ASSET PRICE PREDICTABILITY AND MARKET EFFICIENCY: THE CASE OF STOCK AND URANIUM PRICES

by

Kusherova Symbat

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Abstract

This study investigates the predictability of uranium and stock market returns through the lens of the Efficient Market Hypothesis (EMH), which implies that asset prices reflect all available information, making short-term returns unpredictable. I focus on three financial time series: uranium futures prices, Cameco stock prices, and the MSCI Energy Index. Using Autoregressive Moving Average (ARMA) and Vector Error-Correction (VEC) models, I test for weak-form efficiency. By incorporating structural break dummies, the analysis captures major structural and geopolitical events, including the 2008 global financial crisis, the 2011 Fukushima disaster, and Russia's full-scale invasion of Ukraine in 2022. In particular, I study the following questions: Are these markets unpredictable? If not, to what extent can they be forecasted, and which models offer superior predictive performance? The results show moderate predictability in uranium markets and greater weak-form efficiency in stock and energy indices and offer practical implications for investors and policymakers.

1. Introduction

The uranium price prediction accuracy is crucial for both energy policymakers and market participants. Uranium accounts for roughly 26–30 percent of the total cost of nuclear fuel cycles, so precise price forecasts can help to make more informed decisions regarding inventory management and procurement strategies, which may reduce uncertainty in long-term energy cost estimations. (OECD, 2013). At the same time, nuclear power is the second-largest worldwide energy source with relatively low carbon dioxide emissions, making it a cornerstone of any realistic decarbonization strategy (Cole, 2015; BP Statistical Review, 2016).

To examine the time-series predictability and market efficiency of the uranium market, I use daily data on uranium futures prices, Cameco company stock prices, and the MSCI World Energy Index, from January 2007 to February 2024. The selected time frame illustrates multiple structural and economic shocks (the 2008 global financial crisis, the 2011 Fukushima nuclear disaster, and Russia's invasion in 2022), which makes it particularly relevant to assess the market under different volatility periods.

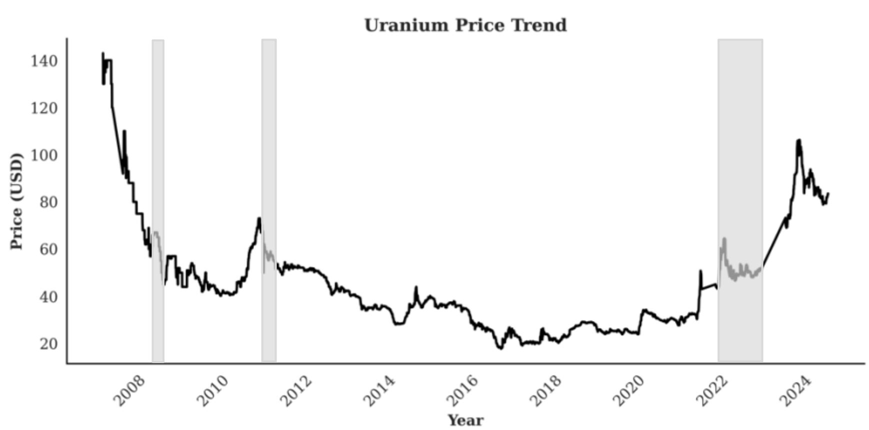

Figure 1: Uranium price trend

Figure 1 provides a visual inspection of the uranium futures and depicts several fluctuations corresponding to global economic and geopolitical events. Following a sharp decline during the 2008 financial crisis, uranium prices remained relatively stable until the 2011 Fukushima disaster, which significantly reduced global nuclear energy demand. This event led to a long-term decline in uranium prices, exacerbated by oversupply and reduced investment in new reactor builds. For instance, Ferstl et al. (2012) document a significant decline in the stock prices of German nuclear power generating firms after the German government decided to terminate nuclear power generation in the aftermath of the Fukushima-Daiichi accident in 2011. A moderate recovery began in early 2022, as the uranium sector has experienced renewed investor interest and a pronounced price rally. Following Russia's full-scale invasion of Ukraine on February 24, 2022, concerns over European reliance on Russian gas and coal triggered a dramatic re-evaluation of alternative energy sources (Nerlinger & Utz, 2022). Coal prices spiked by nearly 150 percent within weeks, while fears of Russian gas cut-offs prompted countries to revisit nuclear capacity plans (Tollefson, 2022; Nerlinger & Utz, 2022). Against this backdrop, uranium prices have climbed steadily, mirroring the broader shift in national energy priorities and the commitments made at COP26 to accelerate the transition away from fossil fuels toward low-carbon power five times faster than historical rates (COP26, 2022).

The Cameco stock price follows a similar trajectory (Appendix Figure A2), though with additional volatility associated with firm-specific performance and market sentiment. Notably, a gradual upward trend since 2022 aligns with broader optimism about nuclear energy's role in the global energy transition. In contrast, the MSCI Energy Index aligns more with crude oil price cycles and macroeconomic activity, particularly during the Russia-Ukraine military conflict: global energy demand collapsed and then rebounded sharply.

Despite this heightened attention, the uranium market remains relatively opaque and less liquid than major commodity markets such as oil and natural gas. Low trading volumes, concentrated supply chains, and geopolitical sensitivities all contribute to price dynamics that may deviate from classical market-efficiency assumptions. A natural starting point for exploring market predictability is the Efficient Market Hypothesis (EMH), which states that market prices reflect all available information, making future price changes essentially random (Fama, 1970). In finance, EMH is typically divided into three forms: weak form, where past prices contain no predictive power; semi-strong form, where publicly available information is already incorporated into prices; strong form, where even private or insider information is reflected (Fama, 1970).

In this study, I focus on weak-form efficiency, asking whether past values of uranium futures and related assets can help predict future price movements. While the theory of weak-form market efficiency has guided decades of financial economics, there exists some empirical evidence that suggests that many markets exhibit at least some degree of return predictability (Ang & Bekaert, 2007). Notably, stock market returns may appear predictable not due to inefficiency per se, but due to time-varying expected returns driven by changing risk premia and macroeconomic cycles. I aim to address four interrelated questions: (1) Are uranium and related stock markets efficient in the weak-form sense? (2) If not, to what extent are they predictable? (3) Which traditional models are most effective for forecasting these time series? (4) How do the findings vary across different assets? I address these questions by applying two widely used forecasting models: The Autoregressive Moving Average (ARMA) model, commonly used for univariate time series forecasting, and the Vector Error Correction (VEC) model, used to capture long-run equilibrium relationships among cointegrated variables, accounting for the possibility that uranium prices, Cameco equity values, and broader energy-sector indices move together over extended horizons. In addition, I assess model performance through out-of-sample forecasting accuracy (using RMSE), check model adequacy via residual diagnostics, and perform the Diebold-Mariano test.

My study makes three main contributions. First, it provides systematic assessments of weak-form efficiency in the uranium futures market. Second, it compares traditional econometric models to determine their effectiveness in capturing predictability in these markets, thereby assessing market efficiency. Third, it situates these findings within the broader policy debate over energy security and decarbonization, offering practical insights for utilities, investors, and regulators.

The rest of the paper is organized as follows: Chapter 2 reviews relevant theoretical and empirical literature on commodity market efficiency and uranium specifically. Chapter 3 describes the data sources, preprocessing steps, and econometric methodology. Chapter 4 presents the main forecasting results and robustness checks. Finally, Chapter 5 concludes with key takeaways and policy implications.

2. Literature review

2.1 Uranium market independence

The uranium market has been a topic of high interest for a long time due to its unique characteristics and strategic importance, especially in the context of nuclear energy. A key feature of this market is its relative independence from other commodity markets (NEA, 2006). Several empirical studies, including early work by Basheer (1979) and Amavilah (1995), support this claim. Basheer and Amavilah indicate that uranium prices often act independently from their substitute fossil fuels, like oil and coal. However, Newcomb and Reiber (1984) performed a theoretical study of potential linkages between uranium and other energy markets. This hypothesis was empirically tested by Kahouli (2011), who found evidence of price relationships, particularly between uranium and coal. He noticed some substitution effects between the two commodities and partial integration with broader energy markets. This divergence in findings highlights the ambiguous nature of uranium price dynamics, which depend on broader macroeconomic and geopolitical factors.

2.2 Efficient markets hypothesis

In parallel, a vast amount of literature was dedicated to the Efficient Market Hypothesis, specifically, a variety of studies were elaborated to test all three types of EMH. Most of them invalidated the semi-strong and the strong forms of EMH, forms that are not supported by financial data, while empirical tests provided mixed results across different markets and time horizons for the weak form of EMH (Titan, 2015). Studies by Kendall & Hill (1953) supported the random walk hypothesis and weak-form efficiency, suggesting that historical prices offer little predictive power. However, subsequent studies of Jegadeesh & Titman (1993) provide evidence of delayed market reactions and price autocorrelations, contradicting both semi-strong and weak forms of EMH. These inefficiencies were further supported by trading studies by Chowdhury (1993), who examined the impact of exchange rate volatility on the trade flows of the G-7 countries. Studies done by behavioral finance scholars like Lo & MacKinlay (1999) and Lo, Mamaynski and Wang (2000) questioned the assumptions of investor rationality underlying EMH. Their research paper employed variance ratio tests to challenge the random walk behavior of asset prices, emphasizing that psychological and behavioral biases can lead to predictable price patterns and inefficiencies.

In the context of commodity markets, the applicability of EMH becomes even more debatable. Unlike major financial assets, uranium is traded in a relatively illiquid and fragmented market, where price formation may not be as transparent or efficient. Thus, this study uses time series models (ARMA and cointegration-based VEC) to test for weak-form efficiency by evaluating the predictability of prices based on their historical data. Several studies applied these models to examine energy and metal markets. For instance, Worthington & Higgs (2006) used a variance ratio and ran a test to assess weak-form efficiency in Asian energy markets. Their results indicate that none of the emerging markets are characterized by random walks and hence are not weak-form efficient (Worthington & Higgs, 2006). It turns out that only developed markets in Hong Kong, New Zealand, and Japan are consistent with the most stringent random walk criteria. Similarly, Kristoufek & Vosvrda (2013) investigated the efficiency of 38 stock market indices using fractal dimension and entropy measures, noting significant deviations from EMH in markets with supply constraints or geopolitical sensitivity, specifically in Latin America.

Thus, my study contributes to two growing research areas: the unique behavior of uranium markets and the evolving debate over market efficiency. By employing ARMA and VEC models, this paper investigates whether the price dynamics of uranium and uranium-related series exhibit features consistent with weak-form efficiency or predictable components that undermine the random walk hypothesis.

3. Data and Methodology

3.1.1 Descriptive statistics

I use daily data on uranium futures prices, Cameco company stock prices, and the MSCI World Energy Index, from January 2007 to February 2024. The dataset includes 3,969 observations for each series, all units expressed in nominal U.S. dollars. Due to the limited availability of public uranium spot price data, uranium futures prices were used as a proxy. These prices represent contracts for future delivery of uranium and reflect market participants' expectations about future supply and demand. Futures contracts are slightly more volatile due to speculative activity, but still remain a reliable indicator of market sentiment in commodities with limited liquidity like uranium. The price series is quoted in USD per pound of U_3O_8, obtained from Investing.com.

Cameco company[1] is one of the world's largest publicly traded uranium producers and an influential player in the global nuclear fuel cycle. Historical daily closing stock prices were sourced from Bloomberg. To contextualize uranium price dynamics within the broader energy market, I also include the MSCI World Energy Index. This index tracks large energy companies across 23 developed markets, providing a benchmark for conventional energy assets such as oil and gas. It also helps to assess whether uranium prices follow similar patterns to other energy-related financial instruments. The MSCI series is also retrieved from Bloomberg.

Table 1 in the Appendix presents a comprehensive statistical summary of the three examined time series, including their respective means, standard deviations, skewness, kurtosis, and other key descriptive statistics. Correlation analysis (Appendix Table 2) indicates a moderate positive correlation between Cameco stock and uranium futures prices, reflecting their dependence on uranium market dynamics. On the other hand, the MSCI Energy Index shows a weaker correlation with uranium prices, suggesting its dependence on different energy sectors like oil and gas. These insights support the choice of including all three series for a better understanding of uranium market predictability in relation to broader energy trends.

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in Appendix Figure 3-4 are included to identify any patterns in the data. The ACF plot illustrates the correlation between the time series and its lagged versions, whereas the PACF plot shows the partial autocorrelation with the impact of other lagged values. These plots guide us in selecting the appropriate parameters (p, q) for the ARMA model. The dominant spikes at lag 1 in the PACF plots suggest that an autoregressive model of order 1 (AR1) can work well with the data's structure.

3.1.2 Stationarity analysis

Before estimating time series models, it is critical to examine the stationarity of each series. Non-stationary series can lead to spurious regressions and misleading inferences. Therefore, this

[1] *Note: Kazatomprom, Kazakhstan's national uranium producer, was considered for inclusion. However, its stock price data has only recently become available following its initial public offering in 2018. To preserve consistency and data coverage, Cameco was retained as the primary equity-level representative of the uranium sector.*

section outlines the procedures undertaken to assess and ensure stationarity, including transformations and unit root tests. To evaluate the stationarity of the logarithmic series, three standard unit root tests were applied: the Augmented Dickey-Fuller (ADF) test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, and the Phillips–Perron (PP) test. To identify optimal number of lags for each series, I apply -varsoc- command, see Appendix Tables 3. Each test offers a complementary perspective, as they differ in their null hypotheses and sensitivity to structural dynamics.

I apply the ADF test including drift and a linear trend to account for the behavior often observed in financial data. The results, summarized in Appendix Table 4, indicate failure to reject the null hypothesis of a unit root for all three series at conventional significance levels, suggesting non-stationarity in levels. The KPSS test (see Appendix Table 5) supports the rejection of the trend stationarity for all series. Similarly, the PP test results (Appendix Table 6) reinforce the earlier conclusions. There is no sufficient evidence to reject the null hypothesis of a unit root. The consistency across these three tests strengthens the conclusion that the original series are integrated of order one, I(1), and thus non-stationary.

3.1.3 Data transformations and trend

I took the first difference of the series to address the issue of non-stationarity. Then, I apply the same stationarity tests as before after lag-order selection (Appendix Table 7). The ADF and PP tests on the differenced series yielded highly significant test statistics (Appendix Tables A8–A10), confirming stationarity. All p-values are well below the 1% level, which provide strong evidence that the log-differenced time series are stationary, i.e., I (0), and therefore appropriate for use in subsequent modeling.

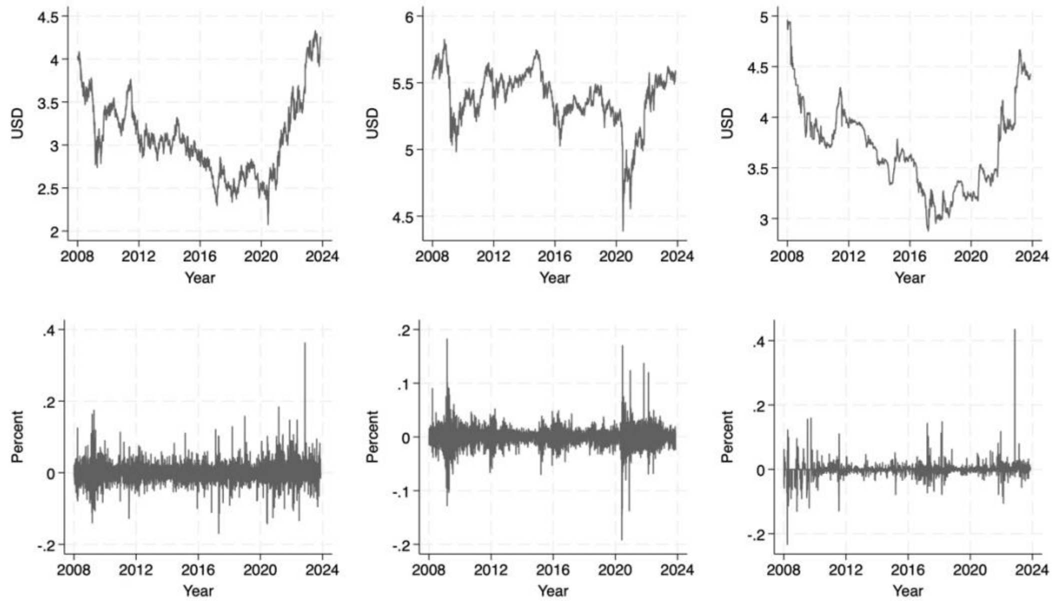

Figure 5. Stationarity Analysis

3.1.1 Robustness Checks

While the standard tests support the transformation, they assume the stability of the underlying data-generating process. However, economic time series often experience structural breaks due to significant global events, such as the 2008 financial crisis or the 2020 COVID-19 pandemic. These breaks may distort stationarity test results, potentially leading to erroneous conclusions. Therefore, visual inspection of the series (see Figure 5) and preliminary residual diagnostics suggest potential outliers or abrupt shifts around those key periods. Contrary to the initial interpretation, these irregularities warrant further investigation.

To explore this issue, I apply the Zivot-Andrews unit root test. This test is particularly suitable for financial and commodity markets, as it allows for one endogenous structural break in either the intercept, trend, or both, making it more flexible in detecting shifts caused by extraordinary events. The results of the Zivot-Andrews test for the log-level series of Cameco stock prices, MSCI index, and uranium spot prices are presented in Appendix Tables 11. In all cases, the test statistics are higher (in absolute terms) than the corresponding 5% critical values, meaning that the null hypothesis of a unit root cannot be rejected. Therefore, even after accounting for a potential structural break, there is insufficient evidence to conclude that the series are stationary. These results are consistent with those of the ADF, PP, and KPSS tests, reinforcing the conclusion of non-stationarity. However, the presence of visually identifiable breaks around 2008 and 2022 suggests that structural changes may still play a role in the dynamics of these markets. To address this, I incorporate break dummies in subsequent ARMA models to better capture these shifts and improve the accuracy of the time series modeling.

3.2 Methodology

3.2.1 ARMA model

The initial model selected for this analysis is the ARMA (Autoregressive Moving Average) model. Given that the data have already been found to be stationary, the inclusion of the differencing component, as in an ARIMA model, is unnecessary. Consequently, I proceed with ARMA on the differenced series, focusing on identifying the optimal values for the p (AR) and q (MA) parameters.

To determine the best-fitting ARMA model, I employed the -arimasoc- command in Stata. The results of this selection process are summarized in Appendix Tables 12, where I display the parameter values corresponding to the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC). As shown in the table, I opted for ARMA(4,5) for Cameco, ARMA(5,4) for MSCI series based on the lowest AIC values, while ARMA(4,4) was preferred for Uranium, as it exhibited the best fit according to these criteria. I rely on AIC results as it aims to find the model that best balances fit and complexity and it is specifically designed to select models that have good out-of-sample forecasting performance.

The results of the ARMA model estimation for each of the variables are presented in Table 13. I find that the AR and MA terms for the first difference of Cameco, MSCI, and Uranium are statistically significant, indicating that these models successfully capture the dynamics of each time series. The standard errors, shown in parentheses, suggest that the estimates are reliable.

3.2.2 ARMA model with structural breaks

To assess the impact of significant geopolitical and economic events on uranium prices, I incorporated dummy variables into the ARMA framework. Each dummy variable represents a single-day structural break corresponding to the onset of a major event: the global financial crisis (15 September 2008), the Fukushima nuclear disaster (11 March 2011), and Russia's invasion of Ukraine (24 February 2022). These variables aim to capture sudden shifts in investor sentiment or structural changes in the uranium market.

The ARMA model for uranium prices estimated with these dummy variables yielded insightful results (Appendix Table 14). The coefficient for the financial crisis dummy is positive and statistically significant at the 1% level ($\beta = 0.0031$, $p = 0.001$), suggesting an abnormal increase in uranium returns immediately following the crisis. In contrast, the Fukushima dummy is statistically insignificant, indicating no immediate structural impact on uranium prices, despite long-term effects often cited in literature. The invasion dummy is marginally significant at the 5% level ($\beta = 0.0017$, $p = 0.051$), highlighting a possible price reaction to heightened geopolitical risk.

These findings support the view that uranium prices exhibit sensitivity to abrupt global events, and accounting for such structural breaks improves the explanatory power of the model. Therefore, including dummy variables is not only statistically justified but also economically meaningful. Compared to the baseline ARMA model without dummies, the extended model with event dummies yielded a higher log-likelihood for uranium prices (10684.85 vs 10689.47), indicating a better model fit.

3.2.3 Multicollinearity and cointegration analysis

However, it is important to note that the variables in question are interdependent and exhibit multicollinearity. For instance, Cameco and Uranium prices are likely to have a strong relationship due to Cameco's role in uranium production, the MSCI energy index reflects macroeconomic trends that may influence both Cameco stock prices and uranium prices. To account for this interdependence, I explored the possibility of using Vector Autoregressive (VAR) or Vector Error-Correction (VEC) models. To examine potential causal relationships between the variables, I performed a Granger Causality test. This test helps identify whether one time series can predict another. The results of the test, illustrated in Appendix Figure 9, show that: Uranium significantly Granger-causes Cameco with a lag of 3 periods; MSCI influences Cameco with a lag of 4 periods; and Uranium Granger-causes MSCI with a lag of 5 periods. Thus, it appears reasonable to proceed with either a VAR or VEC model. However, the choice is ultimately determined by the presence of cointegration among the variables, which I investigate next.

I conducted the Johansen Cointegration Test to assess whether there exists a long-term equilibrium relationship among the time series variables. Since these variables exhibit deterministic trends, I specified the model with a deterministic trend (det_order = 2) to ensure a more accurate test. I determined the optimal number of lags= 4 for the cointegration test using the -varsoc- command in Appendix Table 15. The Johansen test results, presented in Appendix Table 16, indicate that there are at least 2 cointegrating relationships between the variables, as the trace statistics exceed the 5% critical values for rank 0, rank 1. This suggests that the variables are cointegrated, which justifies the use of the Vector Error-Correction Model (VEC) with rank 2**.**

From the output, I have two cointegrating relationships:

$$\ln(\text{Cameco}_t) = 1.11 \cdot \ln(\text{Uranium}_t) - 0.99$$
$$\ln(\text{MSCI}_t) = 0.211 \cdot \ln(\text{Uranium}_t) + 4.61$$

The first cointegrating equation, with ln_Cameco normalized, indicates a strong and statistically significant relationship between uranium prices and Cameco stock prices, suggesting that changes in the commodity price are closely reflected in the company's valuation. The second relationship implies a weaker, marginally significant ($p = 0.067$) association between uranium prices and the MSCI global equity index, possibly capturing broader macroeconomic influences or commodity cycles.

3.2.4 VEC model

Given the cointegration among the variables, I estimate the Vector Error-Correction Model (VEC) to capture both the short-run dynamics and the long-run equilibrium relationships. The results are presented in Table 17. The model specification with two cointegrating relationships and three lags is preferred, as it demonstrates better statistical fit and stability, and aligns with economic theory by allowing for multiple long-term equilibrium relationships between the variables.

The results show a long-term equilibrium relationship between Cameco, MSCI, and Uranium, where Uranium and MSCI negatively affect Cameco in the long run. In the short run, however, Uranium has a significant positive impact on Cameco stock prices. This finding highlights the importance of understanding both short-term dynamics and long-term cointegrating relationships in the energy sector. The VEC model is well-suited for variables that are cointegrated, and as such, both in-sample and out-of-sample forecasting will be performed using this approach.

3.2.5 Residual Diagnostics

To assess the adequacy of the ARMA models, I next perform residual diagnostics, specifically focusing on autocorrelation and the normality of residuals. Time series data often exhibit serial correlation, which can indicate model misspecification. I used residual plots to evaluate the distribution of errors. Ideally, these residuals should be randomly scattered around zero, without significant patterns. The residual plots for Cameco, MSCI, and Uranium series, Appendix Figures 6-8, reveal that the residuals are largely random, centered around zero, and do not exhibit any clear patterns, suggesting that the models adequately capture the data's underlying structure. I also performed the Portmanteau test with 10 lags for autocorrelation in the residuals: Cameco: (p-value = 0.556), MSCI (p-value = 0.564), and Uranium (p-value = 0.591). These results confirm that there is no significant autocorrelation in the residuals at the 5% significance level, suggesting that the ARMA models are correctly specified.

4. Empirical results

4.1 ARMA model forecast

In this section, I evaluate the predictive performance of the selected time series models—ARMA and VECM—by employing both in-sample and out-of-sample forecasts. The objective is to assess the models' ability to replicate the dynamics of financial time series and compare their forecast accuracy.

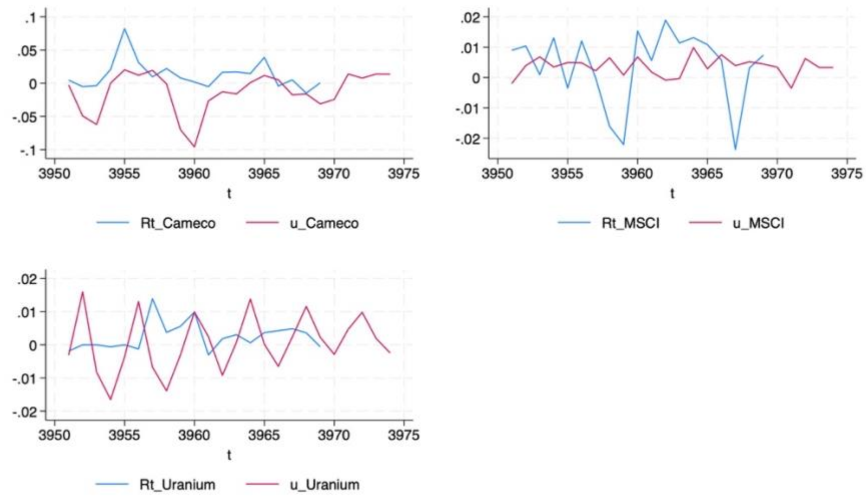

Figure 10. ARMA forecast

I conduct in-sample forecasts prior to out-of-sample forecasting to validate the accuracy of the models. I use the ARMA model to generate forecasts for Cameco, MSCI, and Uranium returns. Figure 10 presents the in-sample forecasts for each series using the ARMA model. Visually, the ARMA forecasts appear to replicate the general trend and volatility of the observed data, particularly the shocks in return series. For Uranium returns, the ARMA model captures the observed dynamics notably well. However, deviations from observed data exist and must be quantified.

4.2 VEC model forecast.

I use the VEC model, estimated based on Johansen cointegration results, to produce forecasts of the log-level series. Figure 11 displays in-sample forecasts, while Figure 12 provides out-of-sample forecasts for the subsequent 7-day period. For VEC model we took a forecast of logarithmic rather than return variables because it is typically used when you have non-stationary variables that are cointegrated**,** because it models both the short-run dynamics (errors) and the long-run equilibrium relationship.

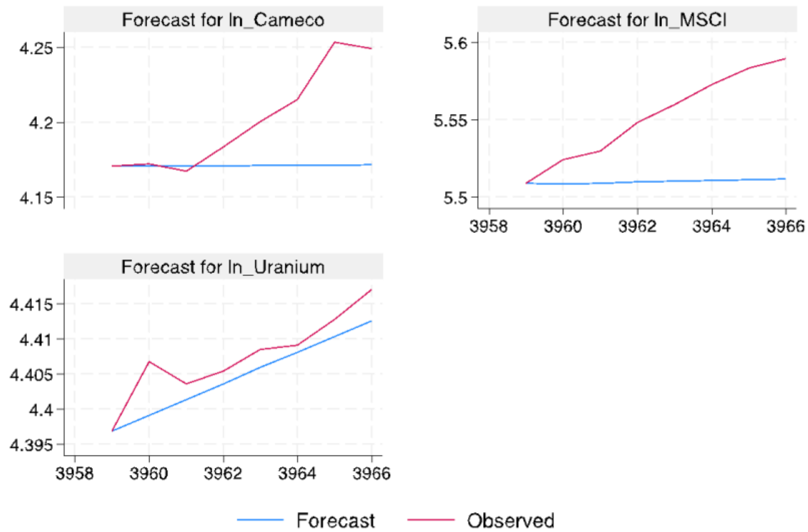

Figure 11. VEC forecast

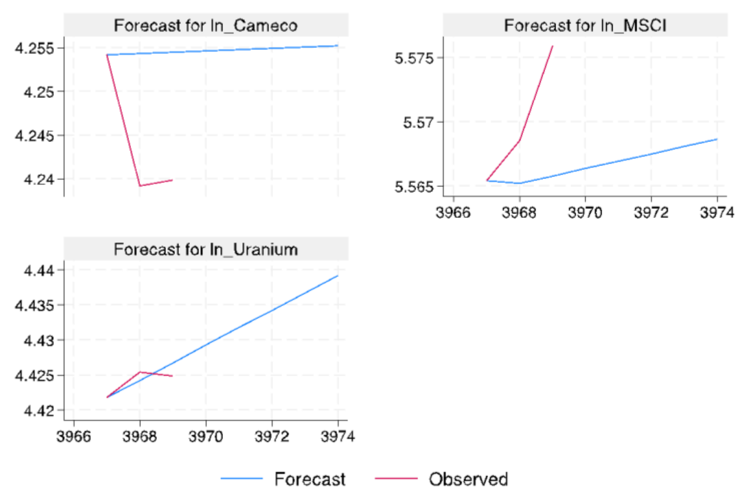

Figure 12. VEC out-of-sample forecast

5. Robustness and Discussion

In contrast to ARIMA, the VECM forecasts appear more stable and smoother. The first model — with two cointegration relationships and three lags — provides a better explanation of the data dynamics and is preferable from an academic perspective. However, in-sample accuracy is lower in capturing short-term shocks, except in the case of Uranium prices, where the model performs comparably well. This may be attributed to the model's emphasis on long-run equilibrium rather than short-run fluctuations.

Out-of-sample forecasts (Figure 12) show that VECM projects moderate fluctuations while preserving the existing long-term structure. However, the forecasts diverge slightly from the observed short-run volatility in the series. To measure forecast performance, I report standard accuracy metrics in Appendix Table A15. The results show that VECM has lower RMSE for all three series, thus exhibiting better forecasting performance.

5.1 The Diebold-Mariano test

To statistically assess whether forecast accuracy differs among models, I employ the Diebold-Mariano (DM) test. In addition to comparing ARIMA and VECM, I introduce an AR(0) model (i.e., a naive forecast assuming returns are unpredictable) as a benchmark, in line with the Efficient Market Hypothesis (EMH), which states that optimal forecasts should be AR(0). If the DM test rejects the null hypothesis of equal forecast accuracy between AR(0) and more complex models, this indicates market inefficiency. Since Stata lacks a built-in DM command, I manually perform the test by computing the loss differentials based on squared forecast errors, evaluating predictive accuracy in terms of Mean Squared Error (MSE), consistent with the original test formulation (Diebold & Mariano, 1995). Results are reported in Appendix Tables 18 and 19.

The findings show that VECM forecasts are statistically significantly more accurate than both ARIMA and AR(0) across all three series, suggesting predictability and some degree of inefficiency in the market. Moreover, I compute the relative RMSE improvement (%) between VECM and AR(0) forecasts as a direct measure of inefficiency. The t-test results and RMSE comparisons collectively suggest that while ARIMA models demonstrate some forecasting ability by producing statistically significant mean errors, the VECM models achieve superior predictive performance without introducing systematic bias. The substantial reductions in RMSE across all variables, particularly the 92.1% improvement observed for Uranium, highlight the effectiveness of modeling cointegration relationships. Overall, the evidence supports the notion that uranium-related financial series exhibit predictable components that can be better captured using a cointegrated framework rather than simple univariate models.

6. Conclusion

In this paper, I examine the efficiency and predictability of the uranium market and related stock indices by analyzing the dynamic relationships between uranium spot prices, the Cameco Corporation stock, and the MSCI World Index. Grounded in the framework of the Efficient Market Hypothesis (EMH), the study aimed to evaluate whether these markets fully and instantaneously reflect available information or whether predictable patterns persist, allowing for potential arbitrage opportunities.

To ensure the validity of subsequent econometric modeling, extensive preliminary analyses were conducted. Unit root tests—including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS—indicated that all series were non-stationary in levels but became stationary after first differencing, confirming their integration of order one, I(1). Recognizing the limitations of traditional stationarity tests in the presence of structural breaks, I employ the Zivot-Andrews test, revealing significant breaks coinciding with major global disruptions, such as the 2008 financial crisis and the 2022 Russia-Ukraine conflict. Incorporating these breakpoints helped to avoid potential biases in inference and to better model the true underlying dynamics.

In addition to standard ARIMA models, dummy variables were introduced to capture the immediate effects of these structural events. The results demonstrated that uranium prices are highly sensitive to abrupt global shocks, with statistically significant immediate effects observed following the 2008 financial crisis and, to a lesser extent, Russia's 2022 invasion of Ukraine. Including these break dummies improved model fit and enhanced the explanatory power, underscoring the economic importance of accounting for structural breaks when modeling commodity prices.

Subsequent correlation and cointegration analyses suggested meaningful relationships among the variables, particularly between uranium prices and Cameco's stock price, and between Cameco and the broader MSCI Index. This justified the use of the Vector Error Correction Model (VECM), which effectively captured both the short-run dynamics and long-run equilibrium interactions. The results from the VECM revealed that uranium prices significantly influence Cameco's stock price in the long run, while the MSCI index contributes more prominently to short-run adjustments.

These insights support a semi-strong form of market efficiency—where macroeconomic and market-wide information is rapidly reflected in prices, but some degree of predictability remains, especially in sector-specific linkages.

Out-of-sample forecasting performance further enhanced these insights. Compared against ARIMA and a naive AR(0) benchmark model, the VECM consistently achieved lower Root Mean Squared Errors (RMSEs) across all series. The Diebold-Mariano (DM) tests confirmed that forecast accuracy improvements were statistically significant. Notably, the VECM achieved a remarkable 92.1% reduction in RMSE for uranium prices relative to the AR(0) model, providing strong evidence of predictability and market inefficiency.

Overall, the empirical findings contribute to the ongoing debate about informational efficiency in commodity-linked markets. While global indices like MSCI exhibit characteristics consistent with efficient markets, the behavior of uranium and uranium-related equities indicates partial inefficiencies, likely due to the unique geopolitical, regulatory, and supply-demand dynamics of the nuclear energy sector. These results carry practical implications for investors, policymakers, and risk managers seeking to understand and model the transmission mechanisms between energy commodities and financial markets. Also, my work highlights the importance of incorporating structural breaks and long-run cointegration relationships in the modeling of commodity prices, particularly for niche markets like uranium. Ignoring such features risks underestimating predictability and mischaracterizing market dynamics.

Future research could expand on these findings by exploring non-linear modeling approaches, examining the impact of specific geopolitical events, or incorporating high-frequency data to capture intraday market reactions. Moreover, as the global energy transition accelerates, understanding the financial behavior of critical materials like uranium will remain vital for navigating the evolving landscape of energy markets and investment strategies.

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Appendix Tables

Table 1.

Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max	Variance	Skewness	Kurtosis
Cameco	3,969	24.606	13.003	7.970	75.81	169.08	1.68	5.68
MSCI	3,969	222.073	42.169	80.500	338.25	1778.27	-0.33	3.23
Uranium	3,969	44.286	21.409	17.750	143.0	458.38	1.74	7.01
Rt_Cameco	3,968	0.000427	0.0274	-0.169	0.362	0.00	0.82	15.19
Rt_MSCI	3,968	0.000166	0.0178	-0.191	0.182	0.00	-0.19	19.47
Rt_Uranium	3,968	-5.30e-06	0.0164	-0.233	0.435	0.00	4.43	154.81

Table 2.

Correlation Matrix

	Cameco	MSCI	Uranium
Cameco	1.0000		
MSCI	0.4786	1.0000	
Uranium	0.8676	0.4642	1.0000

Table 3.

Lag-order Selection

Sample: 5 thru 3969
Number of observations: 3,965

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2476.740	–	–	–	0.204	1.250	1.250	1.251
1	8667.800	22289*	1	0.000	0.001	-4.371	**-4.37002***	**-4.36798***
2	8668.950	2.302	1	0.129	**0.00074***	**-4.37122***	-4.370	-4.366
3	8669.100	0.309	1	0.578	0.001	-4.371	-4.369	-4.364
4	8669.200	0.200	1	0.655	0.001	-4.370	-4.368	-4.362

* indicates optimal lag
Endogenous: `ln_Cameco` Exogenous: `_cons`

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	598.175	–	–	–	0.043	-0.301	-0.301	-0.300
1	10342.200	19488*	1	0.000	0.000	-5.216	**-5.21463***	**-5.21259***
2	10343.600	2.650	1	0.104	**0.000318***	**-5.21592***	-5.214	-5.211
3	10343.600	0.058	1	0.810	0.000	-5.215	-5.213	-5.209
4	10345	2.797	1	0.094	0.000	-5.216	-5.213	-5.208

* indicates optimal lag
Endogenous: `ln_MSCI` Exogenous: `_cons`

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2212.340	–	–	–	0.179	1.116	1.117	1.118
1	10774.600	25974	1	0.000	0.000	-5.434	-5.433	-5.431
2	10782.300	15.377	1	0.000	0.000	-5.437	**-5.43552***	**-5.43245***
3	10782.600	0.789	1	0.375	0.000	-5.437	-5.435	-5.431
4	10784.800	**4.2111***	1	0.040	**0.000255***	**-5.43745***	-5.435	-5.430

* indicates optimal lag
Endogenous: `ln_Uranium` Exogenous: `_cons`

Table 4.

Augmented Dickey–Fuller Test for Unit Root

Number of obs = 3,966 Number of lags = 2
Variable: ln_Cameco H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-1.305	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) 0.887.

Number of obs = 3,966 Number of lags = 2
Variable: ln_MSCI H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-2.705	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) 0.234.

Number of obs = 3,966 Number of lags = 4
Variable: ln_Uranium H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-1.522	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) 0.822.

Table 5.

Kwiatkowski–Phillips–Schmidt–Shin Test for Unit Root

Statistical Result	ln_Cameco	ln_MSCI	ln_Uranium
T-statistics	20.2	7.38	20.7
Critical Value 5%	0.146	0.146	0.146
Critical Value 1%	0.216	0.216	0.216

Table 6.

Phillips–Perron Test for Unit Root

Number of obs = 3,968 Newey–West lags = 9
Variable: ln_Cameco Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-5.534	-20.700	-14.100	-11.300
Z(t)	-1.517	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.525.

Number of obs = 3,968 Newey–West lags = 9
Variable: ln_MSCI Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-15.705	-20.700	-14.100	-11.300
Z(t)	-2.793	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.059.

Number of obs = 3,968 Newey–West lags = 9
Variable: ln_Uranium Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-6.427	-20.700	-14.100	-11.300
Z(t)	-2.451	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.128.

*** *Critical value at 5% significance level for Z(rho)=-14.1, Z(t)=-2.86*

Table 7.

Lag-order Selection for the first difference

Sample: 6 thru 3969
Number of observations: 3,964

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	8635.130	–	–	–	0.000751	-4.35627	**-4.35571***	**-4.35469***
1	8636.220	2.185	1	0.139	**0.000751***	**-4.35632***	-4.35519	-4.35315
2	8636.320	0.203	1	0.652	0.000751	-4.35586	-4.35418	-4.35111
3	8636.430	0.218	1	0.641	0.000752	-4.35542	-4.35317	-4.34907
4	8637.490	2.114	1	0.146	0.000752	-4.35544	-4.35263	-4.34752

* indicates optimal lag
Endogenous: `Rt_Cameco` Exogenous: `_cons`

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	10352.800	–	–	–	0.000316	-5.22290	**-5.22233***	**-5.22131***
1	10353.800	2.141	1	0.143	**0.000316***	**-5.22293***	-5.22181	-5.21976
2	10354.100	0.522	1	0.470	0.000316	-5.22256	-5.22087	-5.21780
3	10354.900	1.567	1	0.211	0.000316	-5.22245	-5.22020	-5.21611
4	10355.100	0.410	1	0.522	0.000316	-5.22205	-5.21924	-5.21412

* indicates optimal lag
Endogenous: `Rt_MSCI` Exogenous: `_cons`

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	10681.400	–	–	–	0.000267	-5.38872	-5.38816	-5.38713
1	10688.300	13.734*	1	0.000	**0.000267***	**-5.39168***	**-5.39056***	**-5.38851***
2	10688.600	0.548	1	0.459	0.000267	-5.39131	-5.38963	-5.38656
3	10690.200	3.165	1	0.075	0.000267	-5.39161	-5.38936	-5.38527
4	10690.300	0.281	1	0.596	0.000267	-5.39117	-5.38836	-5.38325

* indicates optimal lag
Endogenous: `Rt_Uranium` Exogenous: `_cons`

Table 8.

Augmented Dickey–Fuller Test for the first difference

Number of obs = 3,966 Number of lags = 1
Variable: Rt_Cameco H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-44.714	-2.327	-1.645	-1.282

p-value for Z(t) = 0.000.

Number of obs = 3,966 Number of lags = 1
Variable: Rt_MSCI H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-44.510	-2.327	-1.645	-1.282

p-value for Z(t) = 0.000.

Number of obs = 3,966 Number of lags = 1
Variable: Rt_Uranium H0: Random walk with or without drift

	Statistic	1%	5%	10%
Z(t)	-42.964	-2.327	-1.645	-1.282

MacKinnon approximate p-value for Z(t) 0.000.

Table 9.

Phillips–Perron Test for the first difference

Number of obs = 3,967 Newey–West lags = 9
Variable: Rt_Cameco Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-3987.668	-20.700	-14.100	-11.300
Z(t)	-64.512	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.000.

Number of obs = 3,967 Newey–West lags = 9
Variable: Rt_MSCI Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-3874.636	-20.700	-14.100	-11.300
Z(t)	-61.527	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.000.

Number of obs = 3,967 Newey–West lags = 9
Variable: Rt_Uranium Random walk without drift, d = 0

	Statistic	1%	5%	10%
$Z(\rho)$	-3888.653	-20.700	-14.100	-11.300
Z(t)	-59.656	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.000.

**** Critical value at 5% significance level for Z(rho)=-14.1, Z(t)=-2.86*

Table 10.

Kwiatkowski–Phillips–Schmidt–Shin Test for the first difference

Statistical Result	Rt_Cameco	Rt_MSCI	Rt_Uranium
T-statistics	0.054	0.042	0.072
Critical Value 5%	0.146	0.146	0.146
Critical Value 1%	0.216	0.216	0.216

Table 11.

Zivot-Andrews Unit Root Results

Statistic	ln_Cameco	ln_MSCI	ln_Uranium
Lag selection	7	7	3
Minimum t-stat	-4.092 at obs. 3256	-3.667 at obs. 3353	-3.825 at obs. 3353
Critical value (5%)	-4.80	-4.80	-4.80

Table 12.

ARMA model parameters

Variable	Max Log Likelihood (LL)	Min AIC	Min BIC	Min HQIC
Rt_Cameco	ARMA(5,5)	ARMA(4,5)	ARMA(0,0)	ARMA(0,0)
Rt_MSCI	ARMA(5,5)	ARMA(5,4)	ARMA(0,0)	ARMA(5,4)
Rt_Uranium	ARMA(5,5)	ARMA(4,4)	ARMA(1,0)	ARMA(1,0)

Table 13.

ARMA regression

Sample: 2 to 3969 Observations: 3968
Log Likelihood = 8649.065 Wald $chi^2(2)$ = 14.13 Prob > chi^2 = 0.0009

Variable	Coefficient	Std. Err.	z	P> $\|z\|$
Rt_Cameco				
Constant	0.0004269	0.0004196	1.02	0.309
ARMA				
AR (L4)	-0.0248134	0.012125	-2.05	0.041
MA (L5)	-0.0349982	0.0111366	-3.14	0.002
σ	0.0273609	0.000122	224.33	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Sample: 2 to 3969 Observations: 3968
Log Likelihood = 10364.88 Wald $chi^2(2)$ = 4.47 Prob > chi^2 = 0.1068

Variable	Coefficient	Std. Err.	z	P> $\|z\|$
Rt_MSCI				
Constant	0.000166	0.0002907	0.57	0.568
ARMA				
AR (L5)	-0.0061382	0.0070894	-0.87	0.387
MA (L4)	0.0127923	0.0066795	1.92	0.055
σ	0.0177557	0.0000657	270.24	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Sample: 2 to 3969 Observations: 3968 Log Likelihood = 10684.85 Wald chi²(2) = 248.48 Prob > chi² = 0.0000				
Variable	**Coefficient**	**Std. Err.**	**z**	**P> $\|z\|$**
Rt_Uranium				
Constant	-6.66e-06	0.0003309	-0.02	0.984
ARMA				
AR (L4)	0.8467274	0.0801438	10.57	0.000
MA (L4)	-0.8178829	0.0845414	-9.67	0.000
σ	0.0163799	0.0000228	716.91	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Table 14.

ARMA regression with break dummies

Sample: 2 to 3969 Observations: 3968 Log Likelihood = 8652.437 Wald chi²(5) = 24.61 Prob > chi² = 0.0002				
Variable	**Coefficient**	**Std. Err.**	**z**	**P> $\|z\|$**
Rt_Cameco				
B_crisis	0.0032530	0.0017553	1.85	0.064
B_fukushima	-0.0008185	0.0010510	-0.78	0.436
B_russia	0.0023460	0.0011407	2.06	0.040
Constant	-0.0022574	0.0015175	-1.49	0.137
ARMA				
AR (L4)	-0.0265372	0.0121451	-2.19	0.029
MA (L5)	-0.0364973	0.0111501	-3.27	0.001
σ	0.0273376	0.0001281	213.48	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Sample: 2 to 3969 Observations: 3968 Log Likelihood = 10365.17 Wald chi²(5) = 5.26 Prob > chi² = 0.3852				
Variable	**Coefficient**	**Std. Err.**	**z**	**P> $\|z\|$**
Rt_MSCI				
B_crisis	0.0002941	0.0012767	0.23	0.818
B_fukushima	-0.0003228	0.0006615	-0.49	0.626
B_russia	0.0006127	0.0009622	0.64	0.524
Constant	0.0000672	0.0011629	0.06	0.954
ARMA				
AR (L5)	-0.0062706	0.0071414	-0.88	0.380
MA (L4)	0.0126244	0.0067318	1.88	0.061
σ	0.0177544	0.000066	268.83	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Sample: 2 to 3969 Observations: 3968 Log Likelihood = 10689.47 Wald chi²(5) = 155.20 Prob > chi² = 0.0000				
Variable	Coefficient	Std. Err.	z	P> $\|z\|$
Rt_Uranium				
B_crisis	0.0029669	0.0010016	2.96	0.003
B_fukushima	-0.0004137	0.0008749	-0.47	0.636
B_russia	0.0017297	0.0009291	1.86	0.051
Constant	-0.0026615	0.0006799	-3.91	0.000
ARMA				
AR (L4)	0.8081976	0.1154385	7.00	0.000
MA (L4)	-0.7807511	0.1207613	-6.47	0.000
σ	0.0163609	0.0000316	517.24	0.000

Note: The test of the variance against zero is one-sided, and the two-sided confidence interval is truncated at zero.

Table 15.

Lag-order selection criteria

Lag	LL	LR	df	p-value	FPE	AIC	HQIC	SBIC
0	-282.919				0.000232	0.144222	0.145908	0.148977
1	30433.1	61432	9	0.000	4.3e-11	-15.3448	-15.3381	**-15.3258**
2	30452.7	39.09	9	0.000	4.3e-11	-15.3501	**-15.3383**	-15.3169
3	30462.0	18.766	9	0.027	4.3e-11	-15.3503	-15.3335	-15.3028
4	30476.8	**29.452**	9	0.001	**4.3e-11**	**-15.3532**	-15.3313	-15.2914

Notes: Optimal lag selection is based on minimizing AIC, HQIC, and SBIC criteria. Endogenous variables: ln(Cameco), ln(MSCI), ln(Uranium). Exogenous: constant term.

Table 16.

Johansen Cointegration Test

Rank	Params	Log-Likelihood	Eigenvalue	Trace Statistic	5% Critical Value
0	30	30452.137	.	49.2499	29.68
1	35	30467.388	0.00766	18.7472	15.41
2	38	30474.623	0.00364	4.2768	3.76
3	39	30476.762	0.00108		

Trend: Constant Sample: 5 to 3969 Number of observations: 3,965 Number of lags: 4

Cointegrating Equations

Equation	Parms	Chi2	P-value
_ce1	1	130.3954	0.0000
_ce2	1	3.3660	0.0666

Identification: beta is exactly identified. Johansen normalization restrictions imposed.

Equation	Variable	Coefficient	Std. Err.	z	P-value	95% Conf. Interval
4*_ce1	ln_Cameco	1	.	.	.	.
	ln_MSCI	0 (omitted)	.	.	.	.
	ln_Uranium	-1.110423	0.0972428	-11.42	0.000	[-1.301016, -0.9198309]
	Constant	0.9898083	.	.	.	.
4*_ce2	ln_Cameco	0 (omitted)	.	.	.	.
	ln_MSCI	1	.	.	.	.
	ln_Uranium	-0.2111418	0.1150844	-1.83	0.067	[-0.4367029, 0.0144194]
	Constant	-4.60683	.	.	.	.

Table 17.

VECM regression

Sample:	3 to 3967			**Number of Obs**	3965
AIC	-15.34133	**Log Likelihood**	30431.18	**HQIC**	-15.33177
Det(Sigma_ml)	4.33×10^{-11}	**SBIC**	-15.31438		
Equation	**Parms**	**RMSE**	**R-sq**	**Chi2**	**P¿Chi2**
D_ln_Cameco	5	0.027157	0.0042	16.66978	0.0052
D_ln_MSCI	5	0.017843	0.0010	3.841622	0.5724
D_ln_Uranium	5	0.015945	0.0128	51.37439	0.0000

Variable	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]
D_ln_Cameco					
ce1 L1	-0.0004693	0.0021345	-0.22	0.826	[-0.0046528, 0.0037141]
ln_Cameco LD	-0.0340752	0.018639	-1.83	0.068	[-0.0706069, 0.0024565]
ln_MSCI LD	0.002676	0.0280384	0.10	0.924	[-0.0522783, 0.0576303]
ln_Uranium LD	0.1022816	0.0272427	3.75	0.000	[0.0488868, 0.1556764]
Constant	0.0000682	0.0004327	0.16	0.875	[-0.0007799, 0.0009162]
D_ln_MSCI					
ce1 L1	0.00151	0.0014024	1.08	0.282	[-0.0012387, 0.0042587]
ln_Cameco LD	-0.0087331	0.0122465	-0.71	0.476	[-0.0327358, 0.0152695]
ln_MSCI LD	0.0297629	0.0184223	1.62	0.106	[-0.006344, 0.0658699]
ln_Uranium LD	0.0047092	0.0178995	0.26	0.792	[-0.0303731, 0.0397915]
Constant	0.0000307	0.0002843	0.11	0.914	[-0.0005265, 0.0005879]
D_ln_Uranium					
ce1 L1	0.0070893	0.0012532	5.66	0.000	[0.004633, 0.0095456]
ln_Cameco LD	0.0073086	0.0109436	0.67	0.504	[-0.0141404, 0.0287577]
ln_MSCI LD	0.014606	0.0164623	0.89	0.375	[-0.0176596, 0.0468716]
ln_Uranium LD	0.056249	0.0159952	3.52	0.000	[0.024899, 0.087599]
Constant	-2.03e-06	0.000254	-0.01	0.994	[-0.0005, 0.0004959]

Table 18.

Diebold-Mariano Test manual

	Observations	Mean Error	t-statistic	p-value
Cameco ARIMA	3,968	0.00128	19.07	0.0000
Cameco VECM	3	0.00007	0.88	0.4714
MSCI ARIMA	3,968	0.00003	4.80	0.0000
MSCI VECM	3	-0.00017	-0.87	0.4752
Uranium ARIMA	3,968	0.00028	9.61	0.0000
Uranium VECM	3	-0.00001	-1.38	0.3018

Table 19.

RMSE Comparison and Inefficiency Measures

	AR(0) RMSE	VECM RMSE	RMSE Reduction (%)
Cameco	0.0274	0.0122	55.6%
MSCI	0.0178	0.0062	65.4%
Uranium	0.0164	0.0013	92.1%

Appendix Figures

Figure 1.

Uranium price trend

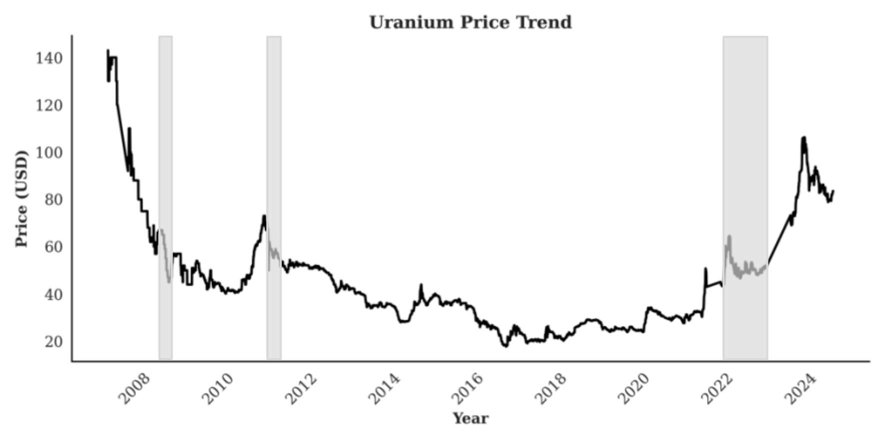


Figure 2.

Cameco stock price trend

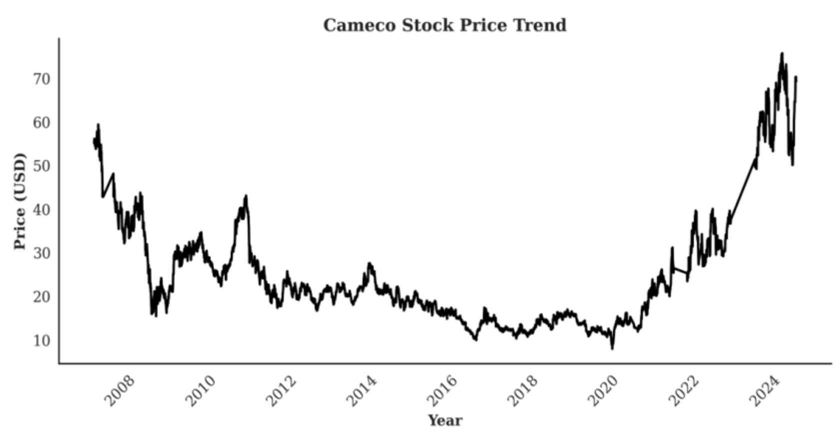


Figure 3.

The ACF and PACF plots

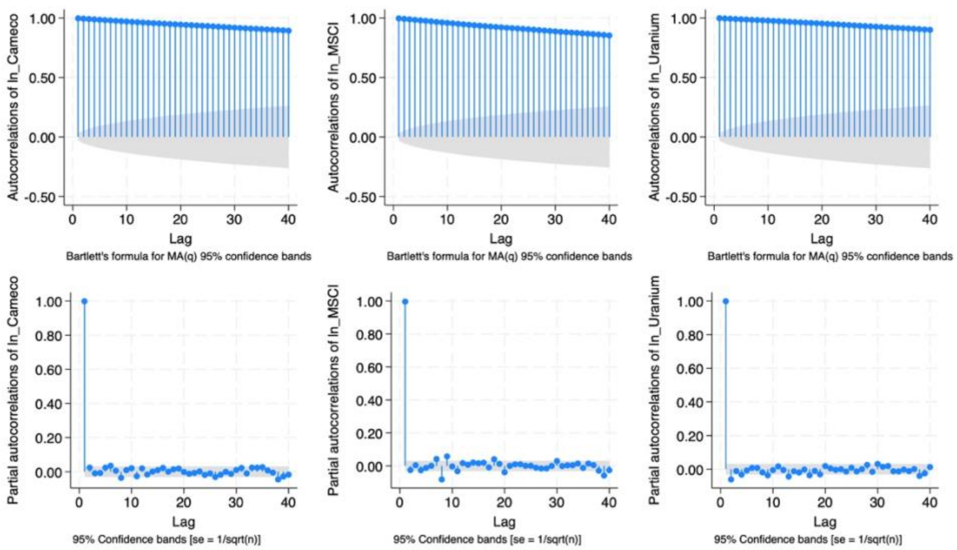


Figure 4.

The ACF and PACF plots for the first difference

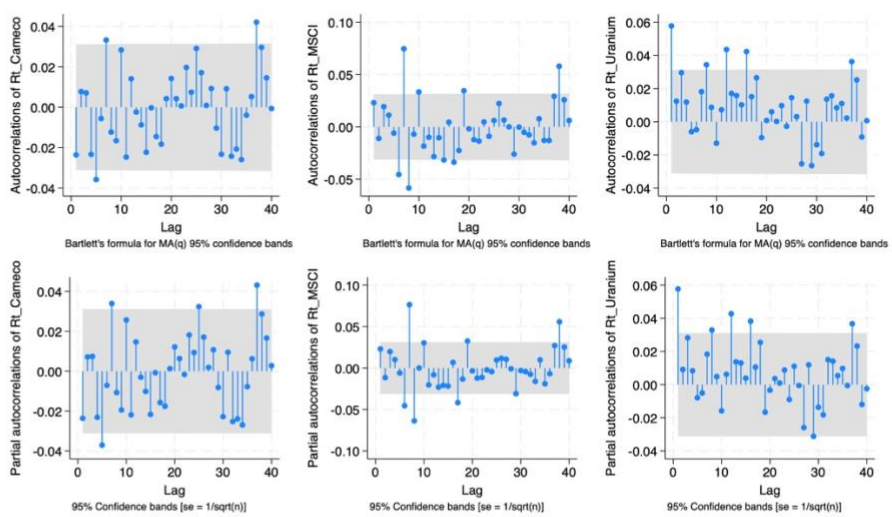
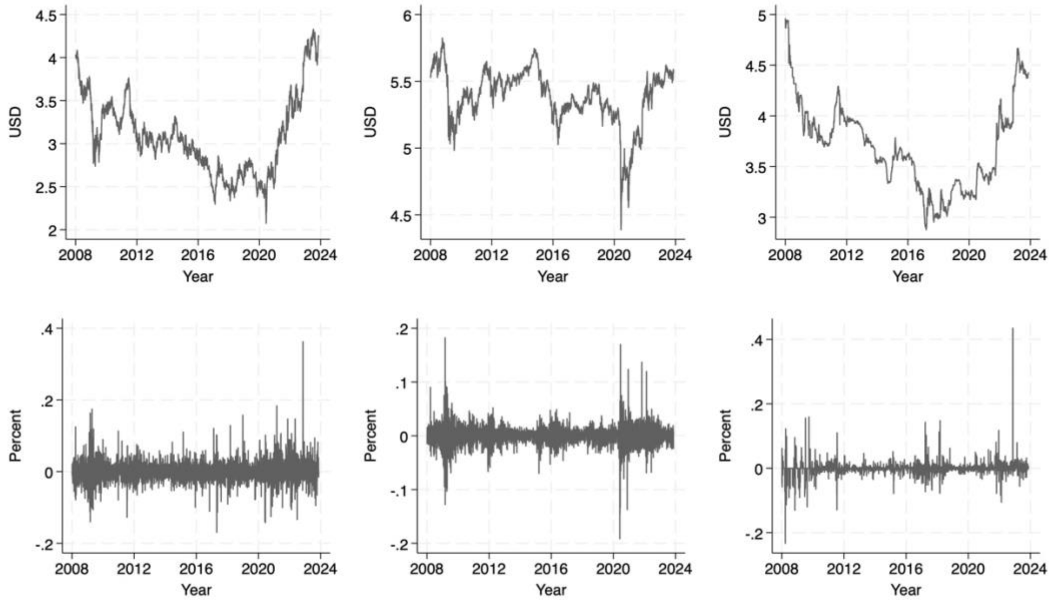


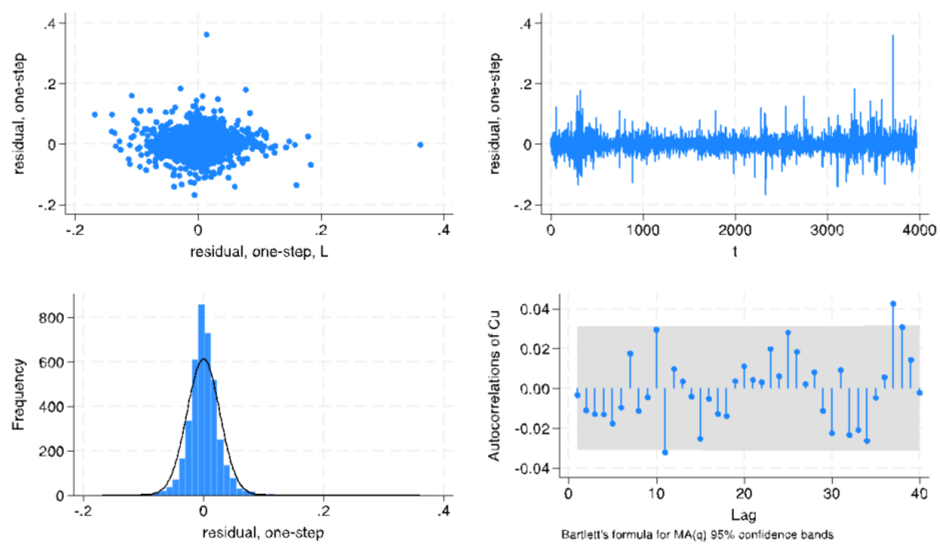
Figure 5.

Stationarity Analysis



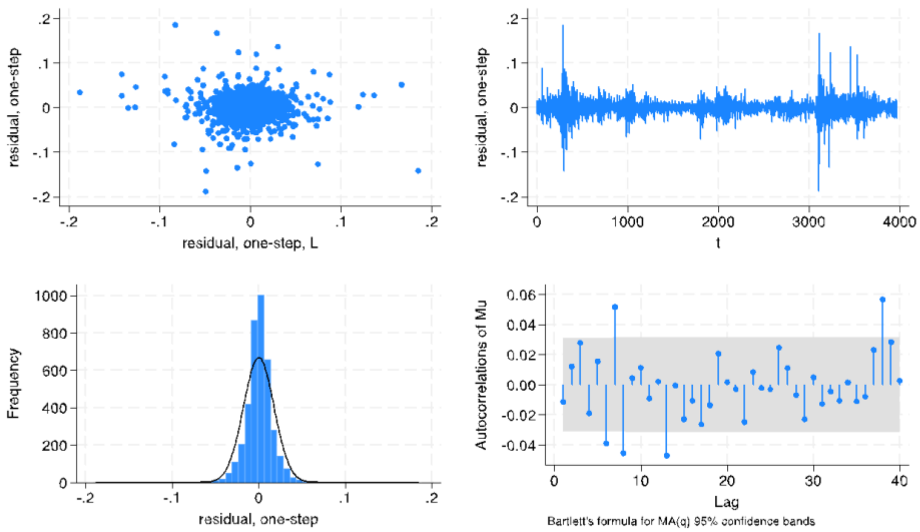
Figures 6.

Residual Diagnostics of Cameco



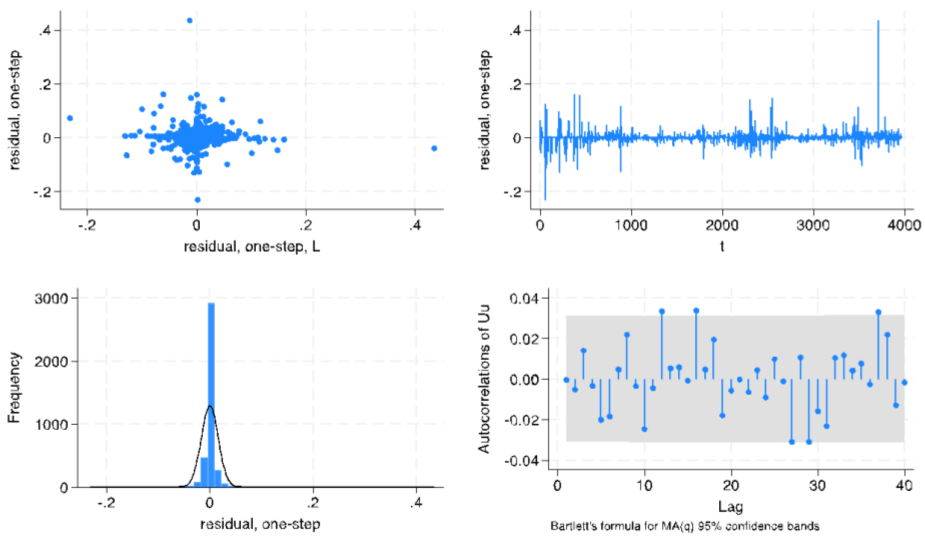
Figures 7.

Residual Diagnostics of MSCI



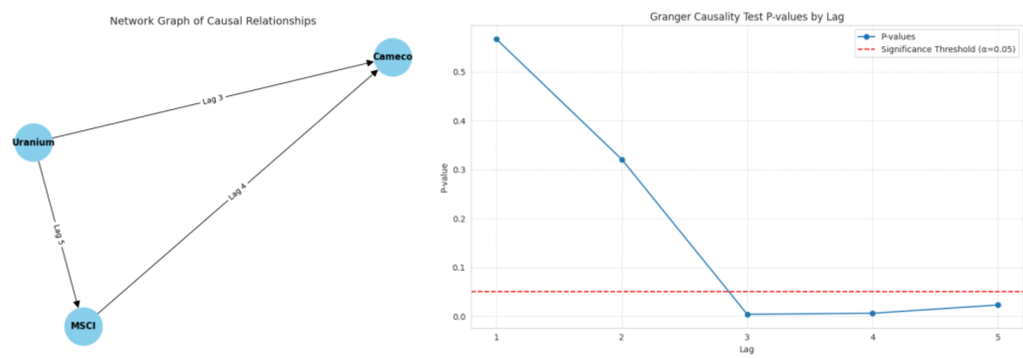
Figures 8.

Residual Diagnostics of Uranium



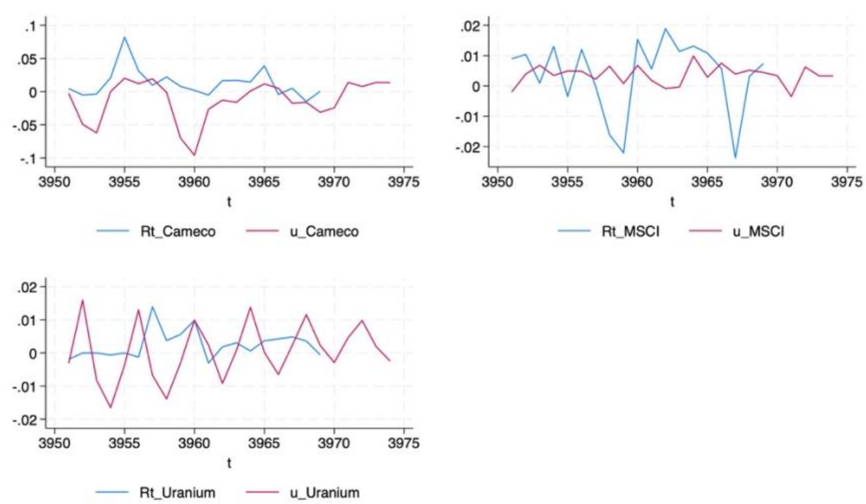
Figures 9.

Granger Causality



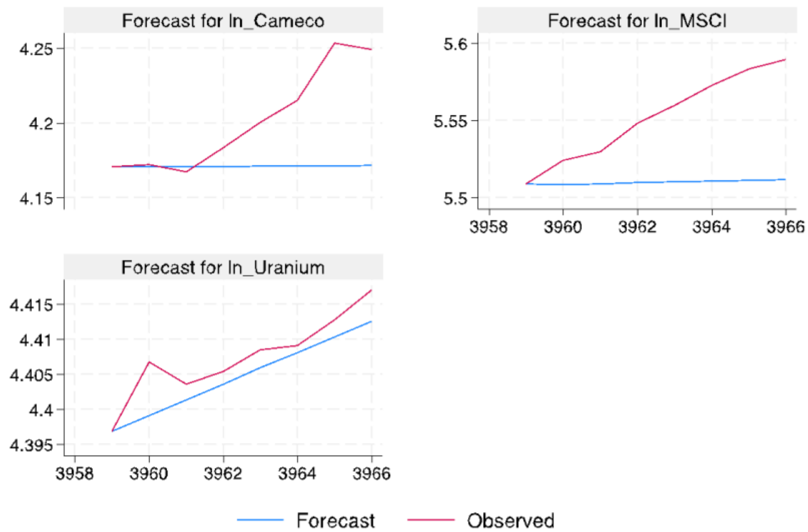
Figures 10.

ARMA forecast



Figures 11.

VEC forecast



Figures 12.

VEC out-of-sample forecast