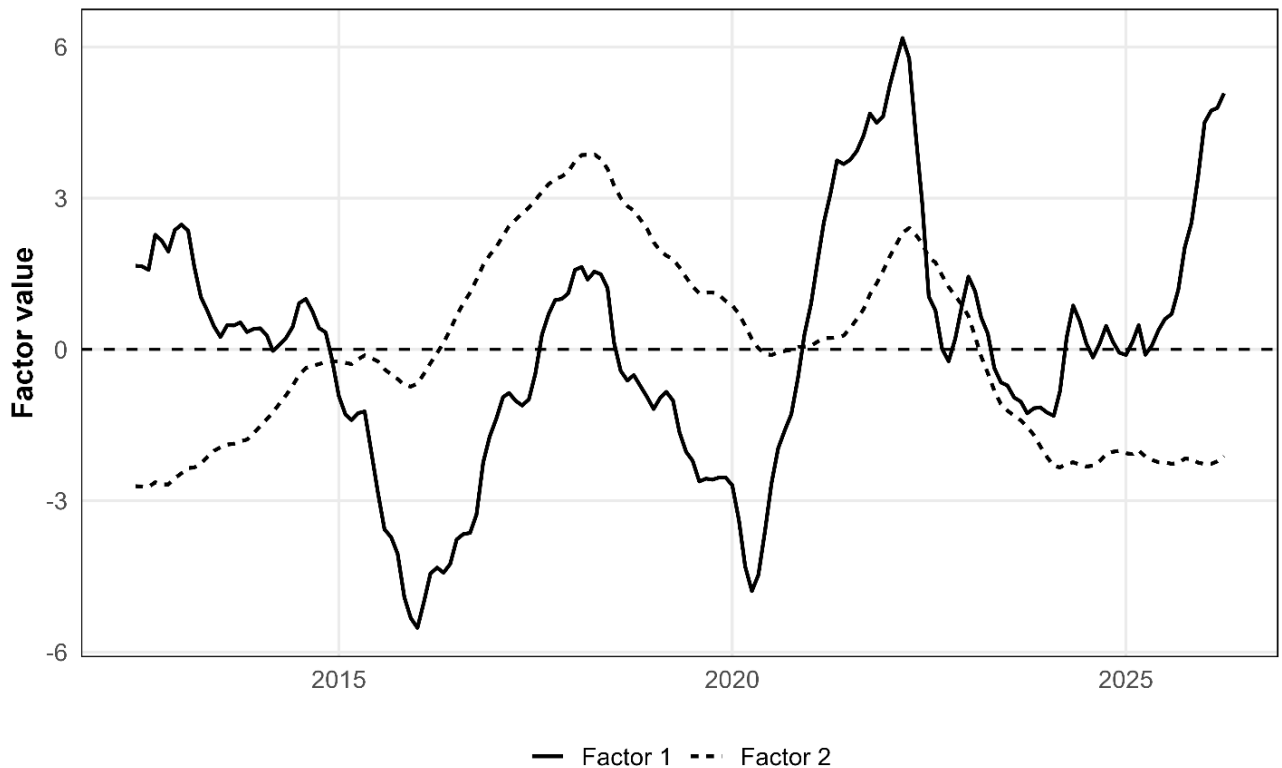
the same underlying market signal despite relying on different estimation procedures. Consequently, the estimated market conditions index is not sensitive to whether a static or dynamic latent factor model is employed.

Taken together, the comparison provides strong evidence that the proposed CMMCI is statistically robust and economically meaningful. The consistency of the PCA and DFM estimates suggests that the common factor reflects broad movements in global critical mineral markets rather than methodological artifacts. Given its ability to explicitly account for persistence and temporal dynamics, however, the one-factor DFM is retained as the preferred measure of aggregate critical mineral market conditions for the remaining analysis.

5.6 Robustness Analysis: Two-Factor Dynamic Factor Model

Although the one-factor DFM provides a parsimonious representation of aggregate critical mineral market conditions, an important question is whether additional latent factors capture economically meaningful variation beyond the primary market conditions index. To address this issue, a two-factor DFM is estimated as a robustness exercise. The objective is to determine whether a second latent dimension provides additional information regarding critical mineral market dynamics.

Figure 8. Two-Factor Dynamic Factor Model



Note: The figure plots the two latent factors obtained from the two-factor DFM. Factor 1 represents the primary market conditions factor, while Factor 2 captures additional common variation not explained by Factor 1.

Figure 8 presents the estimated latent factors from the two-factor DFM. The first factor closely resembles the one-factor CMMCI, indicating that the primary market conditions index is highly stable to the inclusion of an additional latent factor. The second factor exhibits a distinct pattern of variation, suggesting that it captures information not fully reflected in the aggregate market conditions index. This result indicates that while a single dominant factor explains the majority of common variation across critical mineral prices, a secondary dimension of market behavior is also present.

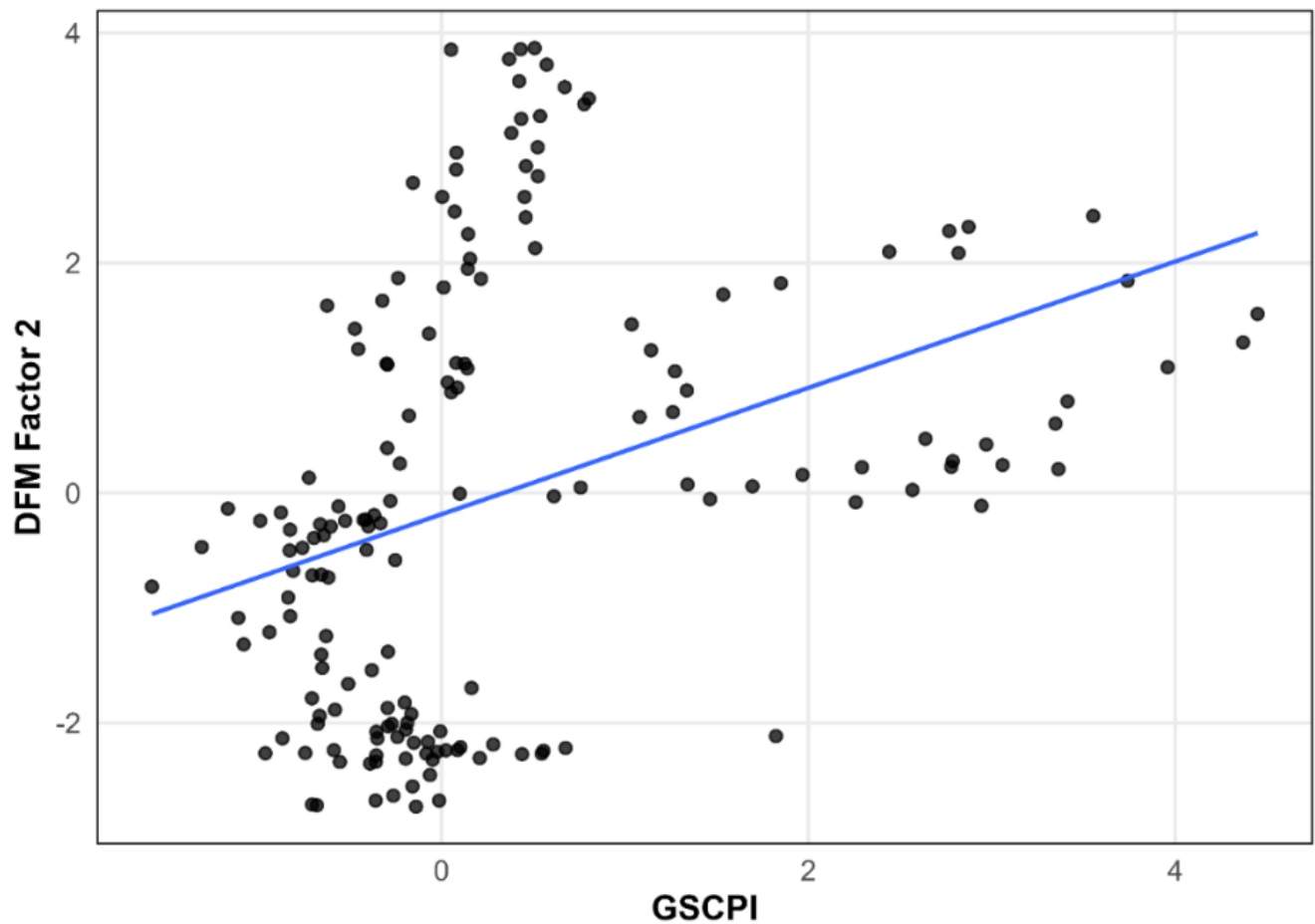
Table 7. Robustness Regression Results for the Second Dynamic Factor

Regression Model	N	Coefficient	p-value	Adj.-R²
Factor 2 ~ GSCPI	167	0.549	<0.001	0.133
Factor 2 ~ GPR	167	-0.005	0.184	0.011
Factor 2 ~ IGREA	167	0.002	0.466	0.003
Factor 2 ~ GEUI	138	-0.846	0.032	0.033

Note: Each regression estimates a separate bivariate relationship between the second latent factor obtained from the two-factor DFM and an external validation variable. Factor 2 is presented as a robustness exercise to assess whether an additional latent dimension captures information beyond the primary CMMCI. GSCPI is the Global Supply Chain Pressure Index; GPR is the Geopolitical Risk Index; IGREA is the Index of Global Real Economic Activity; and GEUI is the Global Energy-Related Uncertainty Index. Regressions involving GEUI use a shorter sample ($N = 138$) because the series is available only through November 2023.

To evaluate the economic interpretation of the second factor, Table 7 reports its relationships with the external validation variables. Unlike the primary factor, the second factor exhibits only weak relationships with global real economic activity and geopolitical risk, with neither variable providing meaningful explanatory power. Likewise, the relationship with the Global Energy-Related Uncertainty Index (GEUI) is statistically weaker and explains relatively little variation. In contrast, the Global Supply Chain Pressure Index (GSCPI) remains positively associated with the second factor and explains a larger share of its variation than the remaining validation variables. These results suggest that the second latent factor primarily reflects additional supply chain-related dynamics rather than broad global market conditions.

Figure 9. Second Dynamic Factor versus Global Supply Chain Pressure Index



Note: The figure plots the second factor from the two-factor DFM against the Global Supply Chain Pressure Index (GSCPI). The fitted line is obtained from the bivariate OLS regression reported in Table 7.

Figure 9 plots the second latent factor against the Global Supply Chain Pressure Index and includes the fitted line from the corresponding bivariate OLS regression reported in Table 7. Although the estimated relationship is weaker than that obtained for the primary market conditions factor, the upward-sloping fitted line indicates that the second factor captures additional variation associated with supply chain disruptions beyond that incorporated into the aggregate CMMCI. This finding is consistent with the interpretation that critical mineral markets contain a secondary dimension related to production bottlenecks, transportation constraints, and logistical frictions.

The two-factor model also provides additional statistical insight. Whereas the one-factor DFM summarizes the dominant common movement across all sixteen minerals, the inclusion of a second factor increases the model's ability to explain cross-sectional variation, with the mean coefficient of determination increasing from approximately 0.343 under the one-factor specification to approximately 0.583 under the two-factor specification. Inspection of the factor loadings indicates that the improvement is concentrated primarily among minerals closely

associated with energy-transition technologies, including lithium, cobalt, vanadium, and platinum, while the estimated first factor remains largely unchanged. Consequently, the principal interpretation of the CMMCI as a broad measure of aggregate critical mineral market conditions is preserved.

Overall, the robustness analysis indicates that although a second latent factor captures additional economically meaningful variation related primarily to supply chain conditions and technology-specific minerals, the one-factor DFM remains the preferred specification for constructing the CMMCI. The stability of the primary factor across alternative model specifications further strengthens confidence in the robustness and economic interpretability of the index.

5.7 Historical Evolution of Critical Mineral Market Conditions

The estimated CMMCI provides a historical record of major changes in global critical mineral markets over the sample period. While the latent factor summarizes the common variation across the sixteen mineral price series, important market events are more clearly identified through Indicator Saturation (ISAT), which detects statistically significant structural changes and discrete shocks without requiring the timing of such events to be specified a priori.

Table 8. Indicator Saturation (ISAT) Summary

Index	Indicator Type	Month	Date	Interpretation
PCA	IIS	4	Sep 2012	Beginning-of-sample effect
PCA	IIS	42	Nov 2015	Commodity market downturn
PCA	IIS	120	May 2022	Russia–Ukraine commodity disruption
PCA	IIS	122	Jul 2022	Continuation of 2022 disruption
PCA	IIS	164	Jan 2026	End-of-sample effect
PCA	SIS	119	Apr 2022	Beginning of 2022 structural shift
PCA	SIS	123	Aug 2022	End (reversal) of 2022 structural shift
DFM	IIS	54	Nov 2016	DFM impulse event
DFM	IIS	122	Jul 2022	Continuation of 2022 disruption
DFM	IIS	123	Aug 2022	End (reversal) of 2022 disruption
DFM	SIS	95	Apr 2020	DFM step shift
DFM	SIS	120	May 2022	Beginning of 2022 structural shift
DFM	SIS	123	Aug 2022	End (reversal) of 2022 structural shift

Note: IIS denotes Impulse Indicator Saturation, which identifies temporary shocks affecting individual observations. SIS denotes Step Indicator Saturation, which identifies persistent shifts in the level of the estimated index. PCA refers to the PCA-based CMMCI, while DFM refers to the one-factor DFM index. The retained indicators were selected using

the ISAT general-to-specific model selection procedure and identify statistically significant departures from the baseline model. The dates shown correspond to the monthly observations retained by the ISAT procedure.

Table 8 summarizes the statistically significant impulse and step indicators retained by the ISAT procedure. The retained indicators identify periods during which observed market conditions departed significantly from the underlying dynamics captured by the one-factor DFM. Because the procedure is entirely data driven, the detected events provide an objective statistical characterization of structural changes affecting global critical mineral markets.

Figure 10. Indicator Saturation (ISAT) Events



Note: The figure plots the PCA-based CMMCI together with the dates of the statistically significant impulse and step indicators retained by the Indicator Saturation procedure. Vertical lines identify retained ISAT events reported in Table 8.

Figure 10 illustrates the timing of the retained ISAT events relative to the estimated CMMCI. Several statistically significant episodes correspond closely with major developments affecting global commodity markets during the sample period. The sharp deterioration in market conditions during 2015–2016 coincides with the global commodity price downturn and weakening industrial demand. Subsequent improvements reflect the recovery in global manufacturing activity and

renewed investment associated with the energy transition. The pronounced movements beginning in 2020 correspond to the COVID-19 pandemic, widespread supply chain disruptions, and the subsequent acceleration in demand for critical minerals as global economic activity recovered. Additional structural changes during 2022 and the years that followed are consistent with heightened geopolitical tensions, continued supply chain constraints, and increasing strategic importance of minerals essential to clean energy technologies.

Importantly, the ISAT results indicate that these episodes represent statistically identifiable changes in market conditions rather than random fluctuations in commodity prices. The estimated break dates closely align with widely recognized economic and geopolitical events despite no prior information regarding their timing being incorporated into the estimation procedure. This correspondence provides additional evidence that the proposed CMMCI captures economically meaningful variation in underlying market conditions.

Taken together, the historical analysis demonstrates that the CMMCI successfully tracks major developments affecting global critical mineral markets over time. Combined with the strong agreement between the PCA and DFM estimates and the favorable validation results, the historical evidence further supports the interpretation of the CMMCI as a robust measure of aggregate critical mineral market conditions suitable for monitoring evolving market dynamics and supporting future empirical analysis, including real-time nowcasting and policy evaluation.

6. Conclusions and Policy Implications

This study develops and validates a CMMCI using two complementary latent factor methodologies: PCA and a DFM. Motivated by the increasing strategic importance of critical minerals, the index summarizes the common variation across sixteen critical mineral prices into a single measure of aggregate market conditions. The resulting index provides a parsimonious measure of aggregate critical mineral market conditions while preserving the common information contained in individual commodity prices.

The empirical results indicate the presence of a dominant common factor governing critical mineral market behavior. Substantial co-movement across the mineral price series provides the statistical foundation for latent factor estimation. PCA indicates that the first principal component explains a substantial share of total variation in the data, while the one-factor DFM produces a highly comparable measure that explicitly incorporates the temporal evolution of market conditions. The strong agreement between the two approaches, reflected in a correlation of 0.967, indicates that the estimated market conditions index is robust to alternative latent factor methodologies.

Validation exercises further demonstrate that the CMMCI captures economically meaningful variation in global market conditions. The estimated index exhibits its strongest relationships with global real economic activity and global supply chain pressures, consistent with the economic importance of industrial demand and production constraints in determining critical mineral prices. More modest relationships with geopolitical risk and energy-related uncertainty further suggest that these factors influence market conditions while operating through broader

economic channels. Collectively, these results support interpreting the CMMCI as a comprehensive measure of aggregate critical mineral market conditions.

The robustness analysis demonstrates that a second latent factor captures additional variation beyond the primary market conditions index, particularly among minerals closely associated with energy-transition technologies and supply chain dynamics. Although the two-factor DFM improves the model's ability to explain cross-sectional variation, the primary factor remains remarkably stable across model specifications. Consequently, the one-factor DFM provides a parsimonious and economically interpretable measure of aggregate market conditions, whereas the second factor captures additional technology- and supply-chain-specific variation.

The Indicator Saturation (ISAT) analysis further confirms the economic relevance of the estimated index. Statistically significant structural changes identified by the ISAT procedure correspond closely with major developments affecting global commodity markets, including the 2015–2016 commodity downturn, the COVID-19 pandemic, the subsequent recovery in global manufacturing activity, and the market disruptions associated with heightened geopolitical tensions beginning in 2022. The close correspondence between statistically identified break points and historically recognized events provides additional evidence that the CMMCI captures meaningful changes in underlying market conditions rather than transitory price fluctuations.

The proposed CMMCI has several practical applications. For policymakers, the index provides a timely measure of aggregate market conditions that may assist in monitoring supply chain resilience, identifying periods of elevated market stress, and evaluating policies designed to strengthen critical mineral supply chains. For industry participants, the index offers a summary indicator of evolving market conditions that may complement firm-level planning, investment decisions, and risk management. More broadly, the CMMCI provides researchers with a transparent and empirically validated measure that can be incorporated into future studies examining commodity markets, supply chain resilience, energy security, industrial policy, and the global energy transition.

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