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FACULTY OF ECONOMICS AND MANAGEMENT

Chair of Banking and Finance
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Seminar Report

Computational Finance and Financial Management

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Introduction

In 2011, following the Fukushima disaster, Germany made the energy policy decision to permanently phase out nuclear power. Under Chancellor Angela Merkel, eight reactors were immediately shut down, and the rest were scheduled to close by 2022. That plan was fulfilled in April 2023, when Germany decommissioned its last remaining nuclear plants effectively reducing its uranium demand to zero. However, the global pandemic had already begun by that time, which resulted in a significant volatility in the uranium market before Germany completed its nuclear phase-out in 2023.

The COVID-19 pandemic in early 2020 disrupted uranium supply chains significantly. Major uranium producers, such as Kazakhstan's Kazatomprom and Canada's Cameco were temporarily shut down or reduced mining activity, causing global uranium production to decline sharply (Kazakhstan output dropped, Canadian mines were halted). With nuclear reactors largely unaffected by demand-side issues, this supply reduction caused uranium spot prices to rise from about $24 to $34 per pound by mid-2020 (Denison Mines, 2021). Thus, while the initial shock of the pandemic created a short-term bullish effect on uranium prices, it did not reverse the long-term bearish structural trend from Germany's nuclear exit. The phase-out has removed a major consumer from the market, and even supply-side problems during the pandemic weren't enough to offset this structural decline in demand.

In the wake of the Russia-Ukraine war, Germany faced an energy crisis as natural gas prices spiked. Rather than go back on their policies on nuclear, Germany doubled down on its renewable transition by scaling wind, solar, and grid infrastructure, while diversifying gas imports from Norway, the Netherlands, and global LNG markets. With one of the world's largest industrial economies fully exiting the nuclear sector, we see a structural reduction in long-term uranium demand (Shannak et al., 2025). This policy shift and possible other reasons contribute to a bearish outlook for uranium prices as we will discuss the forecast later in this paper. This research aims to model, analyze and forecast future behavior and dynamics of the uranium market under such conditions, helping investors and policymakers re-evaluate the potential risks in the nuclear energy supply chain.

Theoretical background

1. Time Series Analysis

Time-series analysis is a statistical technique used to examine data collected from repeated observations of a subject over consistent time intervals. Among the most commonly used frameworks for this type of analysis is the Autoregressive Integrated Moving Average (ARIMA) model. Time series analysis using ARIMA models typically involves two key steps: model identification and parameter estimation. Model identification is about figuring out which ARIMA structure best fits the data, a process that can be complicated and often requires a large number of observations. This step is especially important when the goal is to understand the underlying data-generating process. Once a suitable model is identified, the time series is transformed to remove serial correlation, allowing for accurate estimation of the model parameters. This is usually done using generalized least squares. ARIMA models are defined by three parameters; **p**: the number of autoregressive (AR) terms i.e. how many past values influence the current one, **d**: the degree of differencing needed to make the series stationary and **q**: the number of moving average (MA) terms i.e. how many past errors impact the current value. In practice, lower-order ARIMA models (such as ARIMA(1,1,1)) are commonly used in commodity price analysis, as higher-order models often add minimal predictive value and can be difficult to estimate accurately, especially in the presence of market noise or limited data.

2. Stationarity in Time Series

The Dicky-Fuller test is used to demonstrate the presence of a unit root. A unit root means that the mean and variance of a time series are not constant over time. For time series data that is stationary, the mean and variance will not change over time. The null hypothesis is that the value of a time series Y_t is not stationary and p = 1 and the alternative hypothesis does not contain an unit root meaning p is smaller than one. Also if the T statistic in absolute value exceeds the critical value which is usually 0.05, the time series is stationary. The Augmented Dicky-Fuller test is an extension of the simple DF test to determine whether financial time series data is stationary or not. The ADF test includes additional terms to account for potential trends and serial correlations in time series. The constant term and linear trend term are helpful to capture any trends in the time series. The lagged value can improve the accuracy of the test by reducing type II error when the time series is nonstationary. The ADF test is commonly used to determine the presence of unit roots and is more flexible and accurate since the financial time series data contains trends or serial correlations.

$$\Delta y_t = \alpha + \beta_t + \gamma y_t - 1 + \delta 1 \Delta y_t - 1 + \delta 2 \Delta y_t - 2 + \cdots + \delta p \Delta y_t - p + \mathcal{E}_t$$

- Δy_t is the first difference of the time series y, α is a constant term,
- β_t is a linear trend term,
- $y_t - 1$ is the lagged value of y, $\Delta y_t - 1$, $\Delta y_t - 2$,......,
- $\Delta y_t - p$ are the lagged differences of y up to p lags,
- $\mathcal{E}_t$ is the error term.

3. Differencing and Seasonality

For the purpose of applying ARIMA models effectively, the time series must be *stationary*, that means its statistical properties such as mean and variance should remain constant over time. Real-world data like uranium prices are often non-stationary due to underlying trends or seasonal patterns. One of the most effective techniques to achieve stationarity is differencing, where each data point is replaced by the difference between itself and the previous observation. This removes persistent trends and stabilizes the series.

Seasonality refers to repeating patterns that occur at regular intervals, such as monthly or yearly cycles. Seasonal decomposition helps to break the time series into three components: trend, seasonality, and residuals. This allows us to isolate and remove predictable cycles, making the data more suitable for ARIMA modeling. Understanding whether non-stationarity is caused by trend or seasonality is crucial for the model.

The Black-Scholes model is a foundational approach for pricing European options. It assumes that commodity (or any other asset) prices follow a continuous, log-normal distribution and that markets operate efficiently with no arbitrage. The model requires parameters such as current price, strike price, time to maturity, volatility, and the risk-free interest rate.

Monte Carlo simulation offers a more flexible method for pricing options by modeling thousands of possible future price paths based on randomness and historical volatility. Instead of relying on a fixed formula, this approach includes a range of potential outcomes and finds the average of them to estimate the option's value. In other words, it works by generating thousands (or millions) of possible future price paths based on historical volatility and randomness, calculating the payoff for each scenario, averaging these outcomes, and discounting to present value.

Methodology

Data

Historical Uranium price data from the periods of 2019-2025 was imported as a CSV file. The data was imported into Python using pandas. The dataset was cleaned by converting the date column to datetime and sorted the data in ascending order. With that we calculated daily returns and log returns and then plotted a graph to visualize the prices.

Time Series Analysis

Before applying any time series forecasting model it is important to ensure that the data is stationary, the mean and variance do not change over time. This is a fundamental assumption of the ARIMA model. We first plotted the rolling mean and standard deviation to visually assess if these two properties are stationary. We also began by conducting the Augmented Dickey-Fuller test on raw uranium price data to test for stationarity. We can clearly see in the graph that the rolling mean is not constant overtime and the results of our ADF test show that the test statistic is greater than our critical values therefore confirming that the data is not stationary in its current state. To understand why the data is non-stationary, we performed seasonal decomposition of the time series. The "seasonal_decompose" function from statsmodels takes a non-stationary time series and breaks it down into trend, seasonality, residuals. This decomposition helps identify what non-stationary features are present so we can fit the data to the ARIMA model. This helps isolate patterns and identify whether the trend or seasonality was contributing to non-stationarity. The decomposition revealed a significant upward trend and some evidence of seasonality. These elements are usually the cause of non-stationarity and must be removed before fitting an ARIMA model. After decomposing the data, the series was transformed through differencing. In our case we used first-order differencing which calculated the difference between each observation and its preceding value. This transformation is mathematically represented as: $Y_t' = Y_t - Y_{t-1}$. We then did a second ADF test to test again for stationarity. The new results show the test statistic is much lower than the critical values allowing us to reject the null hypothesis and the graph visually both confirm that the data is now stationary and ready to fit the ARIMA model. Once stationarity was achieved, we proceeded to fit the ARIMA model. We used ARIMA because of its flexibility in capturing both autoregressive (AR) and moving average (MA) components, also accounting for differencing (I) as required. We used the "auto_arima" function so that it would automatically optimize p,d,q parameters.

Monte Carlo Simulation

To conduct a Monte Carlo simulation, we first calculated the necessary statistical parameters to model uranium price behavior for the future. These parameters include *mean, variance,* and *standard deviation* of the daily log returns of historical uranium prices. From these values, *drift* is calculated, which represents the expected daily return adjusted for volatility. The drift is derived using the formula:

$\text{drift} = \mu - (1/2) \times \sigma^2$, *where: μ is the mean of the daily log returns; σ is the standard deviation of the daily log returns*

This captures the average return of the commodity while accounting for volatility of returns, which is important when simulating under Geometric Brownian Motion (GBM).

Next, we created an array of random numbers that follow a normal distribution by using the inverse of the probability curve (called the inverse CDF). These numbers (Z-scores) represent how far a value is from the average in terms of standard deviations. In other words, it represents how much prices could randomly move up or down each day, based on a normal distribution. These random market movements are used to model future uncertainties, therefore, needed for forecasting different future price movements. According to Brownian motion, the daily return is expressed as:

$r = \text{drift} + \sigma \times Z$, *where: Z is a random value drawn from the standard normal distribution*

To simulate price paths, we applied the exponential of these daily returns to reflect percentage-based price changes. We created 50 independent simulations over 182 time frames (approximately 6 months), and it resulted in a matrix of simulated daily returns. Each column represents one potential future path of uranium prices. Using the last actual observed uranium price as a starting point, we recursively generated simulated future prices using:

$S_t = S_{t-1} \times e^r$

This allowed us to construct a forecast table named "price_list" where each column corresponds to a different simulated future price trajectory.

Finally, we created a line graph of all 50 simulated price paths together with a line of best fit calculated by using the average of all simulations. This trend line helps to visualize expected price trajectory under the assumptions of our model. In this part of the code, we conducted Monte Carlo simulation to provide a probable range of outcomes for the next 6 months, reflecting both the randomness of markets and statistical movement of uranium prices historically (last 6 years).

European Call

To estimate the fair value of a European call option on uranium, we applied a Monte Carlo simulation of the Black-Scholes model. The main parameters for the option pricing included the current uranium price, the strike price, time to maturity, risk-free rate, and the annual volatility of uranium, derived from the standard deviation of daily log returns.

The simulation is based on the assumption that asset prices follow a Geometric Brownian Motion (GBM). We simulated 10,000 possible future uranium prices at the option's expiration date using this technique. These prices are modeled using the formula:

$ST = S \times \exp[(r - 0.5 \times \sigma^2) \times T + \sigma \times \sqrt{T} \times Z]$, *where: ST is simulated price at maturity; S is current uranium price; r is risk-free interest rate; σ is annual volatility; T is time to maturity in years; Z is standard normal random variable*

This equation also includes both the drift term and the random shock component from the normal distribution, representing potential market fluctuations, same as the simulation we did for estimation of future prices above. Once all future prices were simulated, we calculated the payoff of the European call option using:

payoff = max(ST − K, 0), *where: ST is simulated price at maturity; K is strike price*

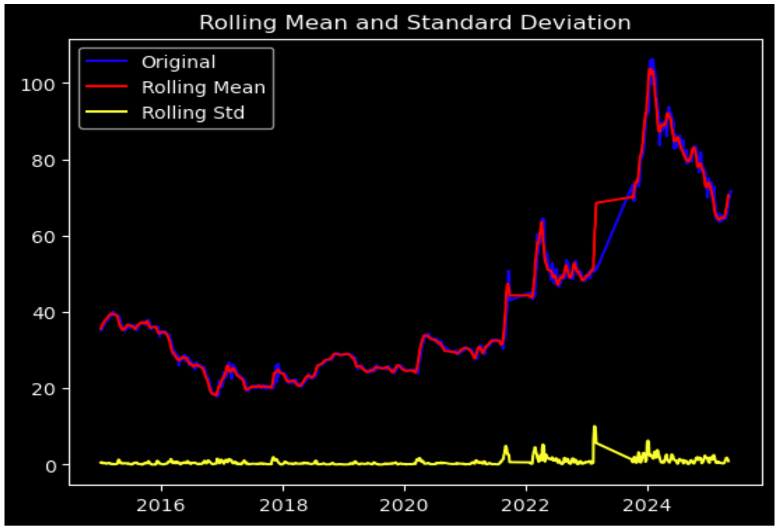
A European call option only pays off at expiration, and only if the underlying price exceeds the strike price (K). The final option price was then calculated as the present value of the average payoff discounted using the risk-free rate:

Call Price = e^(−r × T) × average(payoffs)

This method provides an estimation of how much the option would be worth under various future market scenarios. Additionally, we also generated a graph of 50 random uranium price paths to show the range of possible price trajectories over the 6-month period to depict the uncertainty of the outcomes used in the option valuation.

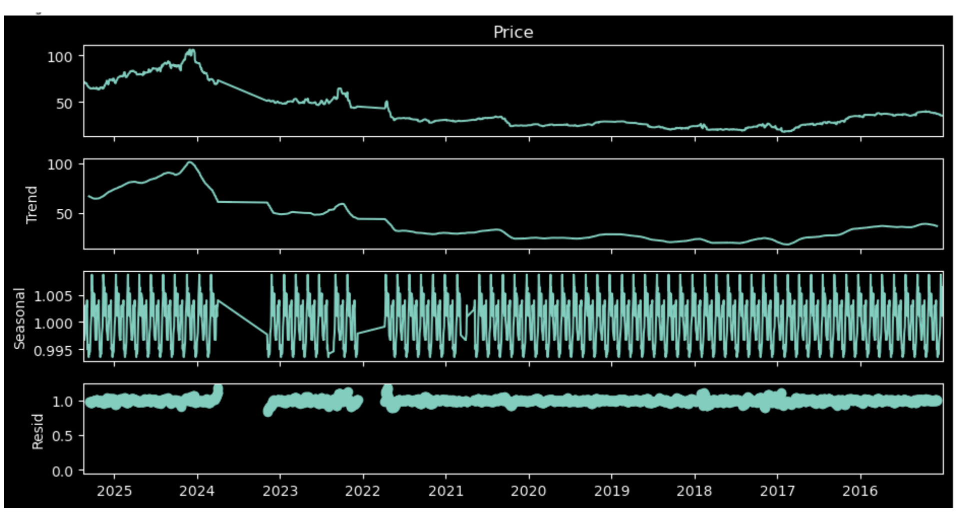
Results

The initial ADF test was applied to the uranium futures price series to determine whether the data was stationary. We also graphed a time series plot of uranium future prices along with the rolling mean and rolling standard deviation. The blue line is the raw uranium price from 2015 to 2025. The red line shows the twelve day rolling window moving average which smooths the price to highlight trends. The yellow line shows the moving standard deviation, which represents volatility overtime. The graph shows clear upward and downward trends especially between 2022 to 2025, indicating non-stationary behaviour. The rolling mean and standard deviation are not flat and constant reinforcing the idea that the data is non-stationary . The test yielded a test statistic of -1.475 with a p-value of 0.545735, which was higher than standard significance thresholds (e.g., 0.05). These results led to the failure to reject the null hypothesis, indicating that the price series was non-stationary.

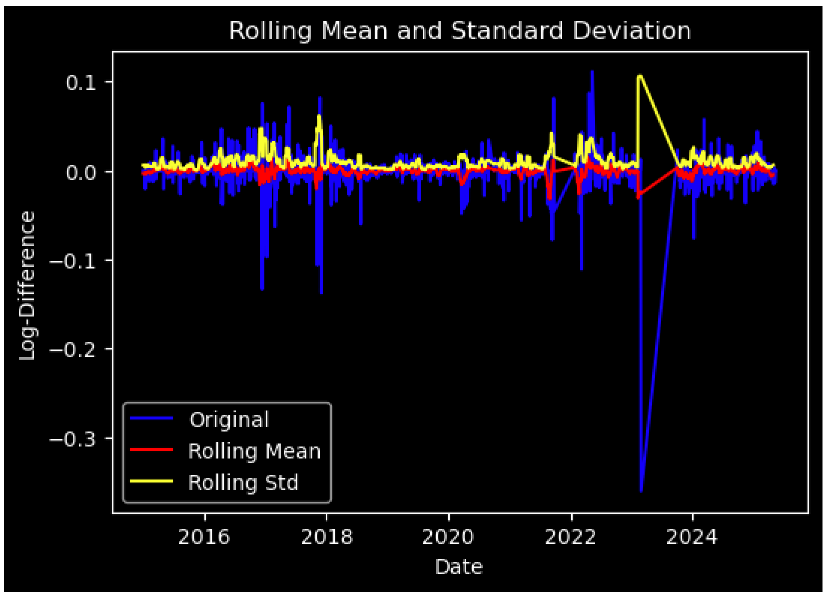



```
Results of ADF test
Test Statistics                 -1.475213
p-value                          0.545735
No. of lags used                13.000000
Number of observations used   2323.000000
critical value (1%)             -3.433168
critical value (5%)             -2.862785
critical value (10%)            -2.567433
dtype: float64
```

To make the data stationary, a seasonal decomposition was performed. This decomposition revealed a persistent upward trend with low seasonal effects and random residuals. The trend component confirmed the visual evidence of non-stationarity. The Price graph shows strong trends and fluctuations especially between the 2022-2023 time period indicating presence of seasonality or noise indicating non-stationarity. The trend graph shows a clear drop around 2023 confirming a strong trend which must be removed or differenced to achieve stationarity. The Seasonal graph clearly shows a repeating pattern oscillating around 1.0 with some breaks in between which could be any kind of irregularity but seems to be minor seasonality. Finally the Residual plot shows what's left after removing trend and seasonality. It represents random noise, although for the most part it seems like random noise there are some fluctuations in 2022 and after 2023 that may indicate increased volatility. After differencing we can now test again for stationarity.



The post-differencing ADF test produced a test statistic of -10.37 with a p-value of ~2.27×10^{-18}. The ADF test statistic is much lower than all the critical values, the p-value is far below 0.01. The graph also shows the differenced series fluctuates around zero and shows no visible trend. Both the rolling mean and rolling standard deviation are mostly stable overtime except for some minor spikes which may be due to some external shock. Given these two confirmations it will now allow us to reject the null hypothesis and confirm that the differenced series is stationary. And we can now fit our ARIMA model.




```
Test Statistic                 -1.037039e+01
p-value                         2.272094e-18
Number of Lags Used             1.500000e+01
Number of Observations Used     2.320000e+03
Critical Value (1%)            -3.433172e+00
Critical Value (5%)            -2.862787e+00
Critical Value (10%)           -2.567434e+00
dtype: float64
```

With the transformed stationary series, the "auto_arima" function was used to identify the optimal parameters for the ARIMA model. The selected configuration ARIMA(2,0,3), includes two autoregressive terms (p=2), no order of differencing (d=0) and three moving average terms (q=3). Among the estimated parameters, AR(2), MA(2) and MA(3) all have p-values < 0.05. AR(2) being significant indicates that the time series is influenced by the value two periods ago. MA(2) and MA(3) being significant means the model is using noise patterns from 2 and 3 periods back to better explain the current value. The models results show that the Ljung-Box test has a p-value of 0.86 which suggests no significant autocorrelation in residuals additionally the test for heteroskedasticity has a p-value of 0.66 which indicates no strong evidence of time-varying variance. The issues we faced with the ARIMA model is that the the Jarque-Bera test strongly rejects the null hypothesis of normality in the residuals, skewness is giving a value of -6.99 which indicates a heavy left skew in the residual while a normal distribution should have zero skew and kurtosis is giving a value of 170.11 which indicates very fat tails, normal kurtosis should be three. To address this issue a GARCH(1,1) model was fitted to the ARIMA residuals. The results showed that both the ARCH term ($\alpha = 0.20$, $p = 0.027$) and the GARCH term ($\beta = 0.70$, $p < 0.001$) were statistically significant, with $\alpha + \beta = 0.90$ indicating strong volatility persistence. The inclusion of GARCH captures the conditional heteroskedasticity present in the data that was not accounted for by ARIMA alone enhancing overall robustness of this time series analysis.

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0]             : AIC=-13026.713, Time=0.37 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=-12983.838, Time=0.03 sec
 ARIMA(1,0,0)(0,0,0)[0]             : AIC=-13024.804, Time=0.02 sec
 ARIMA(0,0,1)(0,0,0)[0]             : AIC=-13023.785, Time=0.05 sec
 ARIMA(1,0,2)(0,0,0)[0]             : AIC=-13020.511, Time=0.20 sec
 ARIMA(2,0,1)(0,0,0)[0]             : AIC=-13020.834, Time=0.21 sec
 ARIMA(3,0,2)(0,0,0)[0]             : AIC=-13023.804, Time=0.47 sec
 ARIMA(2,0,3)(0,0,0)[0]             : AIC=-13027.075, Time=0.63 sec
 ARIMA(1,0,3)(0,0,0)[0]             : AIC=-13018.732, Time=0.34 sec
 ARIMA(3,0,3)(0,0,0)[0]             : AIC=-13023.107, Time=0.34 sec
 ARIMA(2,0,3)(0,0,0)[0] intercept   : AIC=-13018.412, Time=0.40 sec

Best model:  ARIMA(2,0,3)(0,0,0)[0]
Total fit time: 3.075 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 2336
Model:               SARIMAX(2, 0, 3)   Log Likelihood                6519.538
Date:                Wed, 11 Jun 2025   AIC                         -13027.075
Time:                        21:09:16   BIC                         -12992.538
Sample:                             0   HQIC                        -13014.493
                               - 2336
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.1462      0.254     -0.575      0.565      -0.644       0.352
ar.L2          0.7725      0.234      3.308      0.001       0.315       1.230
ma.L1          0.2868      0.255      1.125      0.261      -0.213       0.787
ma.L2         -0.7172      0.273     -2.632      0.008      -1.251      -0.183
ma.L3         -0.1035      0.045     -2.319      0.020      -0.191      -0.016
sigma2         0.0002   9.33e-07    236.034      0.000       0.000       0.000
===================================================================================
Ljung-Box (L1) (Q):                   0.03   Jarque-Bera (JB):            2737299.63
Prob(Q):                              0.86   Prob(JB):                          0.00
Heteroskedasticity (H):               0.66   Skew:                             -6.99
Prob(H) (two-sided):                  0.00   Kurtosis:                        170.11
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

```
Iteration:      1,   Func. Count:      6,   Neg. LLF: 709658113035.0526
Iteration:      2,   Func. Count:     19,   Neg. LLF: 4025615457638.193
Iteration:      3,   Func. Count:     34,   Neg. LLF: 56488710723.952614
Iteration:      4,   Func. Count:     48,   Neg. LLF: -6974.615350092642
Optimization terminated successfully    (Exit mode 0)
            Current function value: -6974.615353606536
            Iterations: 8
            Function evaluations: 48
            Gradient evaluations: 4
```

Constant Mean - GARCH Model Results

Dep. Variable:	Price	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	GARCH	**Log-Likelihood:**	6974.62
Distribution:	Normal	**AIC:**	-13941.2
Method:	Maximum Likelihood	**BIC:**	-13918.2
		No. Observations:	2336
Date:	Fri, Jun 13 2025	**Df Residuals:**	2335
Time:	16:46:14	**Df Model:**	1

Mean Model

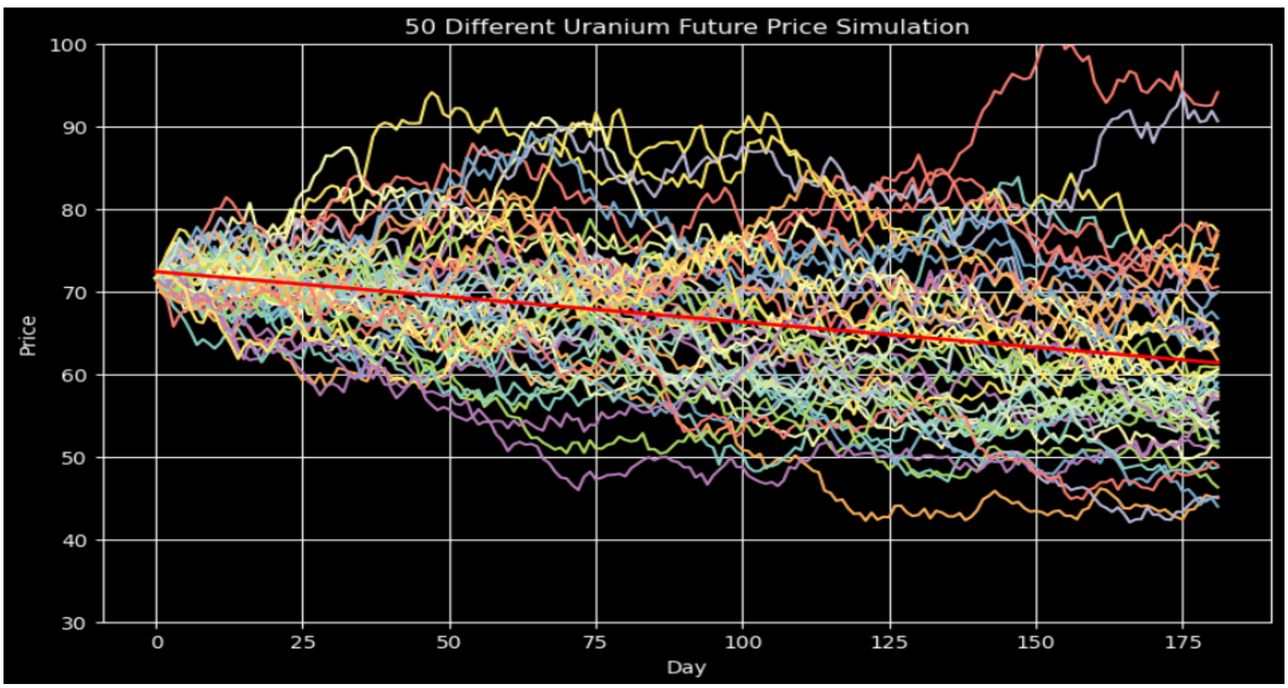
	coef	std err	t	P>|t|	95.0% Conf. Int.
mu	-6.2052e-04	7.798e-04	-0.796	0.426	[-2.149e-03,9.079e-04]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	2.2548e-05	3.247e-12	6.943e+06	0.000	[2.255e-05,2.255e-05]
alpha[1]	0.2000	8.909e-02	2.245	2.477e-02	[2.539e-02, 0.375]
beta[1]	0.7000	3.740e-02	18.716	3.682e-78	[0.627, 0.773]

Coming to the Monte Carlo simulation conducted to forecast future price of uranium, the resulting graph illustrates the range of possible future prices, which reflect the uncertainty and volatility in commodity markets. Most of the paths stay within a moderate range, while a few of them exhibit extreme upward or downward trajectory. This variation captures the nature of price movements and highlights how even small changes in volatility or drift can lead to significantly different outcomes over time.

A line of best fit was also drawn based on the mean of all simulated paths. The negative slope of this line suggests a slight downward trend in the expected uranium price over the simulated period, most likely because of the observed historical drift being slightly negative.

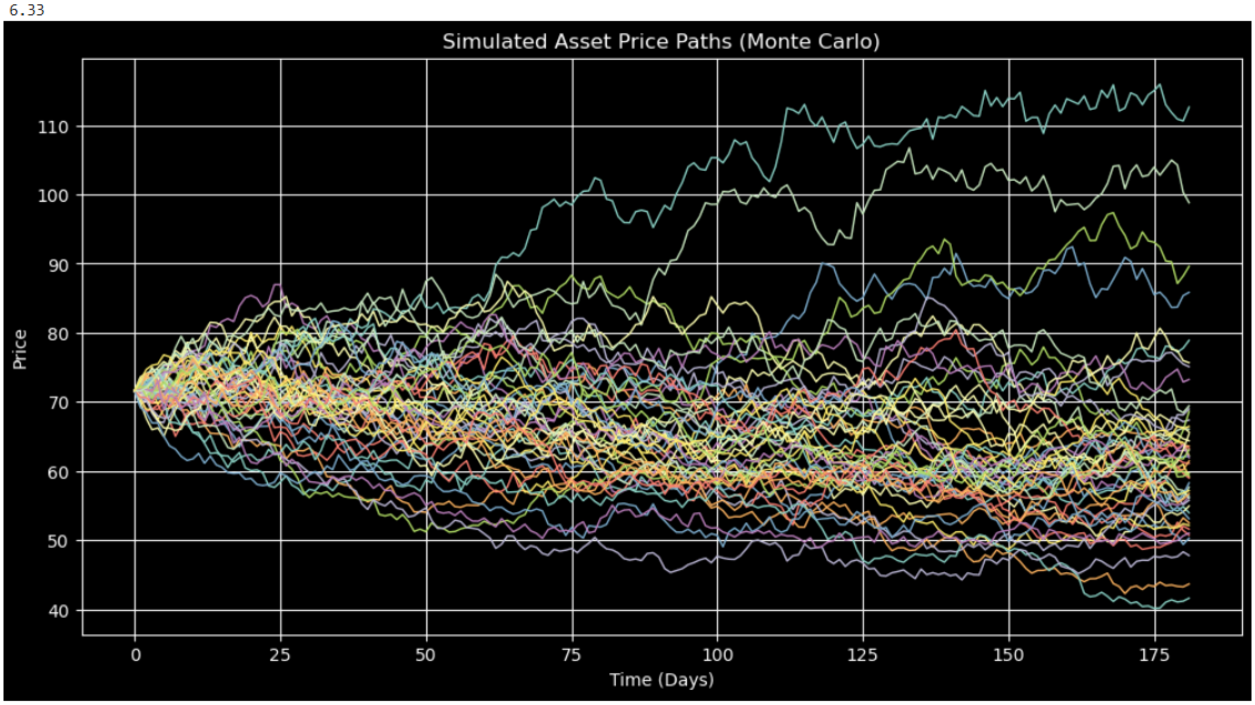


Using the same Monte Carlo framework, we estimated the fair value of a European call option on uranium with a strike price of $20, a maturity of 0.5 years, and a risk-free interest rate of 3.5%. The annual volatility was derived from the historical standard deviation of daily log returns by multiplying by 252 representing the number of average trading days in a year.

The simulation involved 10,000 iterations of potential future uranium prices at option maturity. The payoff for each path was calculated based on the option's value, and the mean of these payoffs was discounted back to the present value to determine the estimated option price.

The resulting estimated value of the European call option was 6.33$, which suggests that the market is suggesting a considerable possibility of uranium prices exceeding the strike price of 70$ within the next 6 months under current market conditions and price volatility, as well as considering the current uranium price being significantly higher than our taken strike price.

```
European Call Option Price:
6.33
```



Conclusion

The main goal of this paper is to analyze and forecast uranium price behavior using time series modeling and option valuation techniques, with a focus on forecasting future price dynamics and derivative pricing under uncertain conditions. Through ARIMA modeling, we identified non-stationarity in the historical uranium price series and addressed it using differencing and seasonal decomposition. While seasonal patterns were not dominant, the presence of trend and volatility confirmed that we needed to transform the model. The final ARIMA(2,0,3) model fit the data well, but the leftover errors showed some problems such as uneven shape and extreme values. To fix this, we used a GARCH model, which helped us better capture the changing volatility in uranium prices.

Next, Monte Carlo simulation gave further insights to this analysis by generating a range of possible uranium price paths over the next six months. The simulated trajectories reflected realistic market uncertainty, with a trend line indicating a slight downward expectation based on historical drift. Using the same simulation framework, a European call option was priced at 6.33$, so the market assigned a considerable probability of prices to stay above 70$ strike price within the short-term (6 months) period.

Although this study provides valuable insights into uranium price behavior and option valuation, it is not without limitations. The ARIMA model assumes linearity and may not fully capture sudden shocks or structural breaks in the market. Similarly, the Monte Carlo simulation relies on historical volatility and assumes a log-normal price distribution, which may not hold under extreme market conditions or in the presence of geopolitical disruptions. Recent conflicts between the United States and Iran, including military strikes on nuclear facilities, show the vulnerability of uranium markets to sudden geopolitical events, as the price of uranium spiked during the last days. Such developments can trigger sharp price increases or supply decreases, which are difficult to predict using traditional statistical models. Additionally, our analysis is based on a single strike price and maturity date (of a European option), which limits the generalizability of the option pricing results.

Future research on this topic can include more adaptive models such as GARCH for volatility, or scenario-based simulations that account for geopolitical risk. Expanding the analysis to include different ranges of option types, strike prices, and different maturities would also help to improve the accuracy and usefulness of option pricing in a market that is sensitive to political news like uranium.

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