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Nowcasting Critical Minerals Market Conditions with Mixed-Frequency Information

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Abstract

This paper develops a mixed-frequency framework for nowcasting the Critical Minerals Market Conditions Index (CMMCI) using daily and weekly financial and market information. Recursive pseudo-real-time estimation evaluates whether high-frequency information improves estimates of current monthly critical mineral market conditions relative to a persistent autoregressive benchmark. Four within-month information vintages are constructed to measure how predictive accuracy changes as information accumulates. A parsimonious specification incorporating the broad U.S. dollar index, U.S. refinery crude-oil inputs, and financial conditions produces progressively larger forecast improvements across the month. Relative to an AR(1) benchmark, root mean squared error reductions increase from 9.13% at the first information vintage to 12.63% at the fourth, with comparable improvements in mean absolute error. Clark–West tests indicate statistically significant predictive gains at each vintage. Results are robust to an alternative out-of-sample period and use of the principal component analysis-based CMMCI as the target. The findings demonstrate that high-frequency information can provide timely and progressively more accurate assessments of evolving critical mineral market conditions.

Keywords

Critical minerals, Nowcasting, Mixed-frequency data, U-MIDAS, Market conditions, Forecast evaluation.

JEL Classification

C53 (Forecasting and Prediction Methods; Simulation Methods), C22 (Time-Series Models; Dynamic Quantile Regressions; Dynamic Treatment Effect Models; Diffusion Processes), Q31 (Demand and Supply; Prices).

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1. Introduction

Critical mineral markets have become increasingly important to energy security, advanced manufacturing, and the global energy transition (Dahl, 2020; International Energy Agency, 2025). Prices for minerals used in batteries, electricity infrastructure, renewable energy technologies, and industrial production respond to changes in global economic activity, supply-chain conditions, financial markets, and geopolitical developments. Hollstein et al. (2021) provide evidence that macroeconomic indicators, particularly industrial production growth and inflation, contain predictive information about commodity returns. More specifically, Tay et al. (2026) find that lithium mining equity returns lead lithium price returns, suggesting that published lithium price indexes incorporate market information with a delay. These findings highlight the importance of timely measures of aggregate critical mineral market conditions.

Recent research also highlights the broader economic significance of critical mineral markets. Concordel et al. (2026) examine the differential macroeconomic effects of critical mineral and oil prices, while Kang et al. (2025) investigate the macroeconomic fragility associated with critical mineral markets. Vespignani and Smyth (2024) examine the relationship between artificial intelligence investment and critical mineral supply risks. Collectively, these studies underscore the importance of monitoring market conditions that may affect economic activity, investment, and supply-chain security.

Ewing (2026), in a technical report published by the Hamm Institute for American Energy, develops the Critical Minerals Market Conditions Index (CMMCI) to summarize common variation across sixteen critical mineral prices. The index is constructed using principal component analysis (PCA) and a dynamic factor model (DFM). The resulting measures exhibit substantial agreement, while external validation indicates that the CMMCI is systematically related to global real economic activity and supply-chain pressures. The DFM-based index provides the primary measure of critical mineral market conditions.

A limitation of a monthly market conditions index is that its contemporaneous value cannot be observed until the underlying monthly information becomes available. This timing problem is particularly relevant for critical mineral markets because financial and market indicators are observed at substantially higher frequencies. Daily and weekly variables may therefore contain information about current-month critical mineral market conditions before the monthly CMMCI can be observed. Nowcasting provides a framework for exploiting this asynchronous information flow.

Nowcasting methods estimate current economic conditions before the target variable is fully observed by combining information that arrives at different frequencies and at different points within the reference period. The literature has developed extensively around dynamic factor and state-space models, which summarize large information sets and permit recursive updating as new observations become available (Meinhold & Singpurwalla, 1983; Bańbura et al., 2010; de Valk et al., 2019). More broadly, mixed-frequency methods are well suited to settings in which higher-frequency indicators may contain information about a lower-frequency target before the reference period is complete.

Recent work has extended nowcasting and short-horizon forecasting beyond conventional macroeconomic applications. Kwas et al. (2022) demonstrate the predictive usefulness of common factors derived from commodity prices and macroeconomic and financial indicators, while Angelidis et al. (2025) compare alternative approaches to forecasting commodity returns. Machine-learning methods have also been applied to commodity-price forecasting, while comparisons of machine-learning and latent-factor approaches illustrate the tradeoff between predictive flexibility and economic interpretability (Dai et al., 2025; Ge et al., 2025). At the same time, real-time forecast evaluation requires models to be assessed using information sets that approximate those available at the forecast origin rather than full-sample fitted values or subsequently revised data (Čapek et al., 2025). These considerations are particularly relevant for critical minerals, where applications of formal nowcasting methods remain limited.

This paper extends the CMMCI framework by developing a mixed-frequency nowcasting model for monthly critical mineral market conditions. The empirical design incorporates daily and weekly financial, market, and economic indicators and evaluates their incremental predictive content relative to a highly persistent autoregressive benchmark. The analysis employs expanding-window pseudo-real-time estimation, with forecasting model parameters estimated recursively using historical observations. Current-month high-frequency information is incorporated sequentially to generate nowcasts of the monthly CMMCI.

An important feature of the analysis is the explicit treatment of information accumulation within the month. Four information vintages are considered, corresponding approximately to 5, 10, 15, and 20 trading days and one through four weeks of current-month information. Initial unrestricted mixed-data sampling (U-MIDAS) models establish the predictive relevance of the high-frequency variables but become increasingly parameter intensive as additional observations enter the information set. The preferred specification therefore uses cumulative within-month information for three high-frequency predictors—the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the National Financial Conditions Index (NFCI)—while maintaining a fixed model dimension across information vintages.

The results indicate that high-frequency information materially improves nowcasts of critical mineral market conditions. Relative to the recursive AR(1) benchmark, the preferred model reduces DFM-based CMMCI root mean squared error (RMSE) by 9.13% at the first information vintage, with the improvement increasing monotonically to 12.63% at the full within-month vintage. Mean absolute error (MAE) improvements similarly increase from 9.49% to 12.53%. Clark–West tests reject equal predictive accuracy relative to the nested AR(1) benchmark at all four information vintages. The results remain qualitatively unchanged when the evaluation period begins in January 2021 and when the PCA-based CMMCI replaces the DFM index as the target variable.

Because the original CMMCI is constructed using full-sample factor estimation, the analysis also evaluates nowcasting performance using a recursively estimated DFM index. This alternative measure is constructed using expanding estimation windows, thereby excluding future mineral-price observations from each monthly factor estimate. The mixed-frequency model continues to outperform the autoregressive benchmark, although the magnitude of the forecasting improvement is smaller. These findings indicate that the predictive contribution of high-frequency information is not dependent on the full-sample construction of the original CMMCI.

The contribution is therefore broader than demonstrating that the CMMCI can be nowcast. The analysis quantifies the incremental value of information within the month. Holding model dimensionality constant, progressively larger current-month information sets generate progressively more accurate estimates of latent critical mineral market conditions. Forecast-error analysis further indicates that the gains are concentrated during relatively large movements in the CMMCI, when timely information about changing market conditions is potentially most valuable.

The remainder of the paper is organized as follows. Section 2 describes the monthly target variable and mixed-frequency predictors. Section 3 presents the nowcasting methodology and pseudo-real-time evaluation framework. Section 4 reports the empirical results and robustness analyses. Section 5 concludes with implications for real-time monitoring of critical mineral markets.

2. Data

The empirical analysis combines the monthly CMMCI with daily, weekly, and monthly economic and financial indicators. The monthly sample begins in June 2012, corresponding to the starting date of the CMMCI developed in Ewing (2026). The primary target variable is the DFM-based CMMCI, denoted CMMCI_DFM. The PCA-based index, CMMCI_PCA, is retained as an alternative target for robustness

analysis. Both measures summarize common variation across sixteen monthly real critical mineral price series.

The CMMCI is developed in Ewing (2026) using monthly prices for sixteen critical minerals over the period beginning in June 2012. Nominal mineral prices are deflated using the U.S. Consumer Price Index and transformed into natural logarithms. PCA and a DFM are then employed to extract common variation across mineral prices. The resulting indices provide aggregate measures of critical mineral market conditions, capturing movements shared across individual mineral markets while reducing the dimensionality of the underlying price information.

Ewing (2026) demonstrates substantial agreement between the PCA- and DFM-based indices and evaluates their relationships with external indicators of global economic activity, supply-chain pressures, and geopolitical risk. The DFM-based CMMCI is adopted as the primary nowcasting target because it explicitly accommodates the dynamic evolution of common market conditions. The PCA-based index provides an alternative measure for assessing the robustness of the nowcasting results. Additional details on index construction, factor estimation, and external validation are provided in Ewing (2026).

To assess the sensitivity of the nowcasting results to full-sample factor estimation, a recursive DFM-based CMMCI is constructed using the same sixteen mineral-price series. The initial estimation window extends from June 2012 through December 2019. Beginning in January 2020, the DFM is re-estimated each month using an expanding sample that includes observations only through the corresponding month. Mineral prices are deflated by the CPI, transformed into natural logarithms, and standardized within each estimation window. Factor orientation is maintained consistently across estimation windows. The resulting recursive index provides an alternative target for evaluating the robustness of the mixed-frequency nowcasting results.

The predictor set is designed to capture information available at different frequencies before the monthly CMMCI is observed. Daily variables include the Nominal Broad U.S. Dollar Index (DTWEXBGS), CBOE Volatility Index (VIXCLS), and 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity spread (T10Y2Y). Weekly variables include the U.S. refinery crude-oil inputs (WCRRIUS2), National Financial Conditions Index (NFCI), St. Louis Fed Financial Stress Index (STLFSI4), and Weekly Economic Index (WEI). Monthly indicators include the Consumer Price Index (CPI), Global Supply Chain Pressure Index (GSCPI), Geopolitical Risk Index (GPR), and Index of Global Real Economic Activity (IGREA).

The high-frequency variables represent several potential channels through which current economic and financial conditions may be related to critical mineral markets. The broad U.S. dollar index captures exchange-rate conditions relevant to internationally traded commodities. Weekly U.S. refinery crude-oil inputs provide an indicator of petroleum refining activity, while the NFCI captures broader financial conditions. Such indexes aggregate information across multiple financial markets to characterize overall financial conditions (Brave & Butters, 2011). Related research demonstrates the usefulness of high-frequency information for monitoring aggregate economic activity (Brave et al., 2019). The remaining variables measure financial-market volatility, the Treasury yield spread, financial stress, and weekly economic activity.

Preliminary model evaluation assesses the incremental predictive content of the candidate high-frequency variables. The results favor a parsimonious specification containing the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the NFCI. The remaining high-frequency indicators provide limited incremental predictive information conditional on these variables and are therefore excluded from the preferred specification. Broader specifications are retained as part of the model-development analysis.

The defining feature of the empirical design is the sequential accumulation of information within each month. The target variable is monthly, whereas the principal predictors are observed daily or weekly. The pseudo-real-time analysis constructs four sequential information vintages using progressively larger

subsets of within-month observations instead of completed-month aggregates. These correspond approximately to the first 5, 10, 15, and 20 daily observations and the first one through four weekly observations, respectively. The vintages are defined using observation dates, not historical publication or release dates, and therefore approximate the information sets available within each month. This structure permits evaluation of whether additional high-frequency observations improve the CMMCI nowcast as the month progresses.

Table 1. Data and Variable Definitions

Variable	Description	Frequency	Role
CMMCI_DFM	Critical Minerals Market Conditions Index, dynamic factor model	Monthly	Primary nowcasting target
CMMCI_PCA	Critical Minerals Market Conditions Index, principal component analysis	Monthly	Robustness nowcasting target
CPI	Consumer Price Index	Monthly	Monthly benchmark predictor
GSCPI	Global Supply Chain Pressure Index	Monthly	Monthly benchmark predictor
GPR	Geopolitical Risk Index	Monthly	Monthly benchmark predictor
IGREA	Index of Global Real Economic Activity	Monthly	Monthly benchmark predictor
DTWEXBGS	Nominal Broad U.S. Dollar Index	Daily	High-frequency predictor; retained
VIXCLS	CBOE Volatility Index	Daily	High-frequency candidate; screened out
T10Y2Y	10-Year Treasury Yield Spread (10-year minus 2-year)	Daily	High-frequency candidate; screened out
WCRRIUS2	U.S. refinery crude-oil inputs (thousand barrels per day)	Weekly	High-frequency predictor; retained
NFCI	Chicago Fed National Financial Conditions Index	Weekly	High-frequency predictor; retained
STLFSI4	St. Louis Fed Financial Stress Index	Weekly	High-frequency candidate; not retained
WEI	Weekly Economic Index	Weekly	High-frequency candidate; not retained

Notes: CMMCI_DFM is the primary nowcasting target, while CMMCI_PCA is used for robustness analysis. High-frequency predictors are screened for incremental predictive content. DTWEXBGS, WCRRIUS2, and NFCI are retained in the preferred parsimonious mixed-frequency specification.

3. Methodology

The empirical objective is to estimate the current monthly value of the CMMCI before the complete monthly information underlying the index is observed. Let C_t denote the CMMCI for month t. The analysis evaluates whether high-frequency information observed during month t improves prediction of C_t relative to models based primarily on information available through month $t-1$. Factor-based forecasting methods provide a related framework for extracting predictive information from multiple economic indicators (Stock & Watson, 2002; Aït-Sahalia & Xiu, 2017).

The baseline model is a first-order autoregression. The AR(1) provides a natural benchmark given the persistence of the CMMCI.

$$C_t = \alpha + \rho C_{t-1} + \varepsilon_t \qquad (1)$$

A monthly-information model provides a second benchmark by augmenting lagged CMMCI information with monthly economic indicators. This specification evaluates whether conventional monthly information improves predictive accuracy relative to persistence alone.

The initial mixed-frequency analysis uses unrestricted MIDAS (U-MIDAS) specifications, building on the mixed-frequency regression framework developed by Ghysels et al. (2007). U-MIDAS allows the available daily and weekly observations to enter the monthly nowcasting equation without imposing a parametric lag-weighting function. This provides a flexible means of evaluating the incremental predictive content of the candidate high-frequency variables. The model-development analysis identifies the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the NFCI as the principal high-frequency predictors.

The unrestricted specification becomes increasingly parameter intensive as information accumulates within the month. The number of high-frequency coefficients in the three-block U-MIDAS model increases from seven at the first vintage to 28 at the fourth. Consequently, changes in forecast accuracy across vintages reflect both additional information and increasing model dimensionality. This makes the unrestricted specification less suitable for isolating the predictive value of sequential information arrival.

The preferred model addresses this issue by replacing individual high-frequency observations with cumulative within-month means. Let $X_{j,t}^{(v)}$ denote the cumulative mean of high-frequency predictor j observed through information vintage v in month t, where j represents the broad U.S. dollar index, refinery crude-oil inputs, or NFCI, and $v = 1, \ldots, 4$. The preferred nowcasting model is specified as:

$$C_t = \alpha + \rho C_{t-1} + \beta_1 X^{v}_{\mathrm{USD},t} + \beta_2 X^{v}_{\mathrm{Oil},t} + \beta_3 X^{v}_{\mathrm{NFCI},t} + \varepsilon_t \qquad (2)$$

where α is the intercept, ρ measures persistence in the CMMCI, and β_1, β_2, and β_3 measure the contributions of the three high-frequency predictors. The specification maintains three high-frequency regressors at every information vintage, allowing forecast accuracy to be evaluated as additional information accumulates without increasing model dimensionality.

This fixed-dimensional specification separates information accumulation from model expansion. Model dimensionality remains constant while the information embodied in each cumulative predictor increases as the month progresses. Differences in forecast performance across vintages can therefore be interpreted as evidence on the incremental predictive value of additional within-month information.

The models are evaluated using expanding-window pseudo-real-time estimation, consistent with the recursive updating principles underlying established nowcasting frameworks (Giannone et al., 2008). At each forecast origin, the forecasting equations are re-estimated using observations through month t−1. Current-month daily and weekly predictors are incorporated according to the four information vintages to generate successive nowcasts of C_t. Following each forecast evaluation, the estimation window expands by one month. The analysis uses observation-based information vintages and assumes availability of the preceding month's CMMCI. Accordingly, the procedure approximates historical information sets without explicitly reproducing publication schedules or subsequent data revisions. The distinction between pseudo-real-time evaluation and forecasting with actual historical data vintages is important because data revisions and information availability can affect measured forecasting performance (Croushore, 2011).

Forecast accuracy is evaluated using root mean squared error (RMSE) and mean absolute error (MAE). RMSE is defined as:

$$\mathrm{RMSE} = \sqrt{\left[\left(\frac{1}{N}\right)\sum_{t=1}^{N}\left(C_t - \hat{C}_t\right)^2\right]} \qquad (3)$$

where C_t is the realized CMMCI, $\hat{C}_t$ is the corresponding forecast or nowcast, and N is the number of out-of-sample observations. RMSE penalizes larger forecast errors more heavily because errors are squared before averaging.

Mean absolute error (MAE) is defined as:

$$\mathrm{MAE} = \left(\frac{1}{N}\right)\sum_{t=1}^{N}\left|C_t - \hat{C}_t\right| \qquad (4)$$

MAE measures the average absolute forecast error and is less sensitive to large errors than RMSE. Together, these measures provide complementary assessments of predictive accuracy. Percentage improvements in RMSE and MAE are calculated relative to the recursive AR(1) benchmark, with positive values indicating lower forecast error for the competing model.

Formal forecast-comparison tests supplement these loss measures. Because the preferred cumulative-information model nests the AR(1) benchmark, Clark–West (2007) tests provide the primary statistical assessment of incremental predictive accuracy relative to the AR(1). Robustness is evaluated using an alternative out-of-sample period beginning in January 2021 and by replacing the DFM-based CMMCI with the PCA-based CMMCI as the forecast target.

An additional robustness exercise addresses potential look-ahead bias associated with full-sample estimation of the original CMMCI. The DFM is initially estimated using June 2012–December 2019 observations and subsequently re-estimated using expanding monthly windows. Each month's factor estimate is obtained from the DFM fitted using mineral-price observations through that month, excluding observations from subsequent months. The recursive index replaces the original CMMCI as the dependent variable in both the AR(1) benchmark and preferred mixed-frequency model. Forecasts are generated over January 2020–April 2026 using the same four information vintages and expanding-window estimation

procedure. Forecast accuracy is evaluated using RMSE, MAE, and Clark–West tests with heteroskedasticity and autocorrelation-consistent standard errors.

Table 2. Model Comparison and Predictor Selection

Panel A. In-Sample Model Comparison

Model	RMSE	MAE	Adjusted R^2	AIC	BIC
AR(1)	0.4703	0.3546	0.9629	226.65	235.99
Monthly benchmark	0.4588	0.3511	0.9638	226.38	248.16
USD U-MIDAS	0.4130	0.3037	0.9674	223.46	295.04
Three-block U-MIDAS	0.3586	0.2637	0.9740	192.63	289.11
Full five-block U-MIDAS	0.3518	0.2570	0.9734	202.22	323.59

Panel B. High-Frequency Predictor Selection

Stage	Predictor	F-statistic	p-value
Univariate screening	DTWEXBGS	2.140	0.0054
Univariate screening	VIXCLS	0.629	0.8858
Univariate screening	T10Y2Y	0.936	0.5432
Univariate screening	WCRRIUS2	2.935	0.0224
Univariate screening	NFCI	8.044	<0.0001
Univariate screening	STLFSI4	3.837	0.0053
Univariate screening	WEI	6.075	0.0001
Full-model conditional	DTWEXBGS	1.868	0.0201
Full-model conditional	WCRRIUS2	2.045	0.0919
Full-model conditional	NFCI	2.132	0.0805
Full-model conditional	STLFSI4	0.859	0.4903
Full-model conditional	WEI	0.537	0.7085
Parsimonious-model conditional	DTWEXBGS	2.431	0.0014

Stage	Predictor	F-statistic	p-value
Parsimonious-model conditional	WCRRIUS2	4.074	0.0038
Parsimonious-model conditional	NFCI	6.962	<0.0001

Notes: Panel A reports in-sample model fit and information criteria. Panel B reports F-tests for the incremental contribution of high-frequency predictors. The preferred parsimonious specification retains the broad U.S. dollar index (DTWEXBGS), U.S. refinery crude-oil inputs (WCRRIUS2), and National Financial Conditions Index (NFCI).

4. Results

The empirical analysis first evaluates whether the candidate high-frequency variables contain incremental information about current critical mineral market conditions. Table 2 reports the in-sample model comparisons and predictor-selection tests. The U-MIDAS results identify the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the NFCI as the preferred combination of high-frequency predictors. These variables form the three-block U-MIDAS specification used to evaluate the contribution of high-frequency information.

As shown in Panel A of Table 2, the three-block U-MIDAS specification produces the lowest Akaike Information Criterion (AIC), while the AR(1) benchmark produces the lowest Bayesian Information Criterion (BIC). The full five-block specification achieves a slightly lower in-sample RMSE but is penalized more heavily for model complexity. Panel B reports the predictor-selection tests, which support retaining the three high-frequency variables in the parsimonious specification.

The unrestricted specification initially produces a nonmonotonic relationship between information accumulation and forecast accuracy. Relative to the AR(1) benchmark, RMSE improvements for the three-block U-MIDAS model decline from 10.48% at the first vintage to 7.81% at the second, 0.36% at the third, and −6.75% at the fourth. However, the number of high-frequency coefficients increases from seven to 28 across these vintages. The deterioration in forecast performance therefore coincides with substantial growth in model dimensionality, making it difficult to isolate the effect of additional information.

Table 3 reports the primary out-of-sample nowcasting results for the parsimonious cumulative-information model, which removes this confounding effect by maintaining three high-frequency predictors at each vintage. The results exhibit a clear monotonic pattern. Relative to the recursive AR(1) benchmark, RMSE improves by 9.13% using approximately five trading days and one week of current-month information. The improvement increases to 10.54% at the second vintage, 11.81% at the third, and 12.63% at the fourth vintage, when approximately 20 trading days and four weeks of information are available.

MAE produces a nearly identical pattern. Improvements relative to the AR(1) benchmark increase from 9.49% at the first vintage to 10.32%, 11.53%, and 12.53% at subsequent vintages. Thus, once model dimensionality is held constant, forecast accuracy improves progressively as additional information becomes available within the month. This result is robust to whether forecast performance is measured using squared or absolute errors.

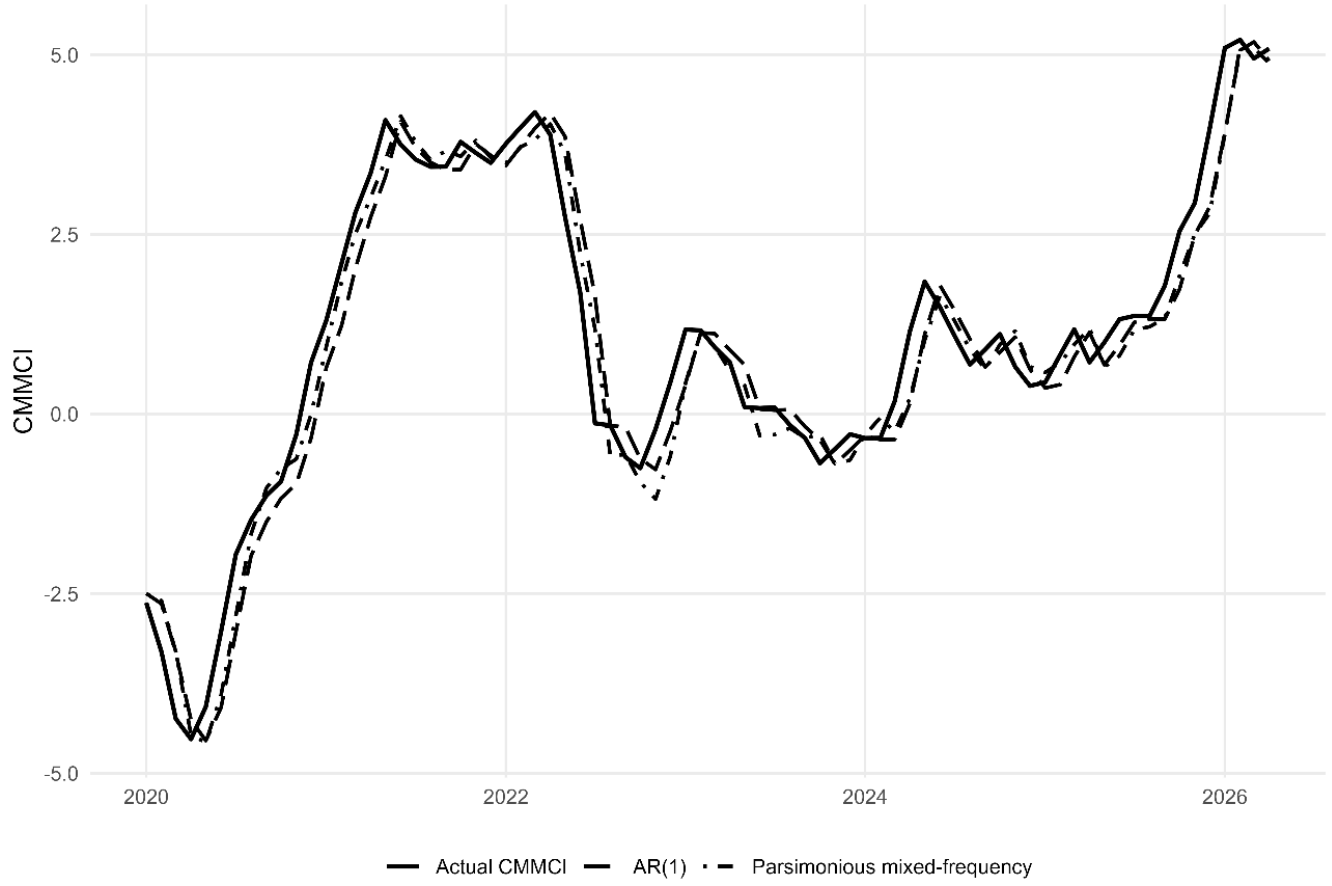
Table 3. Primary Out-of-Sample Nowcasting Performance

Model	RMSE	MAE	RMSE Improvement (%)	MAE Improvement (%)
AR(1)	0.5619	0.4368	0.00	0.00
Monthly benchmark	0.5819	0.4679	−3.57	−7.13
Parsimonious: 5 days + Week 1	0.5106	0.3953	9.13	9.49
Parsimonious: 10 days + Weeks 1–2	0.5027	0.3917	10.54	10.32
Parsimonious: 15 days + Weeks 1–3	0.4955	0.3864	11.81	11.53
Parsimonious: 20 days + Weeks 1–4	0.4909	0.3820	**12.63**	**12.53**

Notes: RMSE and MAE denote root mean squared error and mean absolute error, respectively. Percentage improvements are calculated relative to the recursive AR(1) benchmark. Positive values indicate improved forecast accuracy. The parsimonious mixed-frequency model incorporates cumulative within-month information from the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the National Financial Conditions Index.

Figure 1 compares the realized DFM-based CMMCI with the recursive AR(1) forecast and the preferred fourth-vintage nowcast. The mixed-frequency model more closely tracks several substantial movements in the realized CMMCI, indicating that current-month information provides responsiveness not available from the persistence benchmark alone.

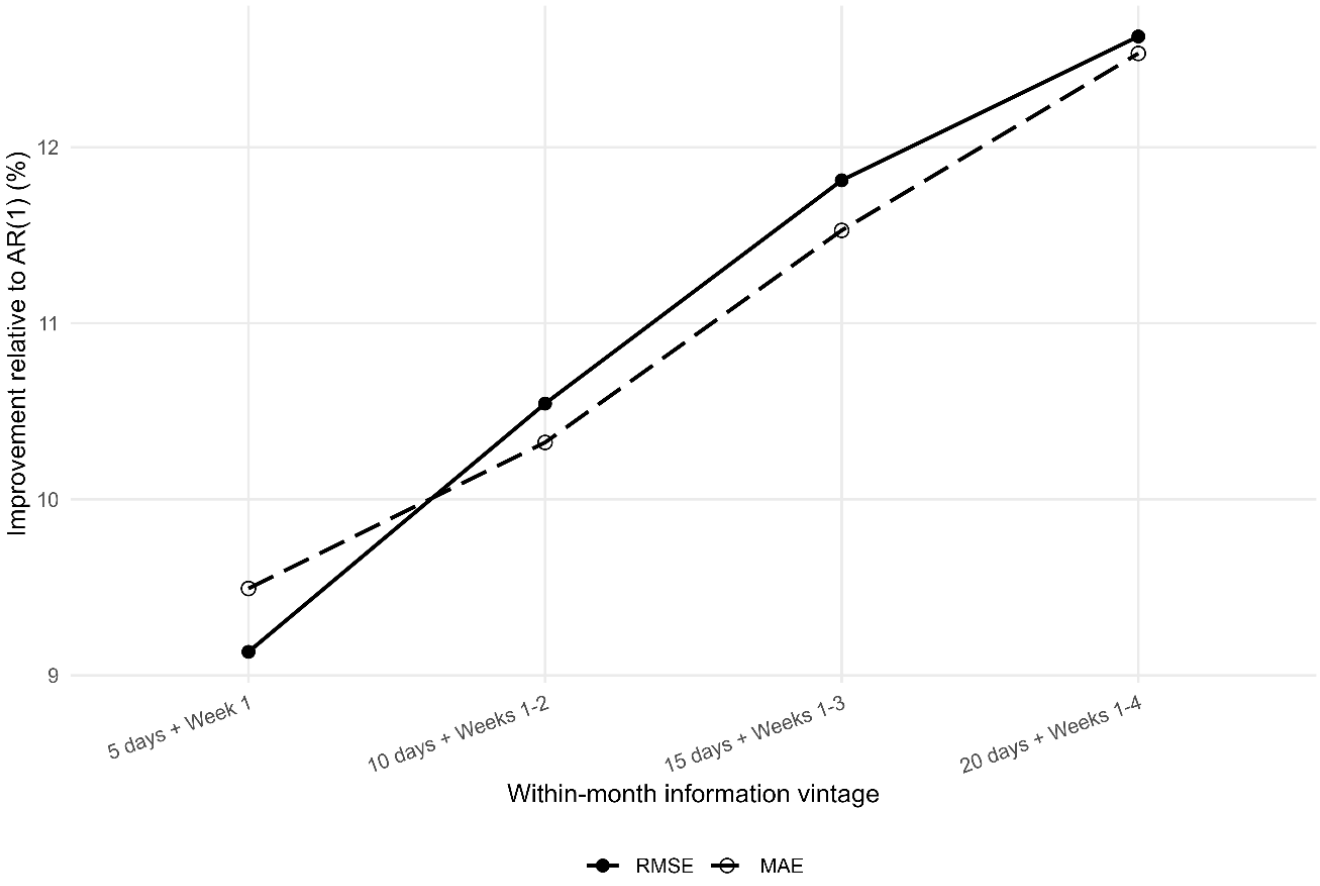
Figure 1. Actual CMMCI and Out-of-Sample Nowcasts



Notes: The figure compares the realized DFM-based Critical Minerals Market Conditions Index (CMMCI) with recursive nowcasts from the AR(1) benchmark and the parsimonious mixed-frequency model. The mixed-frequency specification uses Vintage 4 information, comprising the first 20 daily observations and four weekly observations within each month.

Figure 2 summarizes the principal information-accumulation result. Both RMSE and MAE improvements increase monotonically across the four vintages. High-frequency information therefore provides predictive value early in the month, with additional observations producing further gains as the month progresses.

Figure 2. Forecast Accuracy Improvements Across Information Vintages



Notes: The figure reports percentage improvements in RMSE and MAE relative to the recursive AR(1) benchmark. Positive values indicate improved forecast accuracy. Information vintages incorporate progressively more daily and weekly observations within the target month.

Formal forecast-comparison tests reinforce these results. Table 4 reports Clark–West tests comparing the preferred parsimonious mixed-frequency model with the nested AR(1) benchmark. The test statistics are positive and statistically significant at the 1% level for all four information vintages. The corresponding p-values are 0.00073, 0.00052, 0.00033, and 0.00025, respectively. These findings provide statistical evidence that the mixed-frequency specification improves predictive accuracy relative to the autoregressive benchmark.

Table 4. Forecast Accuracy Tests

Information Vintage	Clark–West Statistic	p-value
5 days + Week 1	3.306	0.00073
10 days + Weeks 1–2	3.411	0.00052
15 days + Weeks 1–3	3.551	0.00033
20 days + Weeks 1–4	3.635	0.00025

Notes: Clark–West tests compare the predictive accuracy of the parsimonious mixed-frequency model with the nested recursive AR(1) benchmark. Positive test statistics favor the mixed-frequency model. All four tests are statistically significant at the 1% level. The dependent variable is the DFM-based Critical Minerals Market Conditions Index (CMMCI_DFM).

Table 5 reports robustness results for alternative empirical specifications, including a shorter evaluation period and the PCA-based CMMCI as the nowcasting target. First, the pseudo-real-time analysis is repeated using an evaluation period beginning in January 2021, thereby excluding 2020. The monotonic information-accumulation pattern remains. At the fourth vintage, the preferred model reduces RMSE by 10.62% and MAE by 9.02% relative to the AR(1) benchmark. The forecasting gains therefore do not depend on observations from the initial COVID-19 period.

Second, the analysis is repeated using the PCA-based CMMCI as the target. At the fourth vintage, RMSE improves by 10.59% and MAE by 11.14% relative to the corresponding AR(1) benchmark. The Clark–West test yields a p-value of 0.00026. The principal result therefore does not depend on whether the CMMCI is constructed using the DFM or PCA approach.

Table 5. Robustness Analysis

Panel A. Alternative Out-of-Sample Evaluation Period: January 2021–April 2026

Model	RMSE	MAE	RMSE Improvement (%)	MAE Improvement (%)
AR(1)	0.5314	0.4024	0.00	0.00
Monthly benchmark	0.5635	0.4510	−6.03	−12.10
Parsimonious: 5 days + Week 1	0.4901	0.3744	7.76	6.96
Parsimonious: 10 days + Weeks 1–2	0.4835	0.3730	9.01	7.30
Parsimonious: 15 days + Weeks 1–3	0.4778	0.3685	10.09	8.41
Parsimonious: 20 days + Weeks 1–4	0.4749	0.3661	**10.62**	**9.02**

Panel B. Alternative Nowcasting Target: PCA-Based CMMCI

Model	RMSE	MAE	RMSE Improvement (%)	MAE Improvement (%)
AR(1)	0.6739	0.5303	0.00	0.00
Parsimonious: 5 days + Week 1	0.6230	0.4802	7.55	9.45
Parsimonious: 10 days + Weeks 1–2	0.6169	0.4786	8.47	9.75
Parsimonious: 15 days + Weeks 1–3	0.6093	0.4754	9.60	10.35
Parsimonious: 20 days + Weeks 1–4	0.6026	0.4712	**10.59**	**11.14**

Panel C. Clark–West Tests: PCA-Based CMMCI

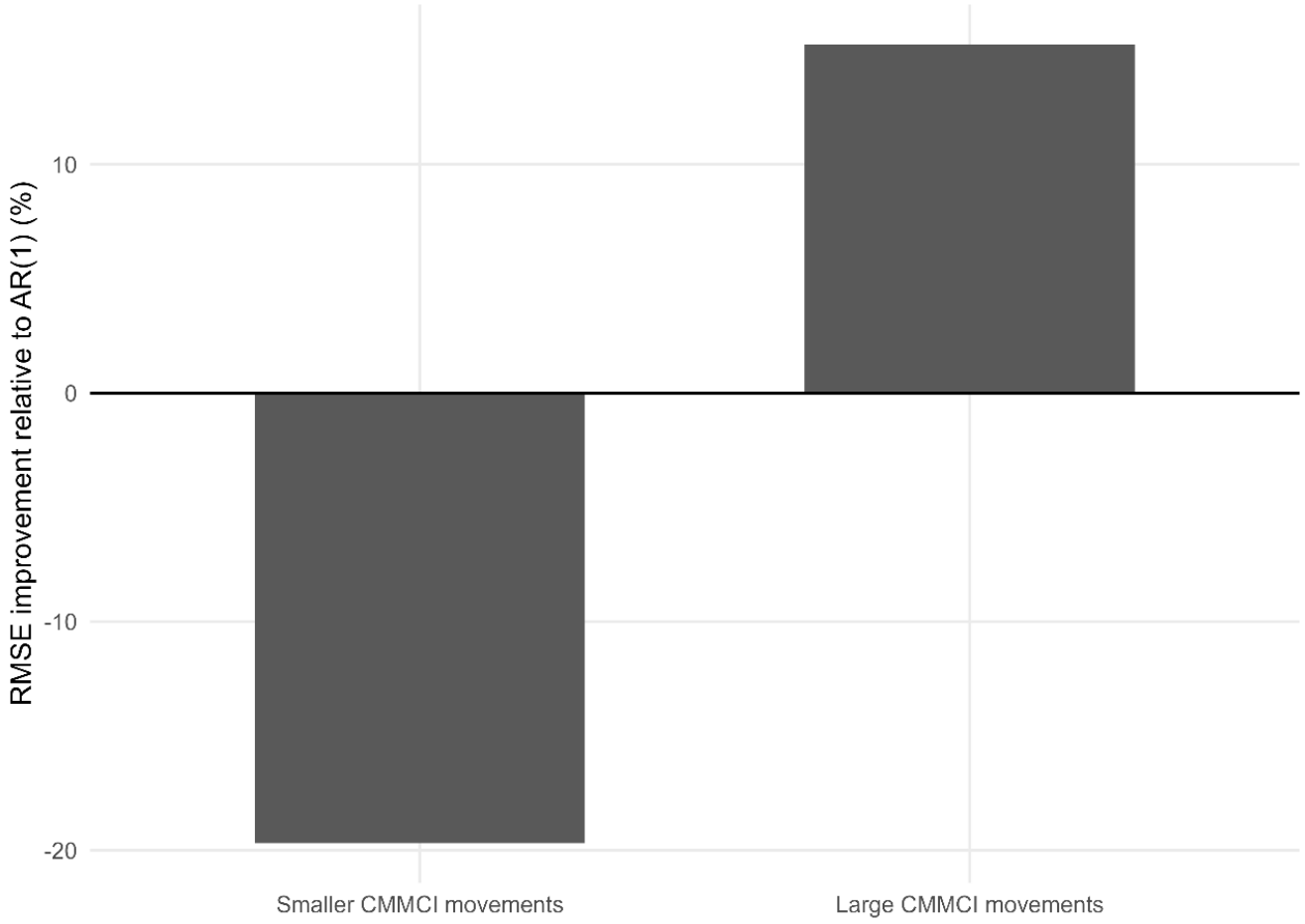
Information Vintage	Clark–West Statistic	p-value
5 days + Week 1	3.319	0.00070
10 days + Weeks 1–2	3.340	0.00065
15 days + Weeks 1–3	3.488	0.00041
20 days + Weeks 1–4	3.632	0.00026

Notes: Panel A evaluates the preferred DFM-based nowcasting specification over the alternative January 2021–April 2026 evaluation period. Panel B reports results using the PCA-based CMMCI as the dependent variable. Percentage improvements in RMSE and MAE are calculated relative to the corresponding recursive AR(1) benchmark; positive values indicate improved forecast accuracy. Panel C reports Clark–West tests comparing the PCA-based parsimonious mixed-frequency specification with its nested AR(1) benchmark. All four tests are statistically significant at the 1% level.

Forecast-error diagnostics provide additional evidence on when high-frequency information is most valuable. Improvements relative to the AR(1) benchmark are concentrated during relatively large movements in the realized CMMCI. This result is consistent with the persistence benchmark performing comparatively well when market conditions change little, while contemporaneous high-frequency information becomes more useful when current conditions depart materially from those observed in the preceding month.

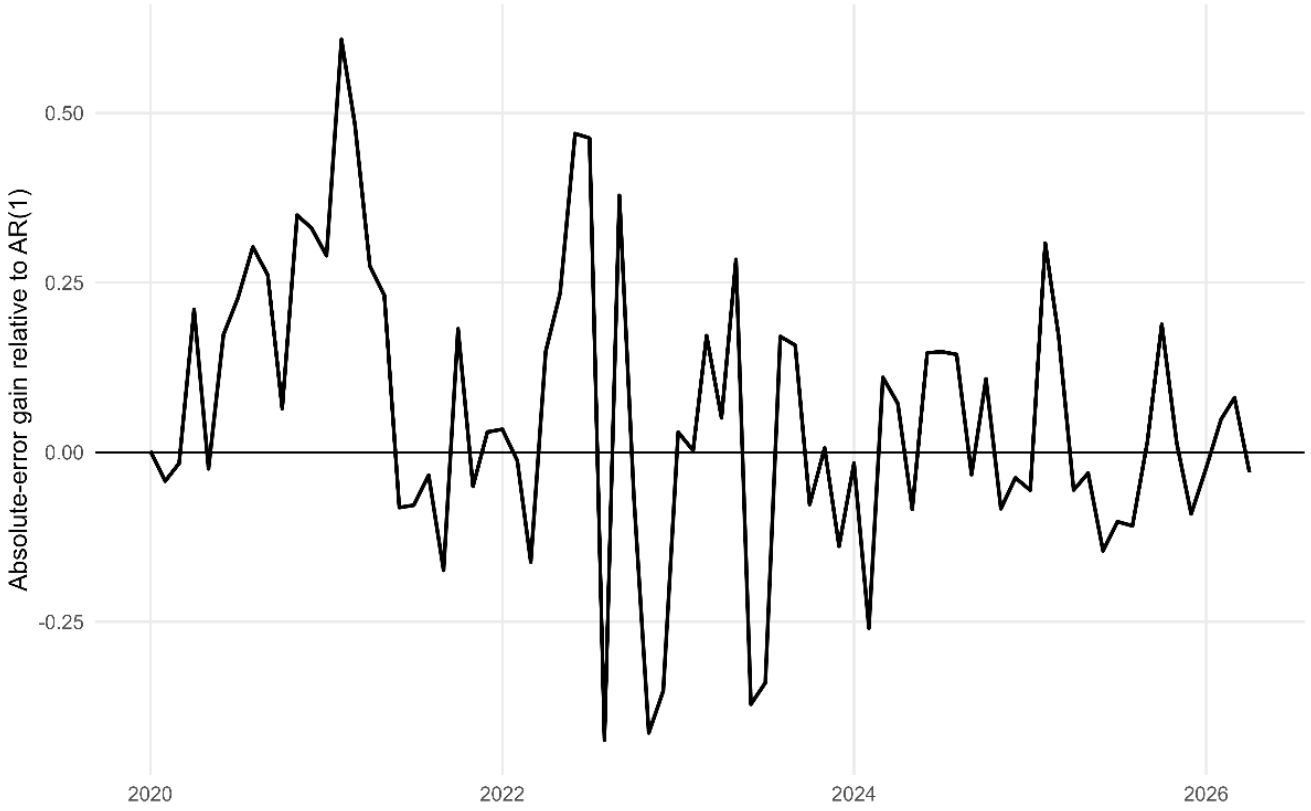
Figure 3 compares RMSE improvements during smaller and larger CMMCI movements. The preferred mixed-frequency model reduces RMSE by 15.25% relative to the AR(1) benchmark during larger movements but produces a 19.68% increase in RMSE during smaller movements. These findings indicate that the predictive benefits of high-frequency information are concentrated during relatively large changes in critical mineral market conditions. Figure 4 reports the monthly difference in absolute forecast errors between the AR(1) benchmark and the preferred mixed-frequency model, illustrating the variation in relative predictive performance across the evaluation period.

Figure 3. Forecast Accuracy Gains by Magnitude of CMMCI Movements



Notes: The figure reports percentage improvements in RMSE for the parsimonious mixed-frequency model (Vintage 4) relative to the recursive AR(1) benchmark. Months are classified according to whether the absolute monthly change in the realized DFM-based CMMCI exceeds its sample median. Smaller movements correspond to changes less than or equal to the median; large movements exceed the median. Positive values indicate improved forecast accuracy. The classification is retrospective and does not represent information available when nowcasts are generated.

Figure 4. Monthly Forecast-Error Gains Relative to the AR(1) Benchmark



Notes: The figure reports the monthly difference in absolute nowcasting errors between the recursive AR(1) benchmark and the parsimonious mixed-frequency model (Vintage 4). Positive values indicate that the mixed-frequency model produces smaller absolute errors, while negative values favor the AR(1) benchmark. Differences are expressed in CMMCI index units.

The large-movement comparison should be interpreted strictly as an ex post characterization of forecast performance. The classification uses the subsequently realized contemporaneous change in the CMMCI and therefore does not represent an ex ante regime classification or forecasting rule. Its purpose is to identify the market conditions under which the high-frequency information produced the largest realized forecasting gains.

Three principal findings emerge. First, daily and weekly financial and market indicators contain incremental information about current critical mineral market conditions. Second, holding model dimensionality constant, nowcast accuracy improves progressively as additional information becomes available within the month. Third, these gains are robust to the evaluation period and construction of the CMMCI and are concentrated during relatively large changes in market conditions.

An additional robustness exercise evaluates whether the nowcasting results depend on the full-sample estimation of the original CMMCI. The analysis replaces the original DFM-based index with a recursively estimated alternative that excludes subsequent mineral-price observations from each monthly factor estimate. The forecasting specifications, four information vintages, and January 2020–April 2026 evaluation period remain unchanged.

Table 6 reports the forecasting results using the recursive DFM index. The preferred mixed-frequency model outperforms the AR(1) benchmark across all four information vintages, with RMSE reductions ranging from 4.89% at the first vintage to 6.11% at the fourth vintage. Forecast accuracy generally improves as additional within-month information becomes available. The Clark–West tests, computed using heteroskedasticity and autocorrelation-consistent standard errors, indicate statistically significant improvements over the benchmark at the 5% level for all four vintages.

The recursive DFM results reinforce the principal finding that daily and weekly economic and financial indicators contain incremental predictive information for critical mineral market conditions. Although the RMSE improvements are smaller than those obtained using the original full-sample CMMCI, the direction and statistical significance of the forecasting gains are preserved. Thus, the preferred model's predictive advantage is not exclusively attributable to full-sample factor estimation.

Table 6. Nowcasting Performance Using the Recursive DFM-Based CMMCI

Out-of-sample evaluation: January 2020–April 2026 (N = 76)

Model	RMSE	MAE	RMSE improvement (%)	Clark–West p-value
AR(1) benchmark	0.6254	0.4701	—	—
Preferred model: Vintage 1	0.5948	0.4454	4.89	0.0152
Preferred model: Vintage 2	0.5926	0.4448	5.25	0.0108
Preferred model: Vintage 3	0.5892	0.4452	5.79	0.0085
Preferred model: Vintage 4	0.5872	0.4440	6.11	0.0067

Notes: The preferred model includes the lagged CMMCI, broad U.S. dollar index, U.S. refinery crude-oil inputs, and National Financial Conditions Index. Vintages 1–4 incorporate progressively larger subsets of current-month daily and weekly observations. RMSE improvement is measured relative to the AR(1) benchmark. Clark–West p-values are one-sided and calculated using heteroskedasticity and autocorrelation-consistent standard errors with four lags.

5. Conclusion and Discussion

This paper develops a mixed-frequency framework for nowcasting the Critical Minerals Market Conditions Index. Building on the CMMCI developed and validated in Ewing (2026), the analysis evaluates whether daily and weekly information improves estimates of current monthly critical mineral market conditions before the underlying monthly information is complete. The empirical framework combines recursive pseudo-real-time estimation with sequential within-month information vintages to approximate the information environment facing a user of the index.

The results indicate that high-frequency information provides meaningful incremental predictive content. A parsimonious specification incorporating the broad U.S. dollar index, U.S. refinery crude-oil inputs, and the NFCI consistently outperforms the recursive AR(1) benchmark in aggregate. More importantly, predictive accuracy improves systematically as information accumulates within the month. RMSE improvement increases from 9.13% at the first information vintage to 12.63% at the fourth, while MAE improvement increases from 9.49% to 12.53%. Clark–West tests indicate statistically significant predictive gains at every vintage.

The sequential information result is the principal contribution of the analysis. Unrestricted U-MIDAS establishes that high-frequency information contains predictive content but becomes increasingly parameter intensive as the month progresses. The cumulative-information specification instead holds model dimensionality constant across vintages. The resulting monotonic improvement in forecast accuracy provides direct evidence that additional within-month information improves the assessment of current critical mineral market conditions.

The results are robust to alternative empirical choices. Excluding 2020 from the out-of-sample evaluation preserves the progressive forecasting gains, indicating that the findings are not driven by the initial COVID-19 period. Replacing the DFM-based target with the PCA-based CMMCI produces similar reductions in forecast error. The principal result therefore does not depend on a particular evaluation period or latent-factor construction of the CMMCI.

Additional robustness analysis using a recursively estimated DFM index provides further support for the principal findings. When the CMMCI is constructed using expanding estimation windows that exclude subsequent mineral-price observations, the preferred mixed-frequency model continues to outperform the autoregressive benchmark. RMSE improvements range from 4.89% to 6.11% across the four information vintages, with statistically significant Clark–West test results. Although these improvements are smaller than those obtained using the original full-sample index, they indicate that the predictive contribution of high-frequency information persists under recursive factor estimation.

The findings have implications for critical mineral market monitoring. Monthly mineral-price information necessarily provides a delayed assessment of current conditions, and evidence from lithium markets indicates that published price indexes may incorporate information with a delay (Tay et al., 2026). In contrast, exchange rates, petroleum refining activity, and financial conditions are observed at higher frequencies. Incorporating these indicators permits the CMMCI to be estimated during the month rather than waiting for a complete monthly information set. Such estimates may be useful for procurement, inventory management, investment, supply-chain planning, and market surveillance, particularly when market conditions are changing rapidly.

The framework also has potential policy applications. Critical mineral markets intersect with energy security, industrial policy, strategic supply chains, and investment in energy-transition technologies, with potentially important macroeconomic implications (Concordel et al., 2026; Kang et al., 2025). A recursively updated CMMCI can provide policymakers and market participants with a compact indicator of evolving aggregate market conditions. The finding that forecast gains are concentrated during relatively large CMMCI movements is particularly relevant because timely information may have its greatest decision value when market conditions are changing substantially.

Several considerations are relevant when interpreting the results. The pseudo-real-time evaluation uses sequential observation-based information vintages and expanding-window estimation, but does not explicitly account for historical publication schedules or subsequent data revisions. The analysis also assumes that the preceding month's CMMCI is available at each forecast origin. Consequently, the results characterize forecasting performance under an approximate historical information structure, rather than a fully reconstructed real-time data environment. Future research could incorporate historical data releases and publication lags to assess the sensitivity of the findings to more restrictive information sets.

The analysis extends the CMMCI from a monthly measure of aggregate critical mineral market conditions to a framework capable of producing increasingly informed within-month estimates. High-frequency information improves current-month estimates, the improvement increases as information accumulates, and the result is robust across alternative evaluation periods and index constructions. Together with the original construction and validation of the CMMCI, these findings establish a framework for systematic, high-frequency monitoring of critical mineral markets.

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