Assignment #2- Energy Exchange Traded Funds Time Series Stylized Facts

MSDS 492- Analysis of Financial Markets

Northwestern University

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AI used in this report for custom coding, background search, and wording clarification. The work is my own.

Contents

Executive Summary

This report examines the financial time-series behavior of three major energy-commodity exchange-traded funds (ETFs): UGA (gasoline), UNG (natural gas), and USO (crude oil). Unlike equities, whose price movements reflect firm-specific fundamentals, these ETFs derive their value primarily from front-month futures contracts rather than physical commodities. As a result, their price behavior captures not only real-time supply and demand dynamics in the energy markets but also the shape of the futures curve, including contango, backwardation, storage costs, and roll-yield effects. The ETFs do not take physical delivery of the commodities but are designed to allow investors to have exposure to the price movements of the products.

Across all three ETFs, the results demonstrate clear random-walk-like behavior in price levels, with extremely high autocorrelation and slow decay across lags. The autocorrelation of daily returns is near zero. Despite this lack of linear predictability, the return series exhibit strong volatility clustering, with absolute and squared-return autocorrelations remaining significantly positive across multiple lags.

The return distributions of all three ETFs deviate meaningfully from normality. UGA and USO show negative skewness and moderate excess kurtosis, while UNG displays unusually wide dispersion and strong seasonality, including pronounced winter-driven variability. QQ plots confirm heavy-tailed behavior, reinforcing Taylor's observation that extreme returns occur more frequently than Gaussian models predict. Strong correlations among lagged prices, spreads, moving averages, and EMAs (often exceeding 0.98–0.99) further mirror Taylor's financial market reviews

Overall, the results show that energy-commodity ETFs exhibit all major stylized facts of modern asset-price dynamics: random-walk behavior of prices, near-zero return autocorrelation, volatility clustering, heavy-tailed return distributions, seasonal patterns, and strong correlation across common price transformations. When combined with the structural mechanics of futures-based ETFs (roll-yield effects and futures-curve volatility) the behavior of UGA, UNG, and USO reflect the underlying commodity markets. These characteristics can be incorporated into any rigorous modeling, forecasting, or portfolio-risk framework involving energy ETF exposures.

Literature Review

Research on commodity ETFs consistently shows that their price behavior reflects both the underlying futures markets and well-known stylized facts of financial time series. Hadad, Malhotra, and Nippani (2022) find that commodity ETFs exhibit non-normal return distributions, sensitivity to macroeconomic shocks, and return patterns that differ significantly from broad equity markets. Their results parallel these findings for UGA, UNG, and USO, which also show heavy-tailed returns, strong seasonality, and low short-term predictability. While their study primarily looked at commodity ETFs from an investment diversification option, some of their findings parallel the Taylor stylized facts.(non normality of returns and fat tails) This reinforces the view that types of ETFs inherit the volatility structure of their underlying commodities.

Similarly, Todorov (2021) demonstrates that ETF rebalancing and derivative-linked exposures can amplify volatility and introduce price pressures unrelated to fundamentals features especially visible in UNG and USO, where squared-return autocorrelations and volatility clustering are pronounced. These structural effects help explain why the ETF results align so closely with classic stylized facts such as volatility persistence, near-zero return autocorrelation, and heavy-tailed distributions.

Together, these studies confirm that the patterns observed in this energy-ETF analysis. The similar findings include random-walk price behavior, strong volatility clustering, non-Gaussian returns, and some seasonal structure. These are consistent with documented behaviors in both broader financial-market research and the specialized literature on commodity ETFs.

Peer-Reviewed Articles on Similar Topics

1. Hadad, Malhotra & Nippani (2022)

Trading Commodity ETFs: Price Behavior, Investment Insights, and Performance Analysis
A rigorous peer-reviewed study examining performance patterns, macro sensitivity, and risk characteristics of commodity ETFs across market regimes.

https://onlinelibrary.wiley.com/doi/pdf/10.1002/fut.22509

2. Todorov (2021) – Bank for International Settlements Working Paper

Passive Funds Affect Prices: Evidence from the Most ETF-Dominated Asset Classes

This research details how ETFs influence futures prices through rebalancing, reinforcing volatility and structural effects.
https://www.bis.org/publ/work952.pdf

Introduction- Explanation of Analysis Conducted

This report examines the time-series behavior and statistical properties of three major energy-commodity exchange-traded funds (ETFs): UGA (gasoline), UNG (natural gas), and USO (crude oil). These ETFs track front-month futures contracts rather than holding physical commodities, meaning their price movements arise from both underlying market fundamentals and the structural effects of the futures curve. As a result, their return behavior reflects factors such as contango or backwardation, storage costs, roll yield, and seasonal delivery cycles which are dynamics that differ fundamentally from those of equity securities.

UGA provides exposure specifically to RBOB gasoline futures **(**Reformulated Gasoline Blendstock for Oxygenate Blending**)** representing the benchmark grade of U.S. gasoline used for financial trading. These futures are for delivery to the New York Harbor, which is the designated delivery point for the NYMEX RBOB contract that UGA tracks.

Similarly, USO tracks NYMEX WTI crude oil futures, whose physical delivery point is Cushing, Oklahoma, and UNG tracks NYMEX Henry Hub natural gas futures, deliverable to Henry Hub in Louisiana—the central pricing point for U.S. natural gas markets. Together, these delivery locations anchor each ETFs price behavior to specific regional markets and infrastructure nodes, shaping how futures prices respond to inventory levels, logistics constraints, and regional demand conditions.

The analysis uses five years of daily adjusted-close data for each ETF. From this dataset, the report constructs price-level charts, moving-average overlays (5-, 10-, and 20-day), daily log-returns, return distributions, density estimates, QQ-plots, and autocorrelation functions for both returns, absolute returns and squared returns. Additional calculations include rolling autocorrelations to assess time-varying dependence, seasonal pattern diagnostics (monthly, day-of-week, and month-year). Cross-ETF adjusted-price overlays further illustrate how the three commodities move together or diverge based on market conditions.

Targets of the Research

This analysis is designed to address three primary research objectives: Evaluate how energy-commodity ETFs conform to the Taylor(2005) stylized facts of financial time series, including

- The distribution of returns is approximately symmetric with fatter tails than the normal distribution.
- Autocorrelations of returns are close to zero, indicating no linear dependence.
- Autocorrelations of absolute returns and squared returns are positive for many lags, indicating linear dependence.

Together, these components establish a robust empirical and theoretical foundation for understanding the behavior of UGA, UNG, and USO and for evaluating their suitability in forecasting, risk management, and portfolio allocation strategies.

Theoretical Framework

The behavior of energy-commodity ETFs can be understood within the broader theoretical structure of modern financial time-series analysis, where asset prices are modeled as stochastic processes exhibiting persistent, well-documented empirical regularities. Taylor's Asset Price Dynamics, Volatility, and Prediction (2005) provides the core foundation for this framework. His treatment of asset-price behavior which includes the random-walk hypothesis, volatility clustering, heavy-tailed return distributions, and autocorrelation structures serves as the theoretical benchmark for evaluating the statistical patterns observed in UGA, UNG, and USO. Taylor outlines the stylized facts that appear across diverse financial markets, emphasizing near-zero autocorrelation of returns, high persistence in volatility, and significant deviations from Gaussian return behavior. These theoretical expectations align directly with the return distributions, autocorrelation patterns, and volatility dynamics observed in the ETF dataset.

In this framework, daily ETF prices are treated as realizations of stochastic processes driven by both fundamental and structural factors. Because commodity ETFs such as UGA, UNG, and USO track futures rather than holding physical assets, their price dynamics follow models in which the underlying futures curve. Taylor's broader discussion of stochastic volatility and ARCH-type processes provides the theoretical justification for interpreting the pronounced volatility clustering and autocorrelation in squared returns observed in this ETF analysis. These models explain why large shocks in commodity markets propagate through ETF prices with persistence, and why simple linear predictability remains minimal.

Theoretical work on commodity ETFs reinforces these foundations. Hadad et al. (2022) showed that commodity-linked ETFs inherit the statistical properties of the futures markets they track, including non-normal returns, sensitivity to macroeconomic shocks, and volatility patterns that diverge significantly from equity markets. These are features consistent with Taylor's stylized facts and fully reflected in the findings for all three ETFs. Similarly, Todorov (2021) demonstrates that ETF rebalancing and futures-curve mechanics can create non-fundamental price pressures, amplifying volatility and contributing to nonlinear dependence. This further validates the theoretical application of stochastic-volatility models and stylized-fact frameworks to the ETF behavior.

Together, these theoretical perspectives establish that the observed behaviors in UGA, UNG, and USO (random-walk price dynamics, near-zero return autocorrelation, volatility clustering, heavy-tailed distributions, and pronounced seasonality) are not anomalies but predictable outcomes grounded in established asset-pricing theory and the structure of futures-based ETF construction. This framework provides the conceptual basis for interpreting the empirical results in this report and for developing accurate expectations about the risks, volatility regimes, and predictive limitations of energy-commodity ETF prices.

Data and Methodology

The code used for this report retrieves the last five years of data for the three selected ETFs from Yahoo Finance.(Feb 2021 to Feb 2026) This includes the daily high, low, open, close, and adjusted close prices. The ETFs don't pay dividends so there is no adjustment required for this. There is potential for share splits so the adjusted close price is used for the analysis. The downloaded data is stored in an Excel spreadsheet to ensure that all analyses are performed on a consistent dataset. If updated data is required, the data-download code block can be re-run at any time.

The sections below contain the details on the ETFs studied

UGA (U.S. Gasoline Fund)

UGA provides exposure to NYMEX RBOB gasoline futures, the benchmark grade of U.S. gasoline deliverable into New York Harbor. Because RBOB prices are heavily influenced by regional inventories, refinery operations, and seasonal demand, UGA's performance reflects dynamics specific to the East Coast gasoline market. The fund gains its exposure by holding front-month RBOB futures and systematically rolling into the next month's contract before expiration, typically during a predefined window each month. This roll process introduces "roll yield," which can be positive or negative depending on whether the futures curve is backwardated or in contango. UGA's daily percentage changes attempt to reflect the daily percentage move of the front end of the RBOB gasoline futures curve, not the physical gasoline market or pump prices.

USO (U.S. Oil Fund)

USO tracks the daily price movements of NYMEX WTI crude oil futures, whose delivery point is Cushing, Oklahoma which is the central hub of U.S. crude oil storage and pipeline flows. This regional linkage means WTI prices, and thus USO's performance, respond to storage availability, pipeline constraints, export demand, and overall crude balances. USO maintains exposure through short-dated WTI futures and rolls its contracts on a scheduled basis before expiry. The structure of the WTI curve plays a key role: in contango environments, roll costs can weigh on returns, while backwardation can enhance them. The daily percentage move in USO is designed to approximate the daily percentage change in near-term WTI futures, not in spot physical crude.

UNG (U.S. Natural Gas Fund)

UNG tracks NYMEX Henry Hub natural gas futures, tied to delivery at Henry Hub in Louisiana, the primary pricing point for U.S. natural gas. As a result, the ETF reflects regional supply-demand fundamentals such as production trends, LNG exports, storage levels, and weather-driven demand. UNG gains exposure through front-month natural gas futures and rolls into subsequent contracts each month based on its stated schedule. Because natural gas futures curves often exhibit strong seasonal patterns and can shift rapidly, roll yield can vary widely from month to month. UNG's daily percentage changes aim to mirror the daily percentage move of front-month Henry Hub futures rather than the spot natural gas market or regional cash prices.

The analysis for this report uses data from 2/4/21 through 2/3/26, representing an approximately five-year window based on available market trading days.

The methodology treats the ETF information as time-series data, focusing on both pricing and return behavior. Several custom features were engineered from the pricing data, including:

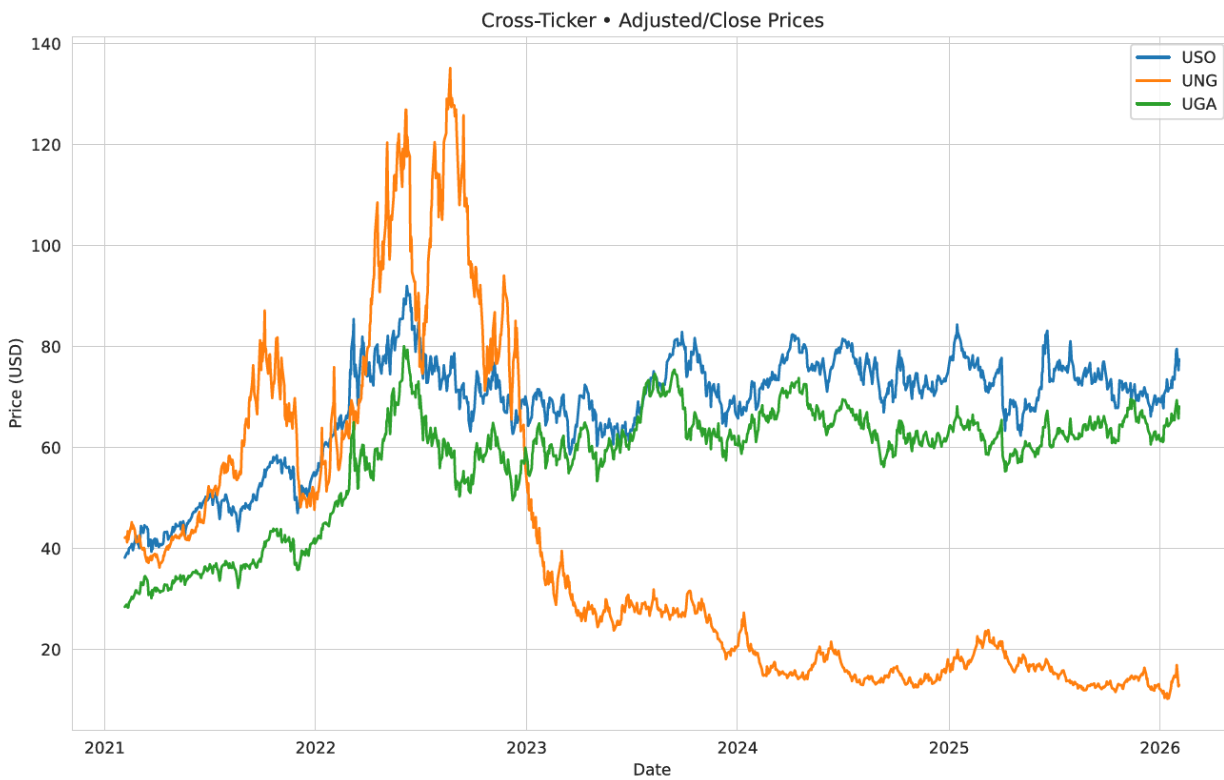
- High minus low price
- Open minus close price
- Moving averages and exponential moving averages over 5-day, 10-day, and 20-day windows
- Lagged closing prices at 1-day, 2-day, and 3-day intervals
- Autocorrelations of closing prices at one-, two-, and three-day lags
- Daily returns were calculated using adjusted closing prices.(log returns)
    - From these absolute and squared returns are calculated
- From these returns, lagged returns were also computed over 1-day, 2-day, and 3-day horizons.
- Seasonal / Calendar Features

Results

For the results the code generates many trends based on ETFS studied. This report will focus on the requirements of the assignment and the results compared to Taylors(2005) stylized facts. The other trends are provided in the code but these are not included in this report.

Adjusted closing price

The adjusted closing price, as reported by Yahoo Finance, reflects the closing price after accounting for ETF stock splits. The funds can have stock splits if the price goes too high or low. This measure provides a more accurate view of each funds long-term performance.



Across all three energy ETFs the time-price trends from 2021 to 2026 shown in the plot above. For USO and UGA there was some slight upward movement marked by cyclical swings that align with known energy-market seasonality, such as gasoline summer demand and winter natural-gas volatility. UNG shows pronounced spikes and crashes, reflecting its well-known sensitivity to weather patterns and storage dynamics. There is a decline in the UGA price over the period reviewed.

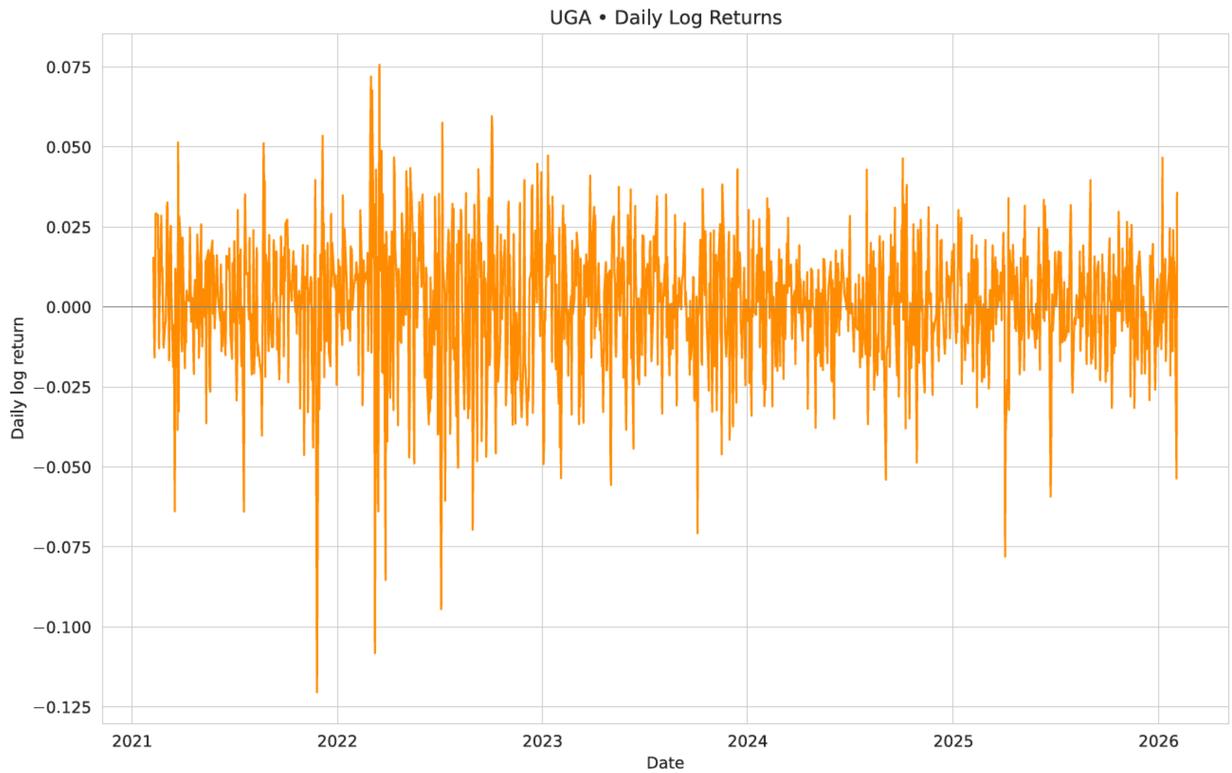
Overall, the long-run trend there is not a clear price direction movement across the energy complex. There are meaningful differences in volatility intensity, with UNG standing out as the most structurally volatile of the three. This makes sense with the commodity-based ETFs and how the forward roll structure is setup for these funds. This trend shows that these are not necessarily good long term investments but funds that give investors exposure to these commodities.

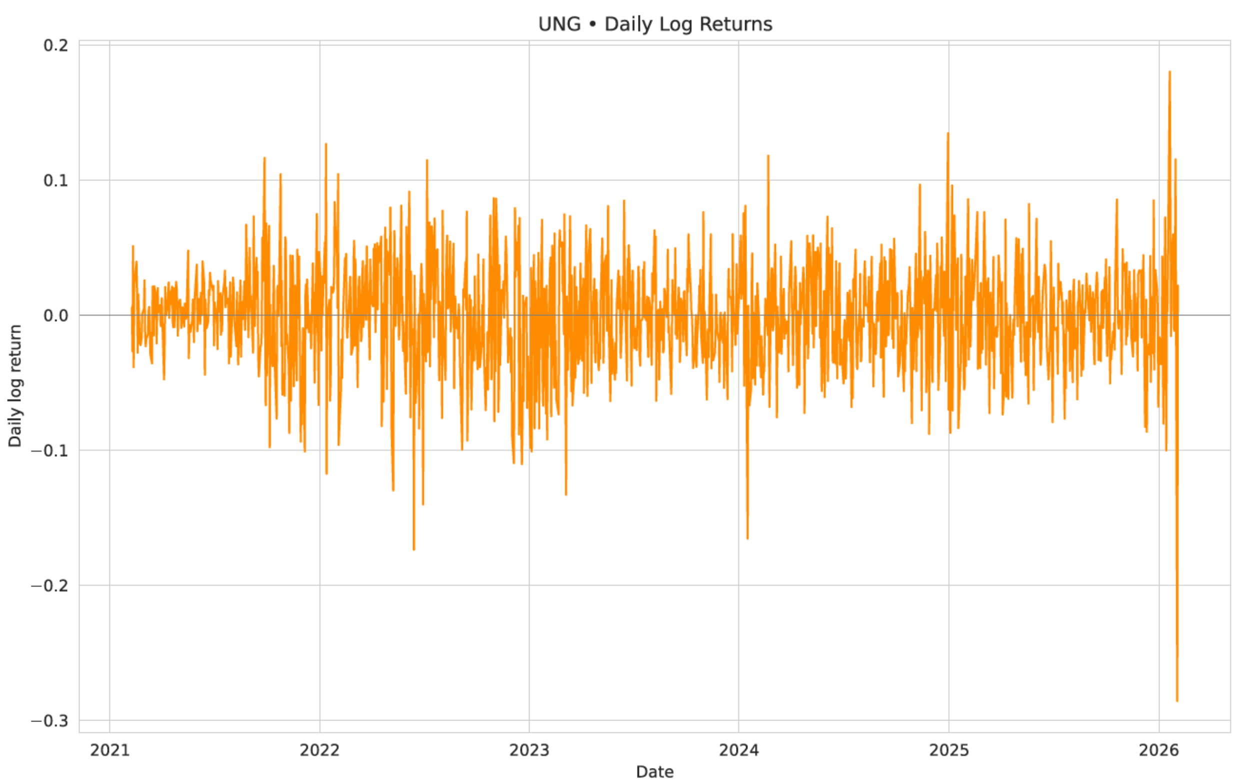
Time Series of Daily Total Returns

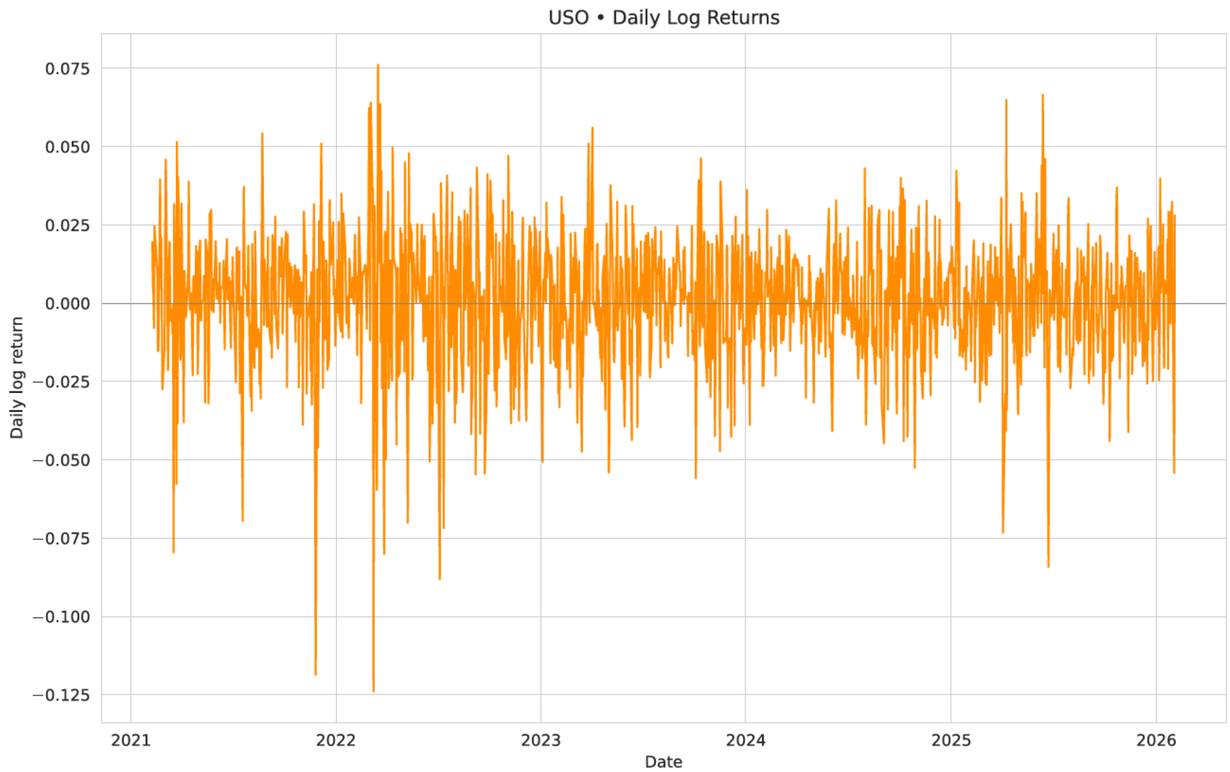
The time-series plots of daily log returns for all three ETFs show that returns fluctuate around a mean close to zero, with frequent sharp spikes that reflect news-driven or supply-demand shocks in the energy markets.(2022 Russia-Ukraine war) UGA and USO display relatively moderate volatility, with most movements staying within a narrow band. As also observed for the price trend UNG exhibits notably larger swings consistent with natural gas's sensitivity to weather patterns, storage cycles, and extreme market shocks.(winter storm Fern Jan 2026) Each ETF shows periods of elevated turbulence followed by calm, indicating that volatility is not constant but arrives in clusters.

These patterns are reinforced by the rolling autocorrelation and lagged ACF plots, which show little to no persistence in raw returns but meaningful structure in squared returns, confirming strong volatility clustering typical of energy commodities. In practical terms, this means past returns offer limited directional forecasting value, but past volatility does forecast future volatility. For portfolio or trading applications, this behavior suggests that risk management and position sizing should adapt dynamically to volatility regimes rather than relying on return momentum or mean reversion signals.

The return volatility plots reveal volatility clustering, where turbulent periods group together rather than occurring randomly which is part of Taylor's(2005) stylized facts for financial markets.


UGA • Daily Log Returns
Daily log return
Date
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
2021
2022
2023
2024
2025
2026

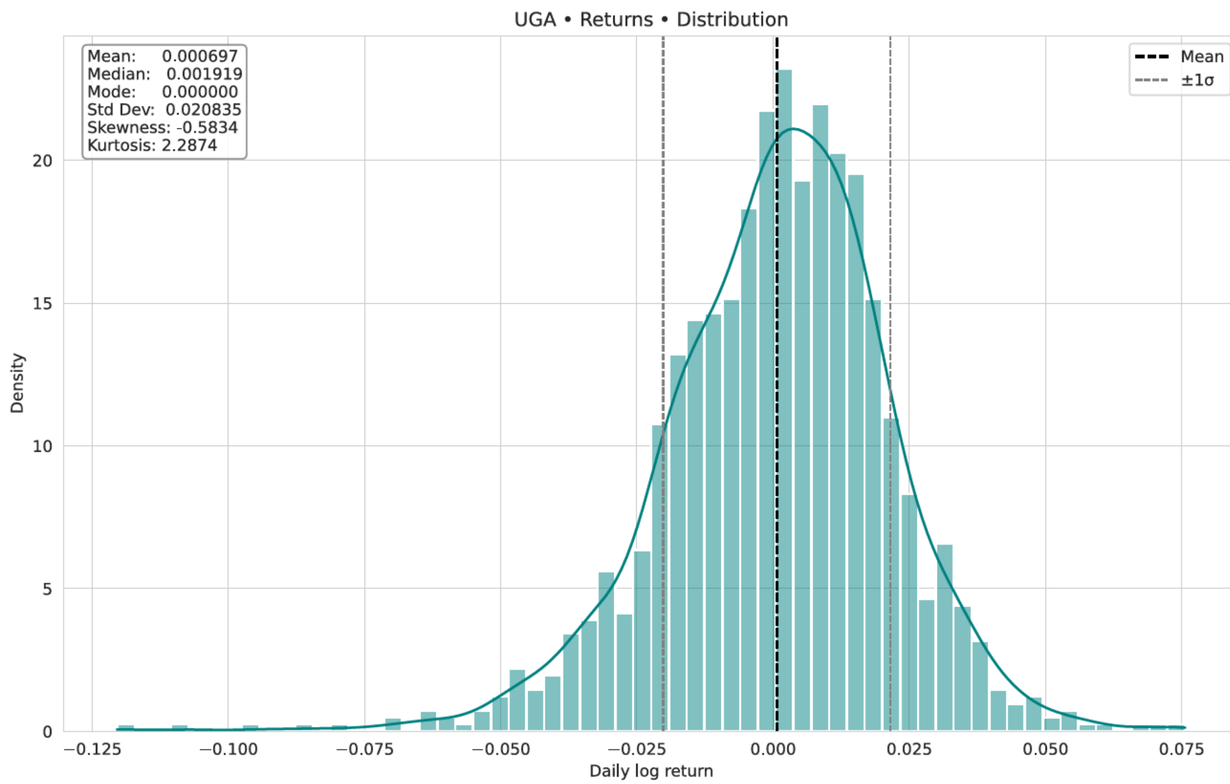

UNG • Daily Log Returns
Daily log return
Date
0.2
0.1
0.0
−0.1
−0.2
−0.3
2021
2022
2023
2024
2025
2026

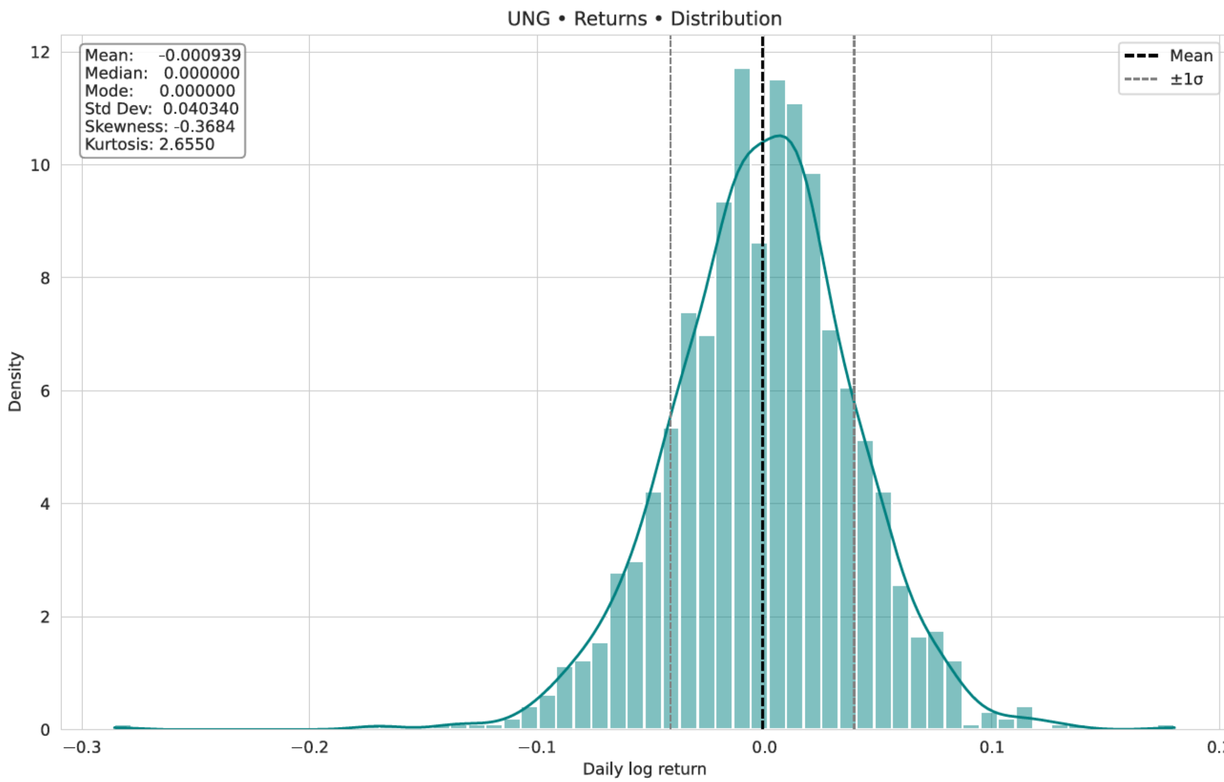


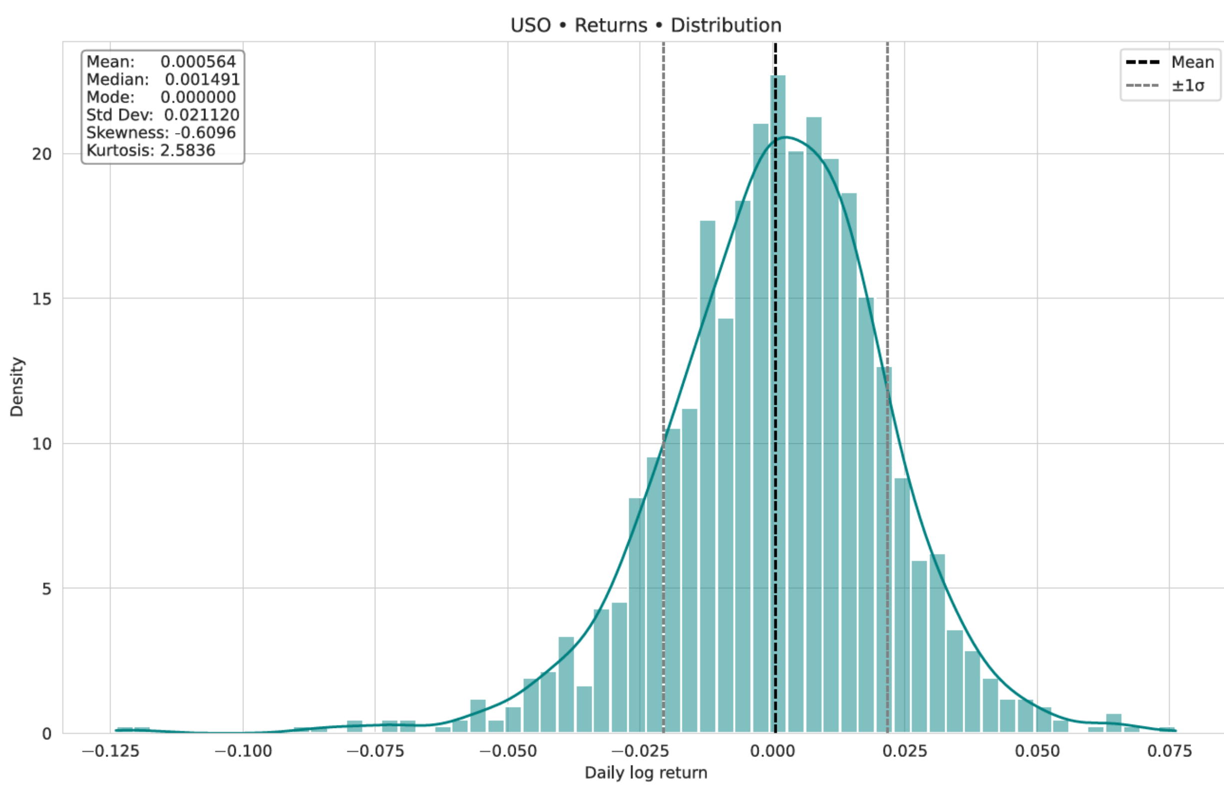
Plots of distributions of daily returns using histograms and density plots

The histograms and density plots for UGA, UNG, and USO show that daily returns cluster tightly around zero, forming steep central peaks but also displaying noticeable heavy-tailed behavior, with more frequent extreme moves than a normal distribution would imply. UNG stands out with the widest dispersion and the thickest tails, reflecting its significantly higher volatility and sensitivity to weather-driven supply-demand shocks. The other ETFs UGA and USO exhibit narrower but still asymmetric distributions with mild negative skew, indicating slightly more severe downside events than upside surges. The density curves further highlight how each ETFs return profile departs from a Gaussian shape particularly in the tails and shoulders. This emphasizes that although most daily price changes are small and stable, all three ETFs remain susceptible to sharp, sudden moves. This combination of clustered small returns and intermittent large shocks underscores the importance of incorporating tail-risk controls and volatility-responsive position sizing in any strategy involving these energy-linked products.

The ETF return patterns are similar to Taylor's (2005) stylized facts well: the distributions show heavy tails, slight negative skewness and sharp central peaks, indicating clear departures from normality.

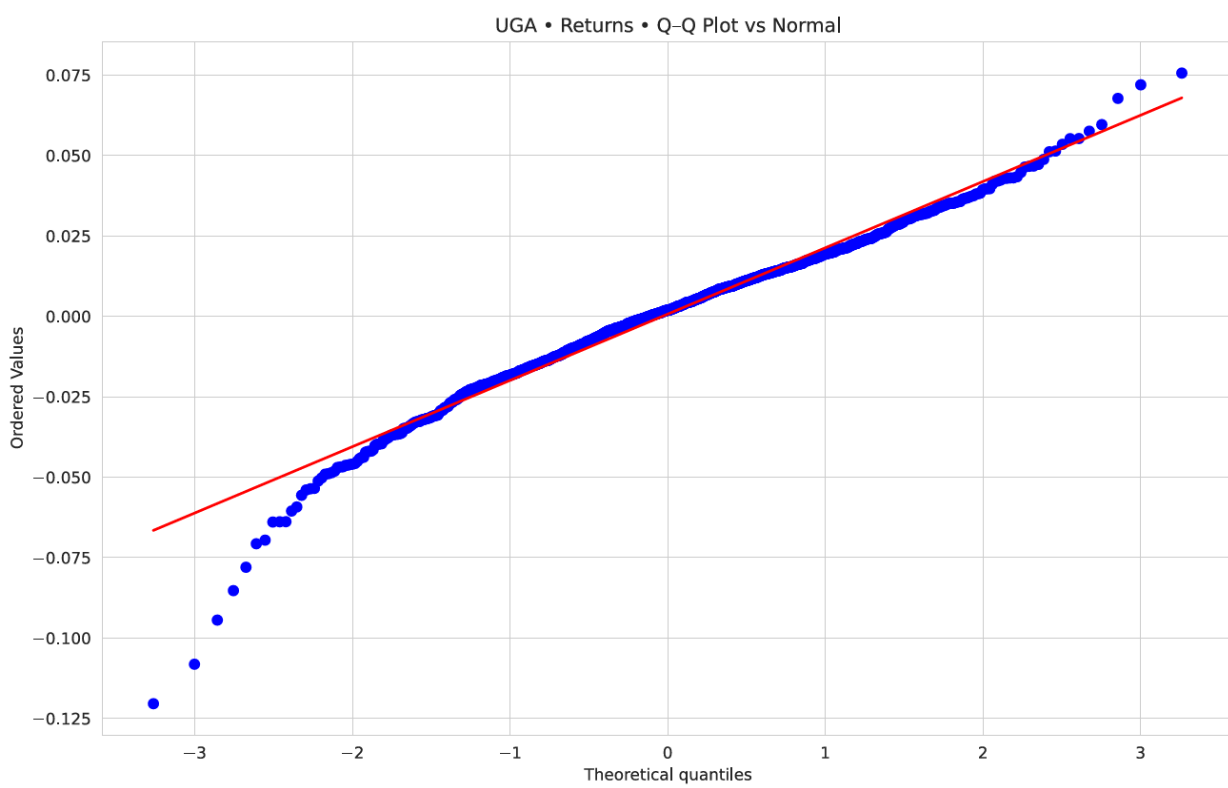


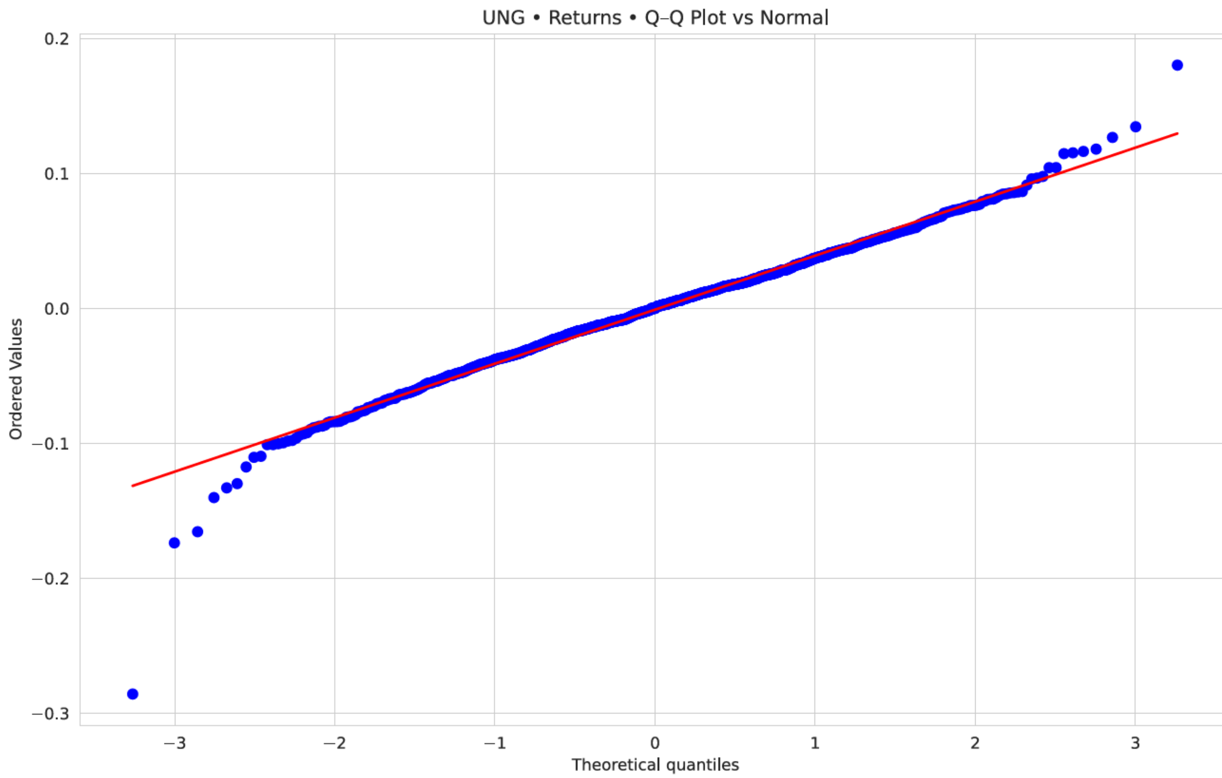

UNG • Returns • Distribution
Mean: -0.000939
Median: 0.000000
Mode: 0.000000
Std Dev: 0.040340
Skewness: -0.3684
Kurtosis: 2.6550
Mean
±1σ
Density
Daily log return

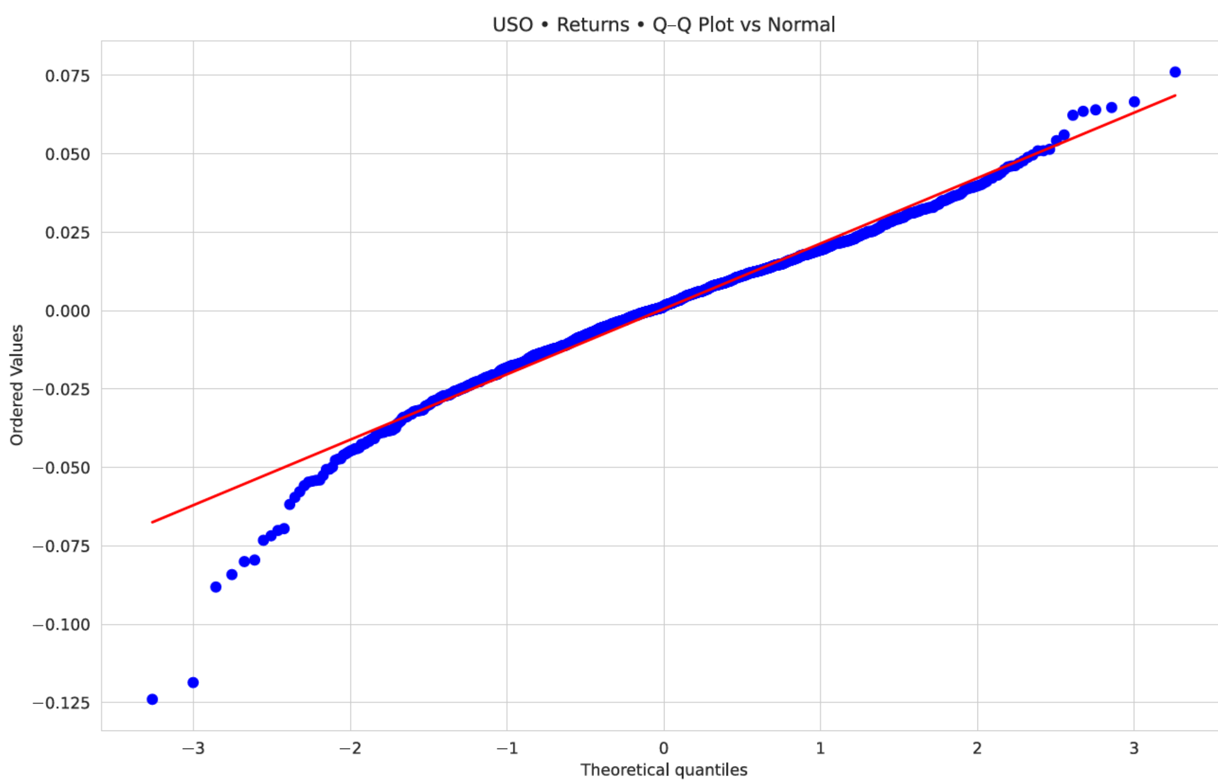

USO • Returns • Distribution
Mean: 0.000564
Median: 0.001491
Mode: 0.000000
Std Dev: 0.021120
Skewness: -0.6096
Kurtosis: 2.5836
Mean
±1σ
Density
Daily log return

Q-Q Plot for daily returns

The QQ plots for UGA, UNG, and USO clearly show that the ETFs' daily return distributions deviate from normality, particularly in the tails, where the plotted points bend away from the 45-degree reference line. This curvature indicates heavy-tailed behavior, with more extreme return values than a Gaussian model would predict. For all three ETFs, the central points lie close to the line which indicates that small daily movements behave somewhat normally. The divergence in both upper and lower tails confirms the presence of fat-tail risk and occasional large shocks. UNG exhibits the strongest tail deviation, consistent with its higher volatility, while UGA and USO show milder but still significant departures from normality. The higher-than-normal frequency of larger negative return events is also shown in each plot which is like the negative skew of the histograms. Overall, the QQ plots reinforce that simple normal-distribution assumptions would underestimate real-world tail risk in these energy ETFs.



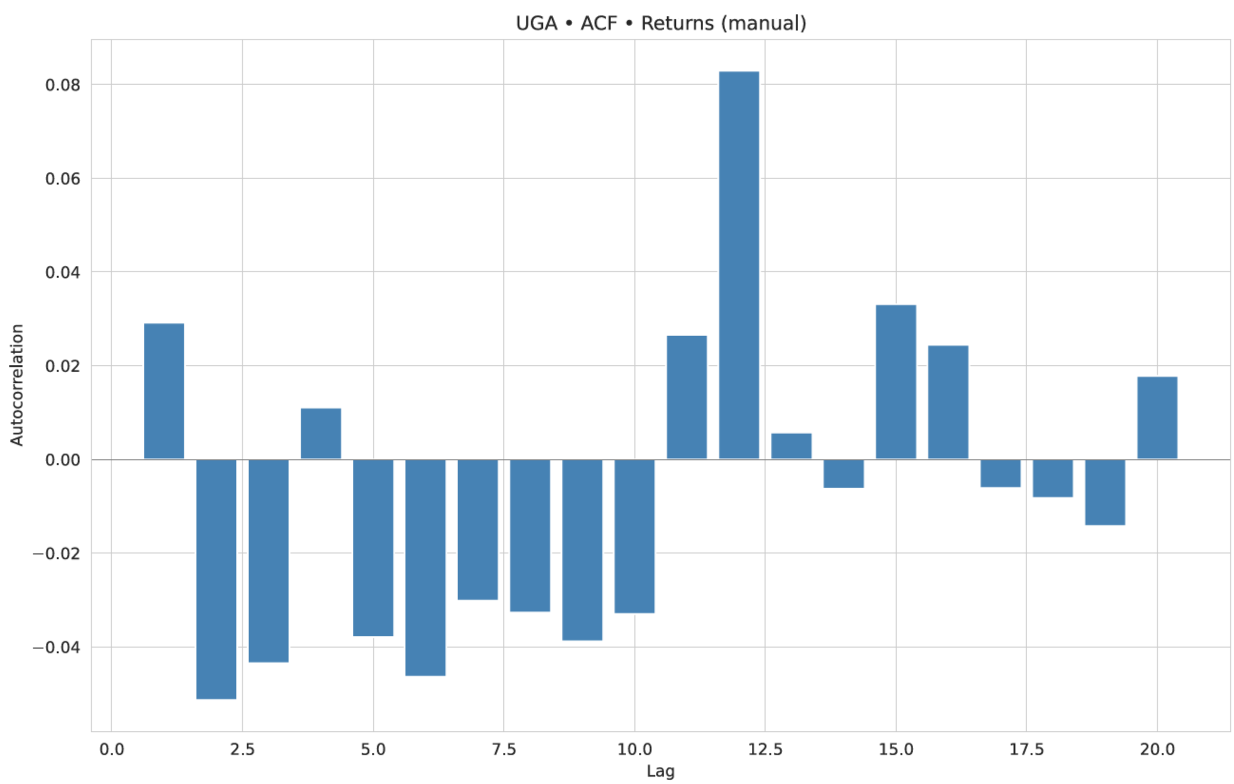

UNG • Returns • Q–Q Plot vs Normal
Ordered Values
Theoretical quantiles
0.2
0.1
0.0
−0.1
−0.2
−0.3
−3
−2
−1
0
1
2
3

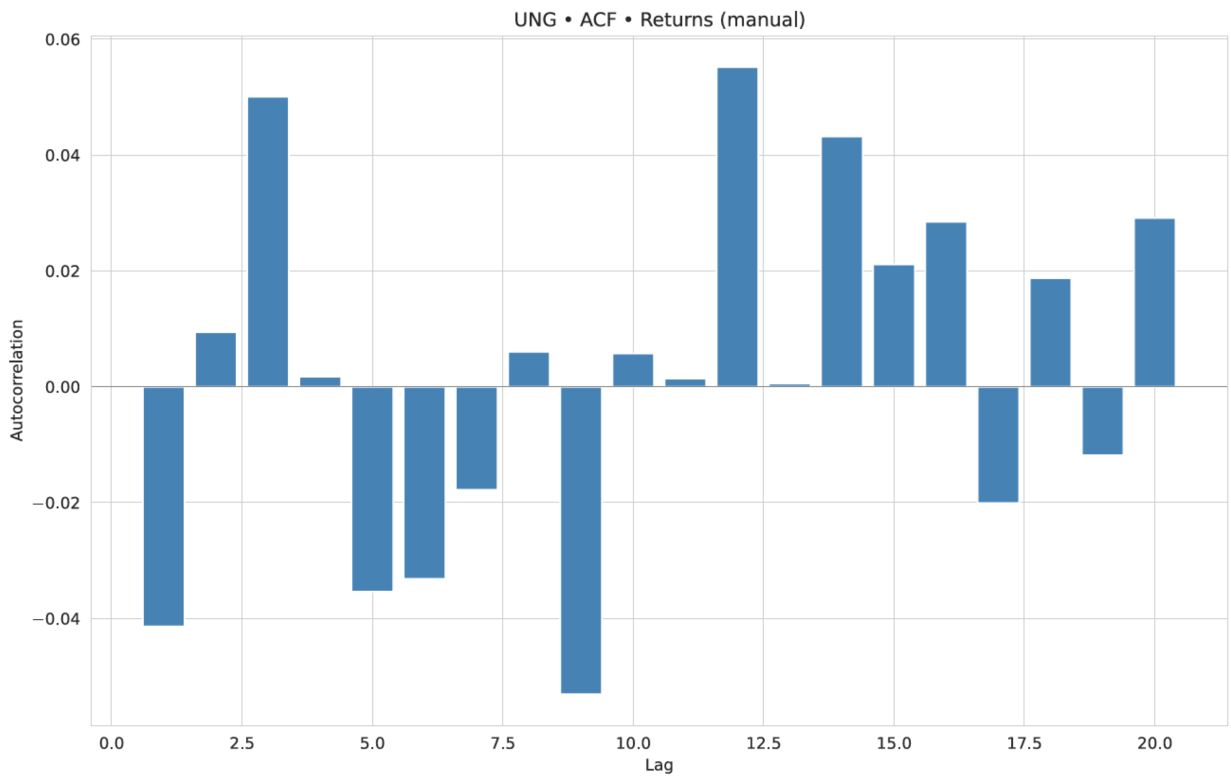

USO • Returns • Q–Q Plot vs Normal
Ordered Values
Theoretical quantiles
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−3
−2
−1
0
1
2
3

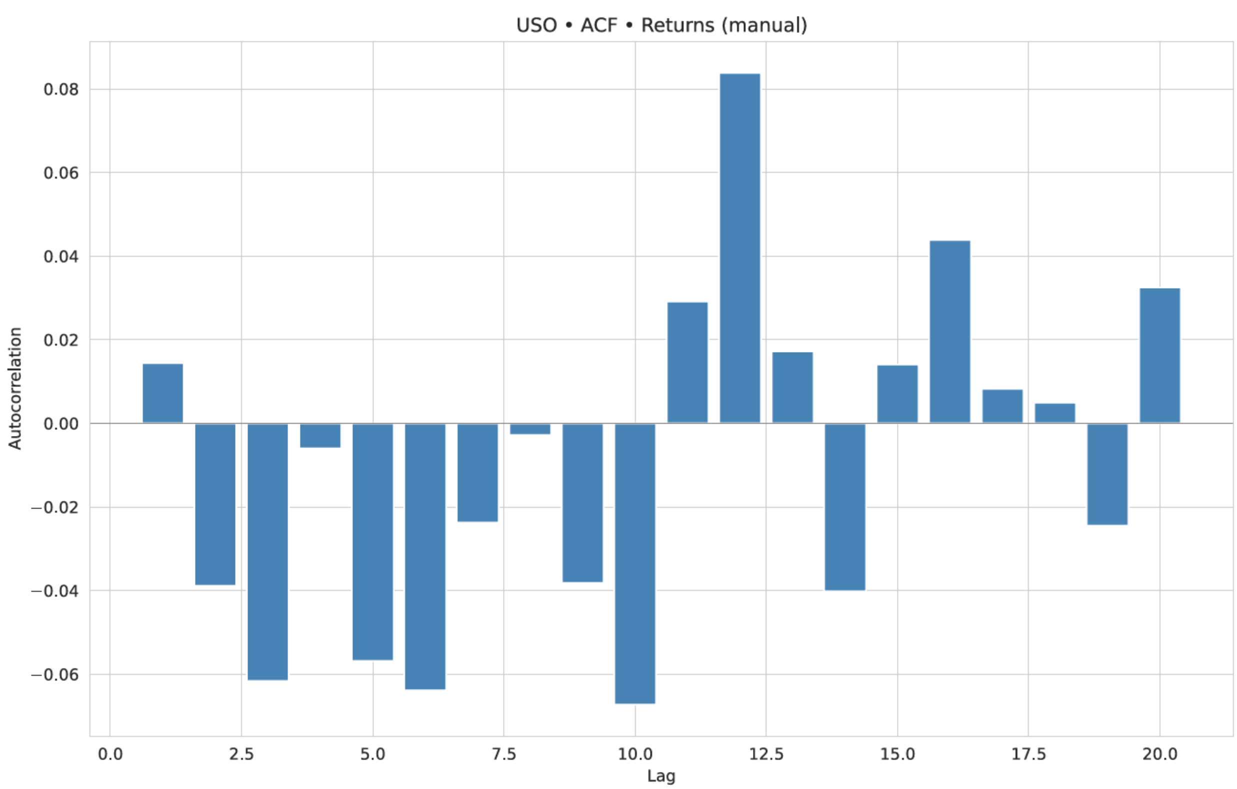
Autocorrelation of Returns

The plots below show the autocorrelation values for the daily returns for 1 to 20 day lag. Consistent with the behavior seen in the return time-series plots, the autocorrelations are very close to zero, generally within ±0.08. These low values indicate that daily returns have little to no predictive relationship with their own past values, reinforcing the idea that returns behave much like random noise in the short term.

It is interesting that UGA and USO show a small positive one day correlation and then multiple negative days. This may be a sign of a slight correlation and then mean reversion however the actual correlation levels are very low.

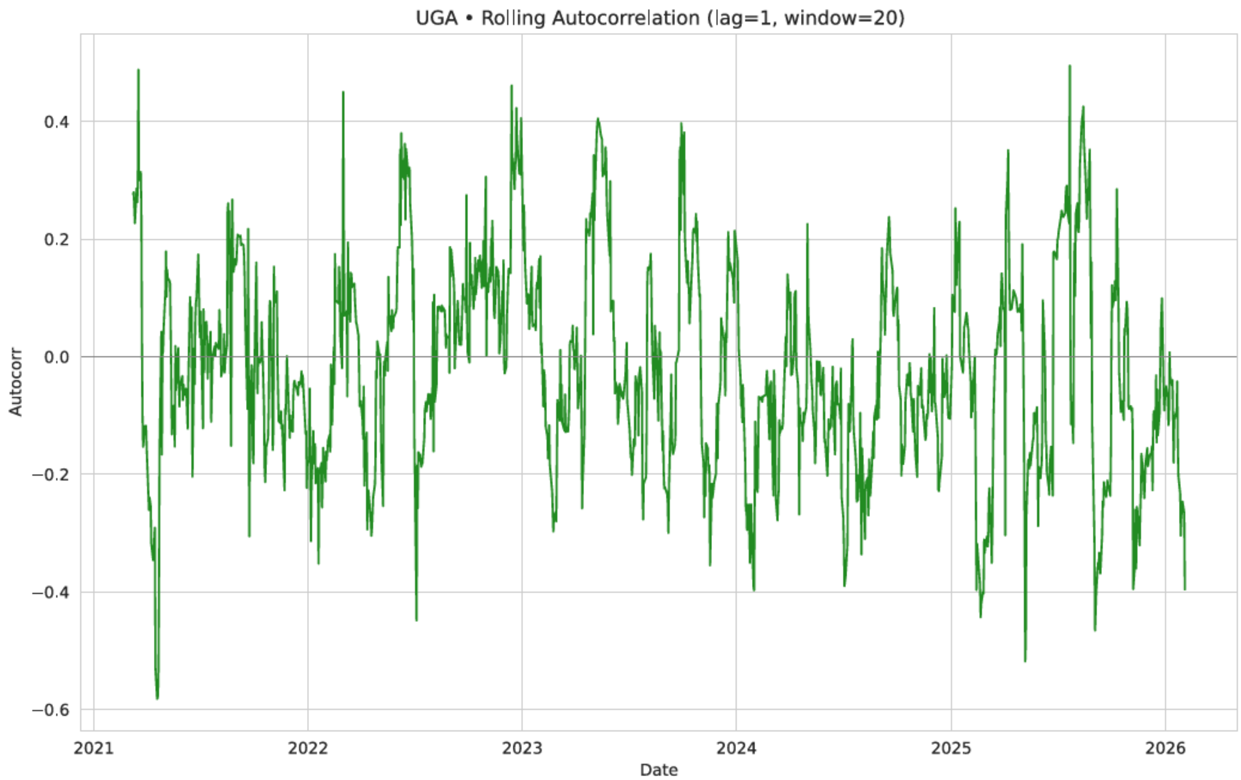


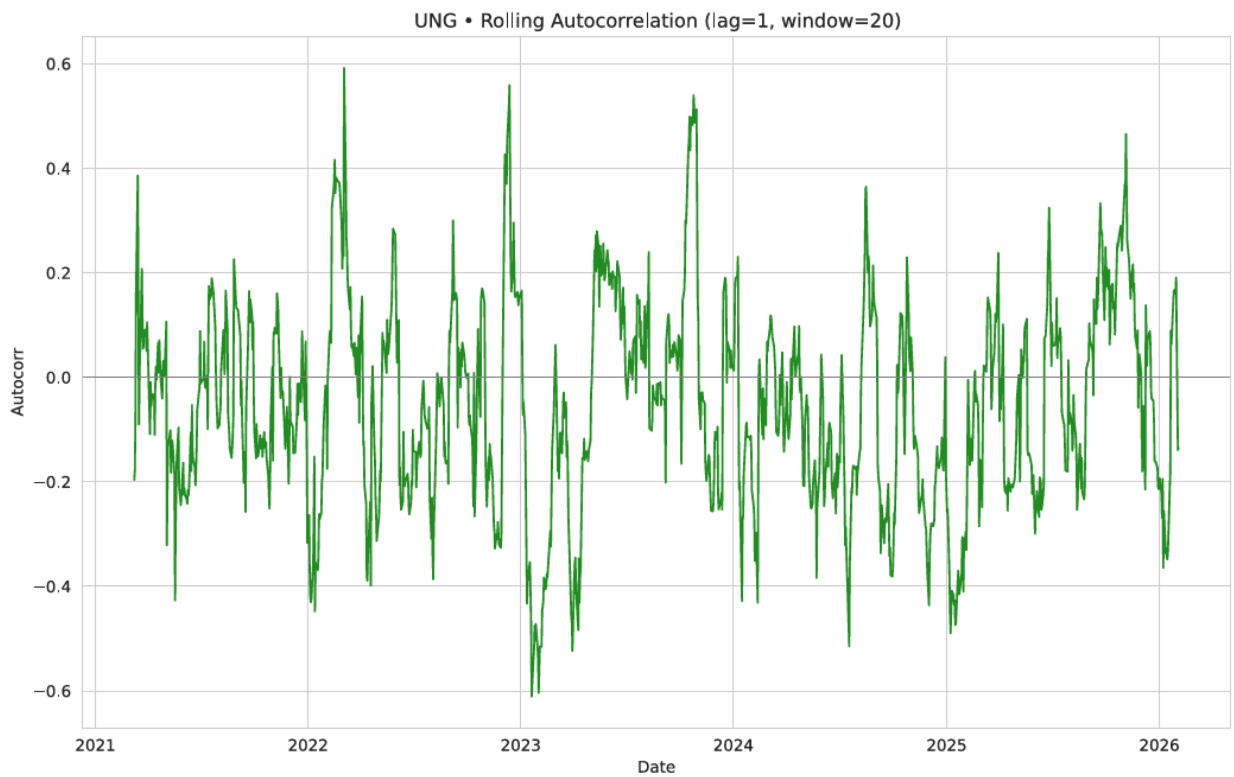

UNG • ACF • Returns (manual)
Autocorrelation
Lag
0.06
0.04
0.02
0.00
−0.02
−0.04
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

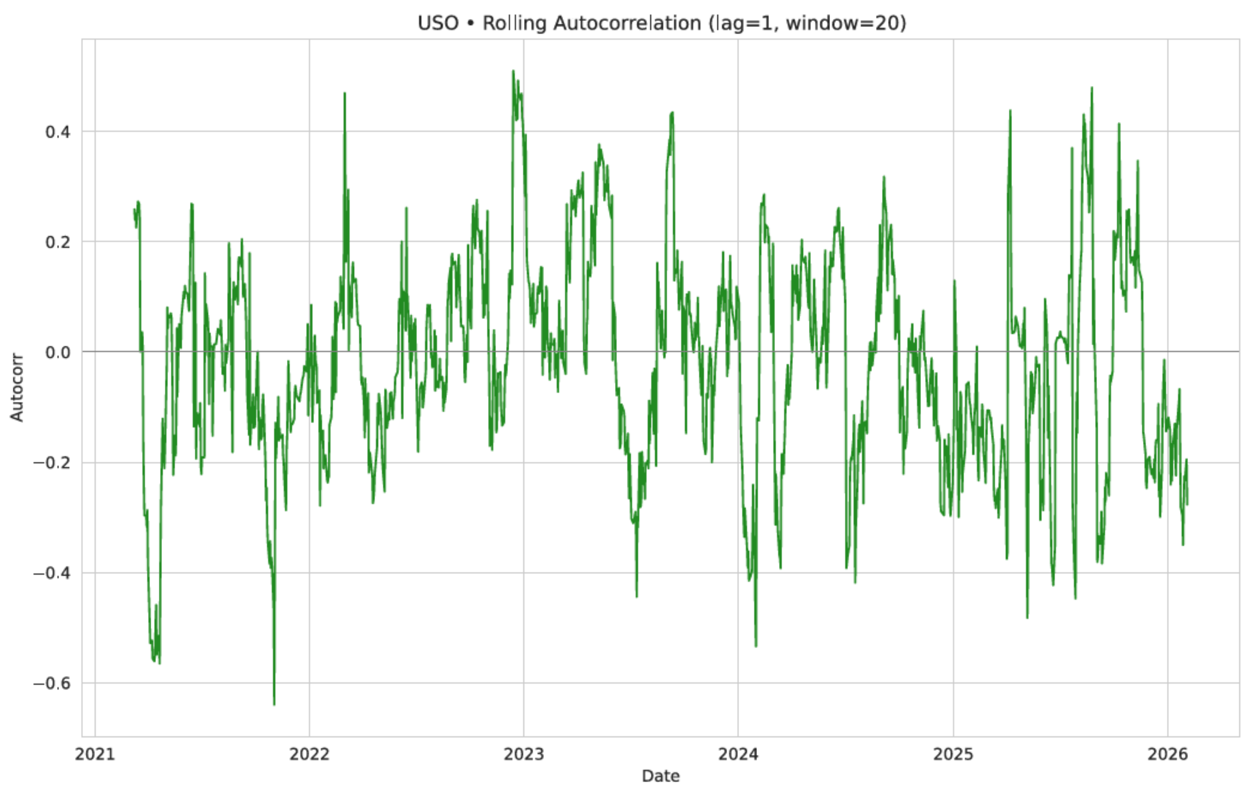

USO • ACF • Returns (manual)
Autocorrelation
Lag
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

Rolling Autocorrelation of Returns

The following plots display the 1-day lagged return autocorrelations calculated over rolling 20-day windows. Across all three ETFs, the results show no consistent or persistent correlation patterns over time. Instead, the autocorrelations fluctuate randomly around zero, indicating a lack of temporal structure in short-term return predictability. This observation reinforces one of Taylor's stylized facts: past returns exhibit minimal correlation with future returns, and return behavior is largely characterized by random variation.



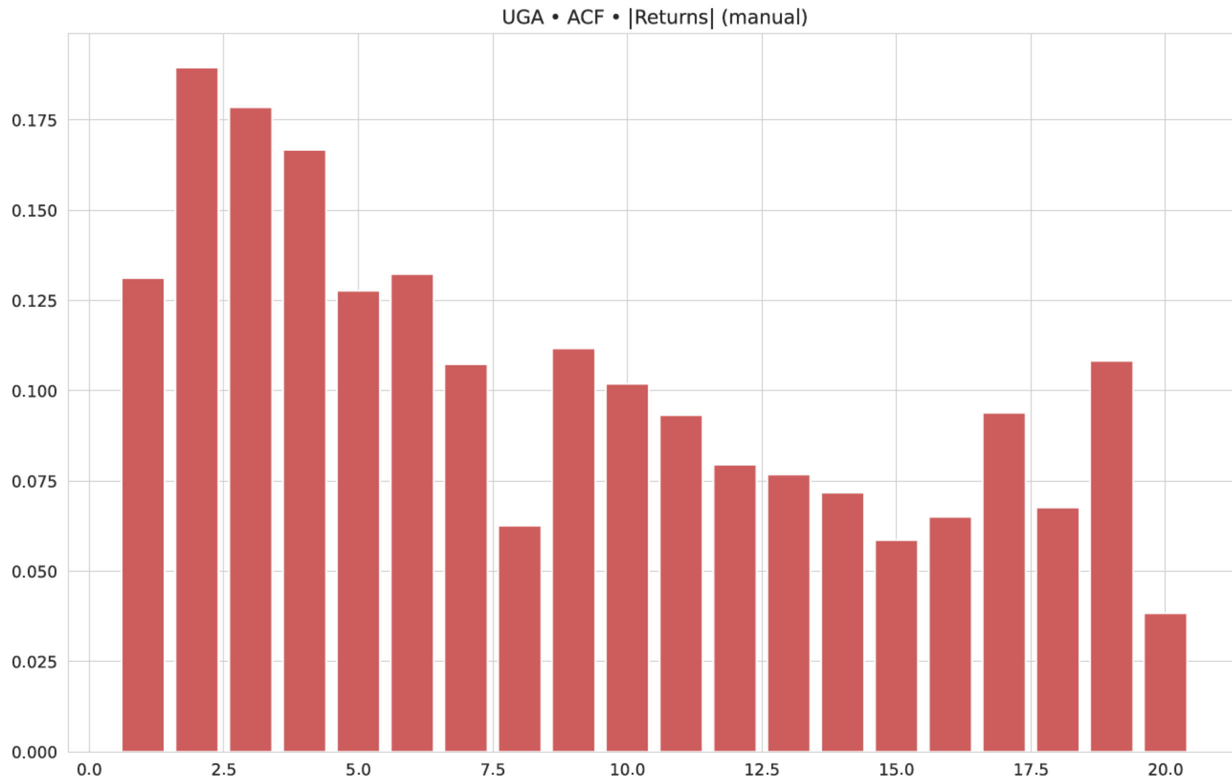

UNG • Rolling Autocorrelation (lag=1, window=20)
Autocorr
Date
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
2021
2022
2023
2024
2025
2026

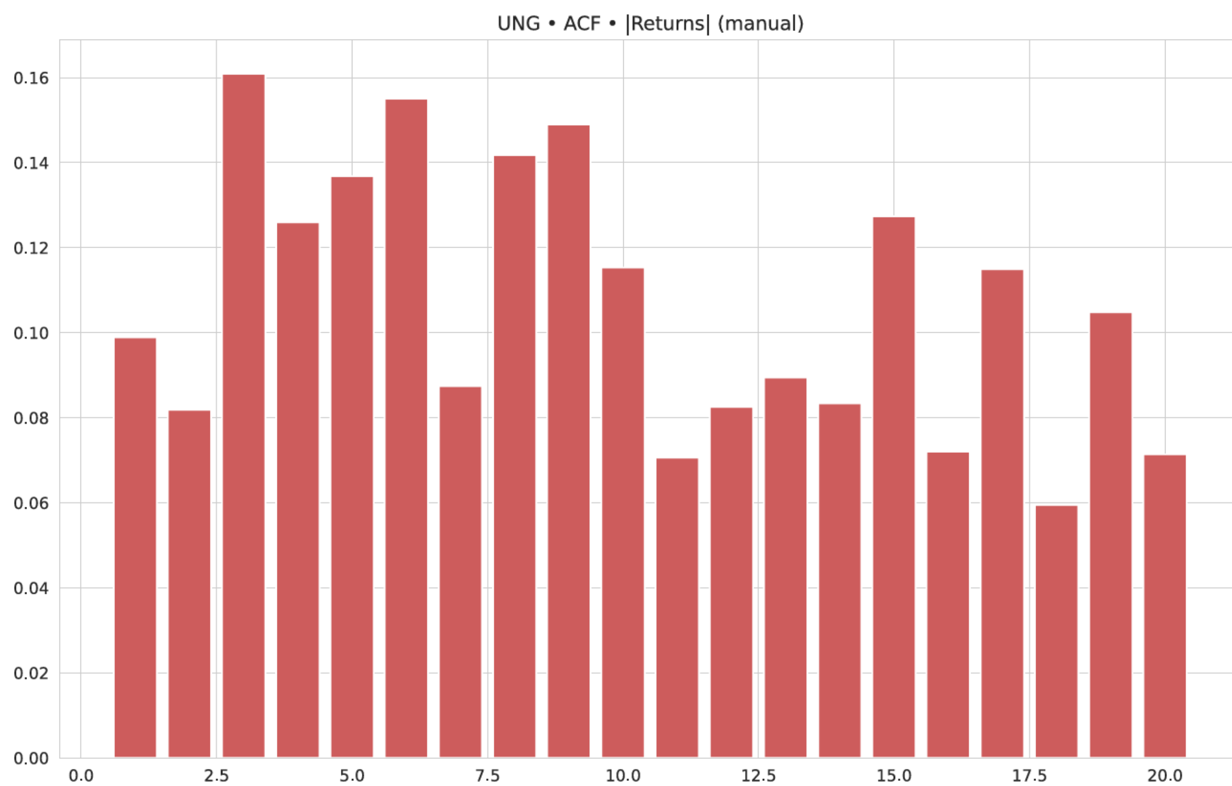

USO • Rolling Autocorrelation (lag=1, window=20)
Autocorr
Date
0.4
0.2
0.0
−0.2
−0.4
−0.6
2021
2022
2023
2024
2025
2026

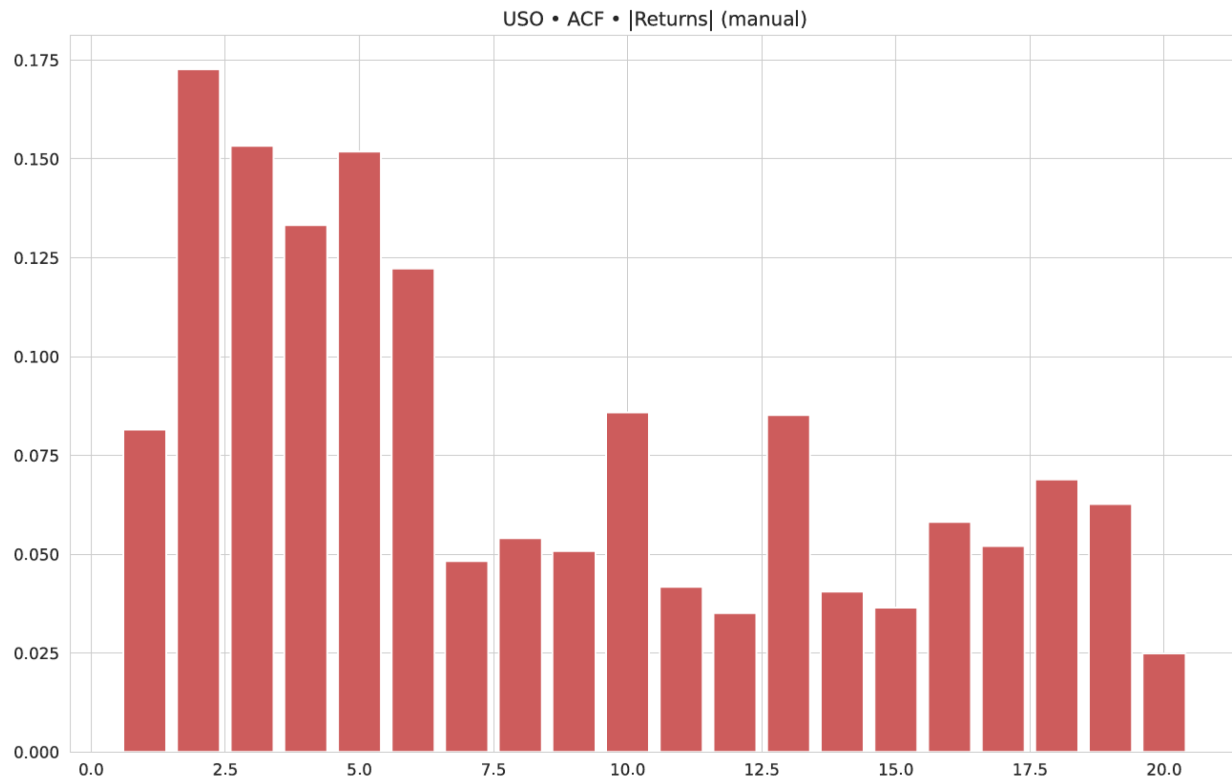
Autocorrelation of lagged absolute returns

The ACF plots of absolute returns for the ETFs show clear evidence of volatility persistence, with autocorrelation values remaining well above zero across multiple lags. The correlation levels for absolute returns are around 0.15—substantially higher than those for raw lagged returns, which are closer to 0.05 or lower. This pattern indicates that large return magnitudes tend to follow other large magnitudes, while small magnitudes follow small ones, creating distinct volatility "regimes" throughout the sample period. The slower decay of these autocorrelations, compared with the raw-return ACF, demonstrates that volatility is time-dependent which is an established characteristic of both energy markets and broader financial markets. This behavior aligns with Taylor's findings on volatility clustering observed in the return time-series plots and supports the use of volatility-responsive models such as GARCH to capture the underlying dynamics.

The autocorrelation trends of absolute returns for UGA and USO display a more consistent pattern over the first few lags. Both series rise to relatively high autocorrelation levels after short lags before gradually returning to typical levels after several days. In contrast, the UNG plot shows more dispersion in autocorrelation values, which may further indicate the higher overall volatility associated with natural gas pricing.


UGA • ACF • |Returns| (manual)
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

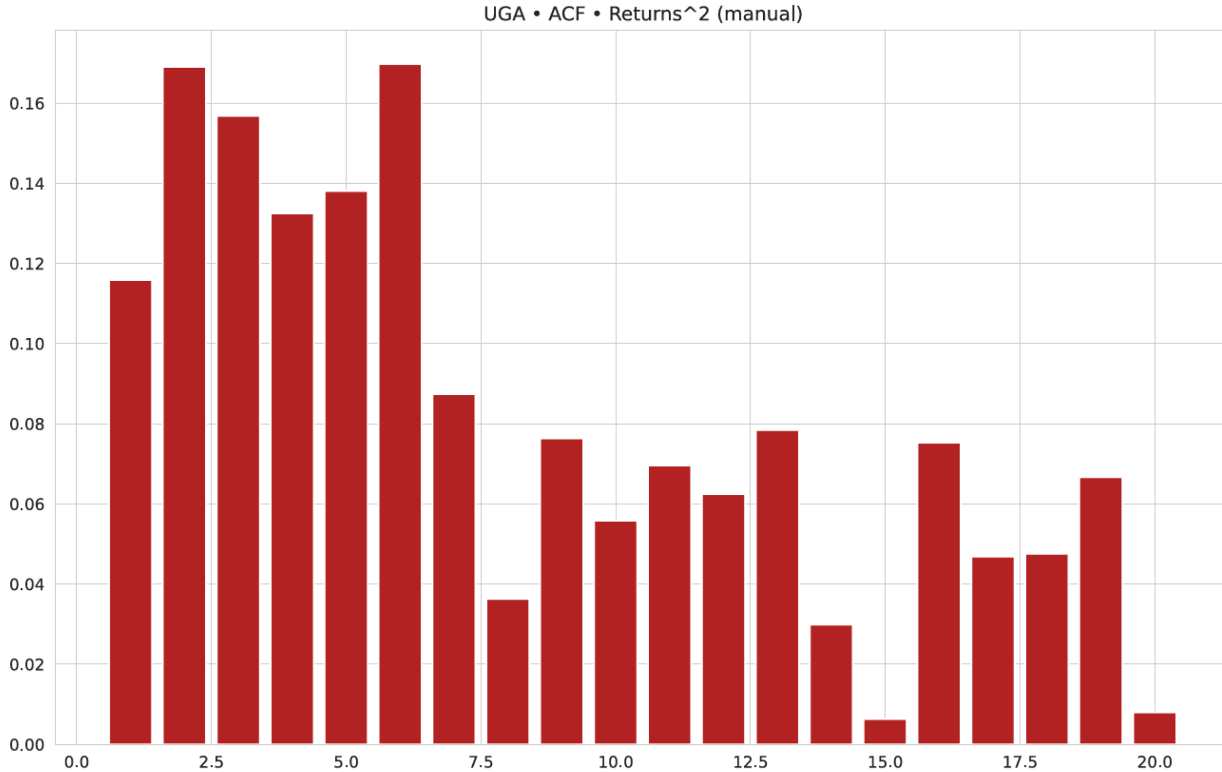

UNG • ACF • |Returns| (manual)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

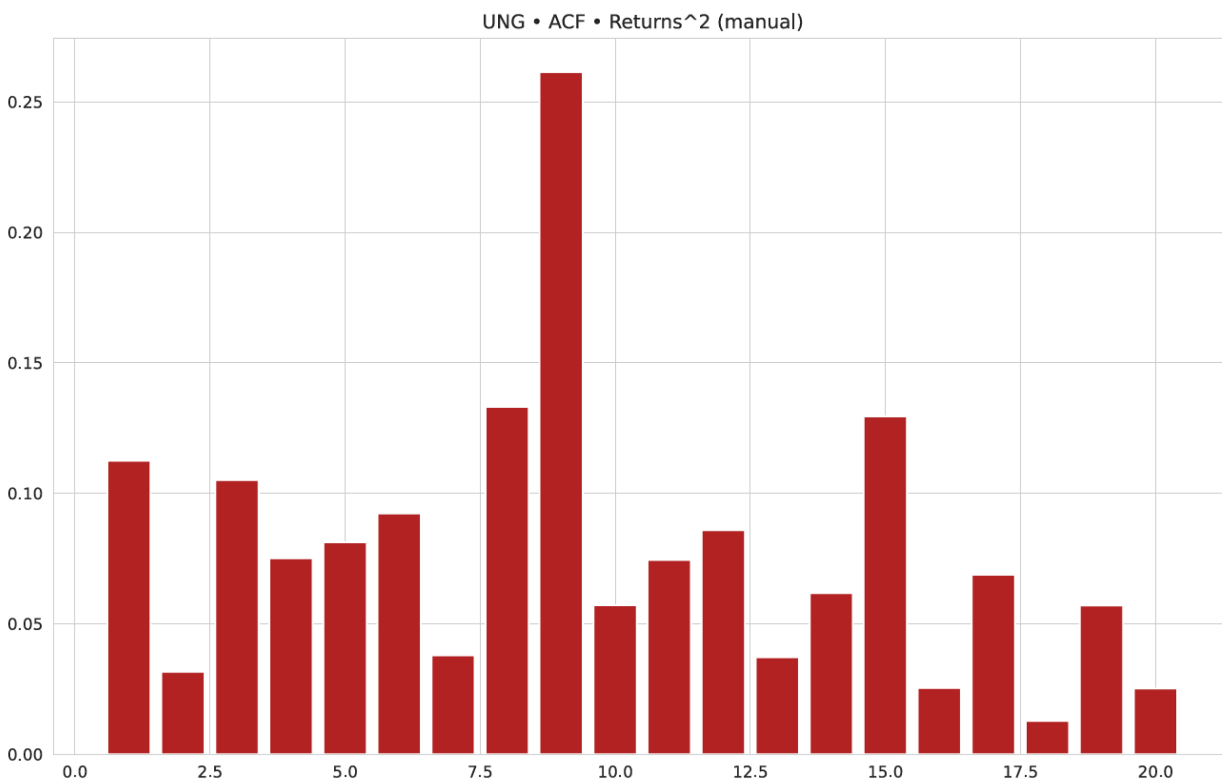


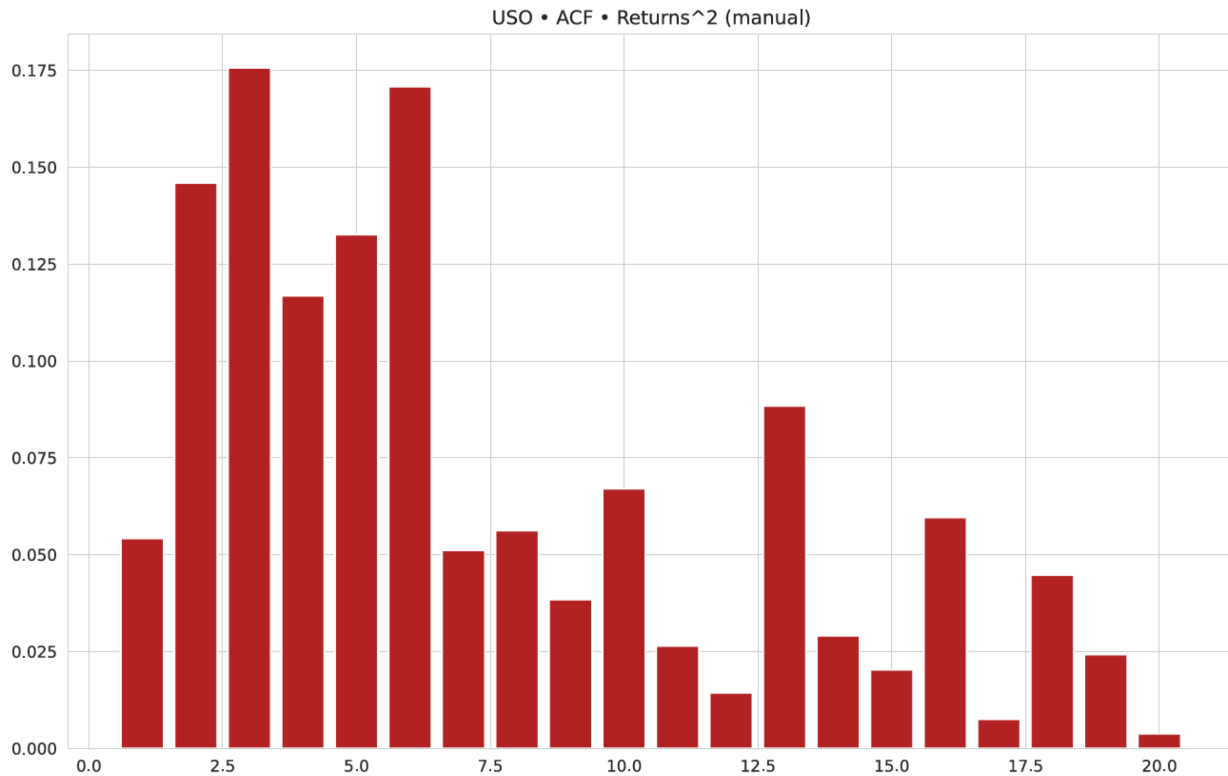
Autocorrelation of lagged squared returns

The results for the lagged squared returns closely resemble those for the absolute returns in UGA and USO. They again show the same general pattern, with higher autocorrelation values than those observed in the raw return data. The decline back to baseline after a few days is somewhat more pronounced for squared returns compared with absolute returns.

However, the UNG squared-return plot displays an unusual feature: at a 9-day lag, it shows a sharply elevated correlation that stands out from the surrounding trend. A review was done to see if this was related to the ETFs futures contract roll timing or other market periodic event, but no basis could be found.   This is likely an unusual sampling artifact arising from the five-year sample period. It doesn't appear this behavior is real and persistent, but if it were it could merit deeper investigation as a potential trading opportunity.


UGA • ACF • Returns^2 (manual)
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


UNG • ACF • Returns^2 (manual)
0.25
0.20
0.15
0.10
0.05
0.00
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0



Seasonal Effects- Monthly returns

We also examined the ETFs for potential seasonal effects to determine whether returns varied based on the time of year. The box plots below display monthly return distributions. As in Taylor's findings, the ETF data does not show statistically significant month-to-month differences, but there are subtle patterns that could offer potential trading opportunities. These small differences are likely sensitive to major economic or geopolitical events, which could easily override seasonal tendencies. Outlier returns are clearly visible in the plots and appear scattered throughout the calendar year. Below are the key observations for each ETF:

UGA-

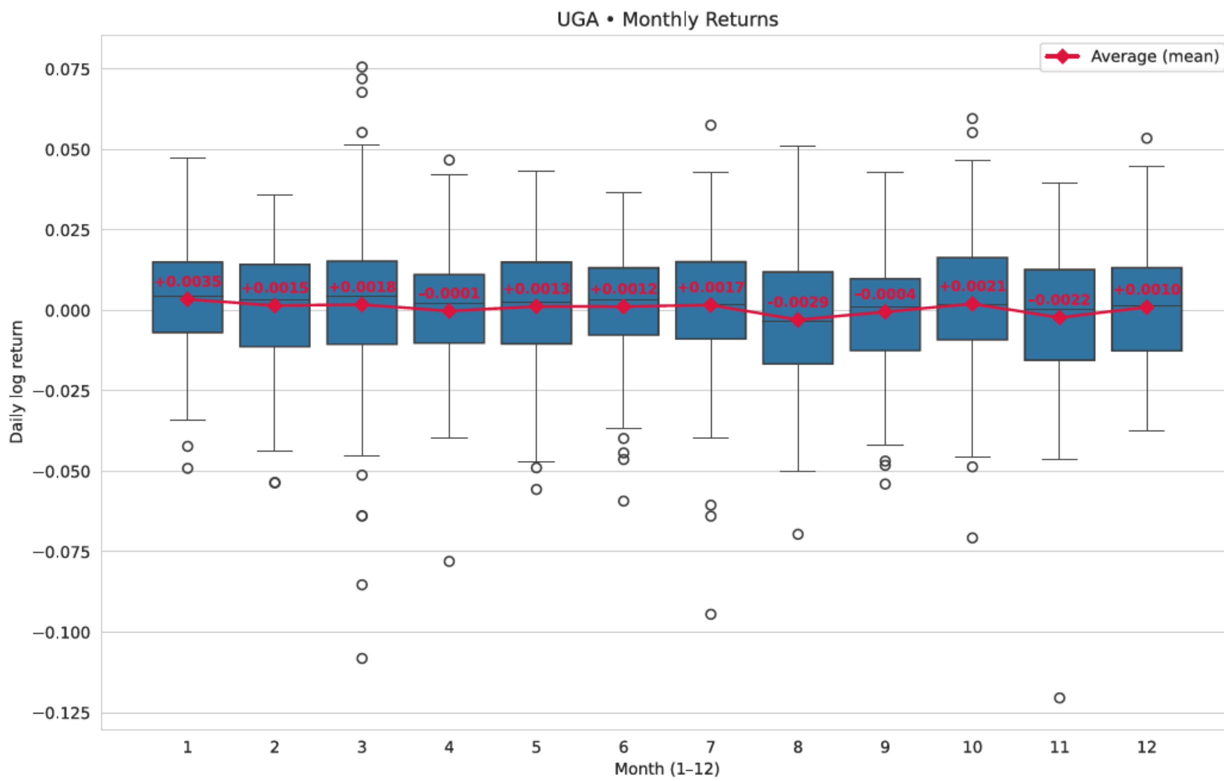
- January shows the highest mean positive return.
- Returns from May through July are consistently positive, consistent with the summer gasoline driving season.
- Slight negative mean in Aug and Sep with the switch to winter gasoline blend specifications and end of summer driving season.(return to school)

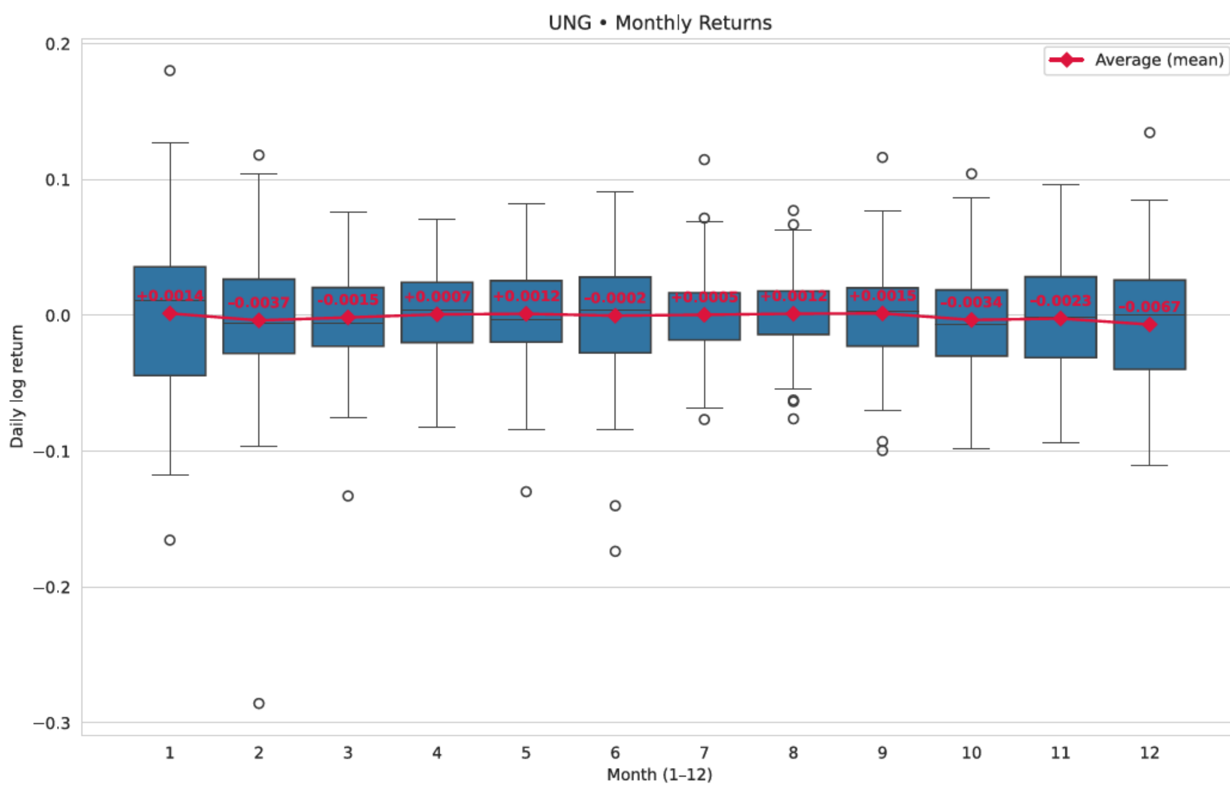
UNG-

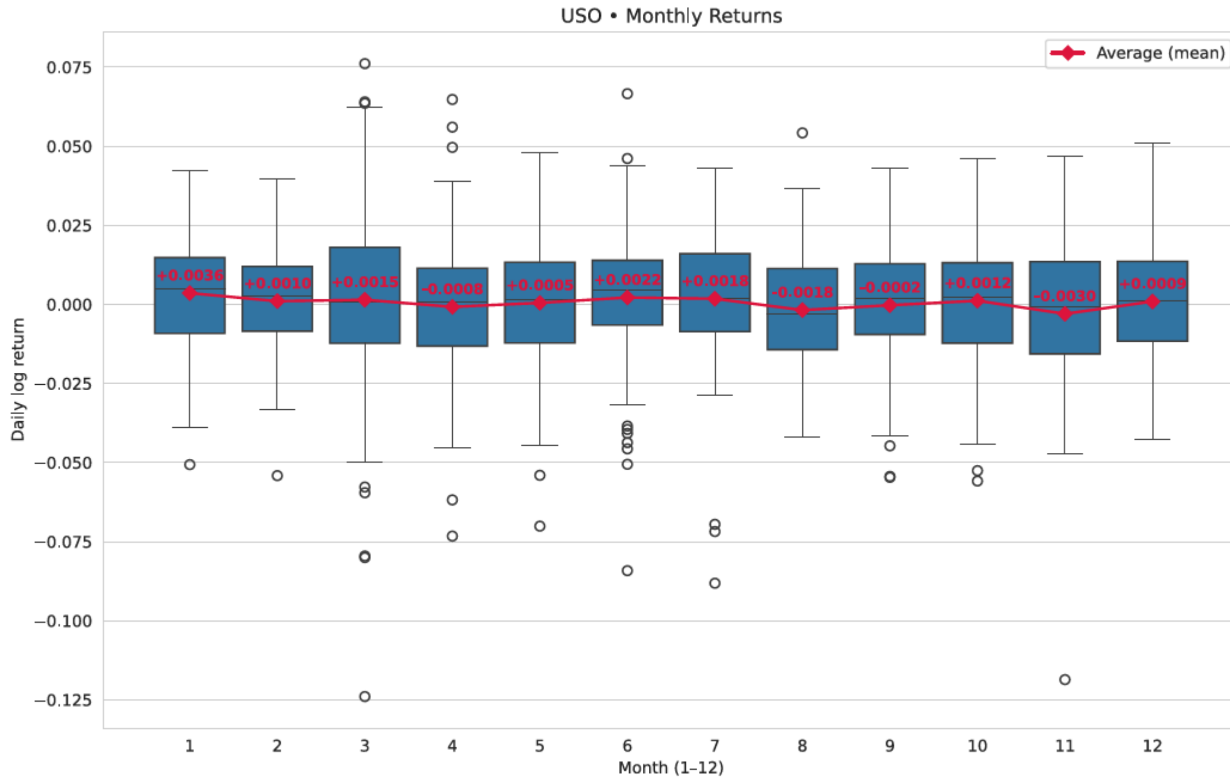
- The following patterns likely reflect winter heating-season effects, with January typically being the coldest month. Inventory withdrawals are managed during these months, and extreme cold snaps can dramatically move natural gas prices—as seen in January 2026 during Winter Storm Fern, which drove significant volatility.
    - January has the highest median return, with the mean also near its maximum.
    - January also exhibits the greatest volatility.
    - December and February show the largest negative mean returns.
- Summer months (June–August) show lower volatility and slightly positive returns due to seasonal cooling demand.

USO-

- January has the highest mean positive return.
- May through July again show consistent positive mean returns, corresponding to the summer driving season.
- Slight negative mean in Aug and Sep with the switch to winter gasoline blend specifications
- This pattern mirrors the seasonal trends seen in UGA.


UGA • Monthly Returns
Average (mean)
Daily log return
Month (1–12)
+0.0035
+0.0015
+0.0018
-0.0001
+0.0013
+0.0012
+0.0017
-0.0029
-0.0004
+0.0021
-0.0022
+0.0010

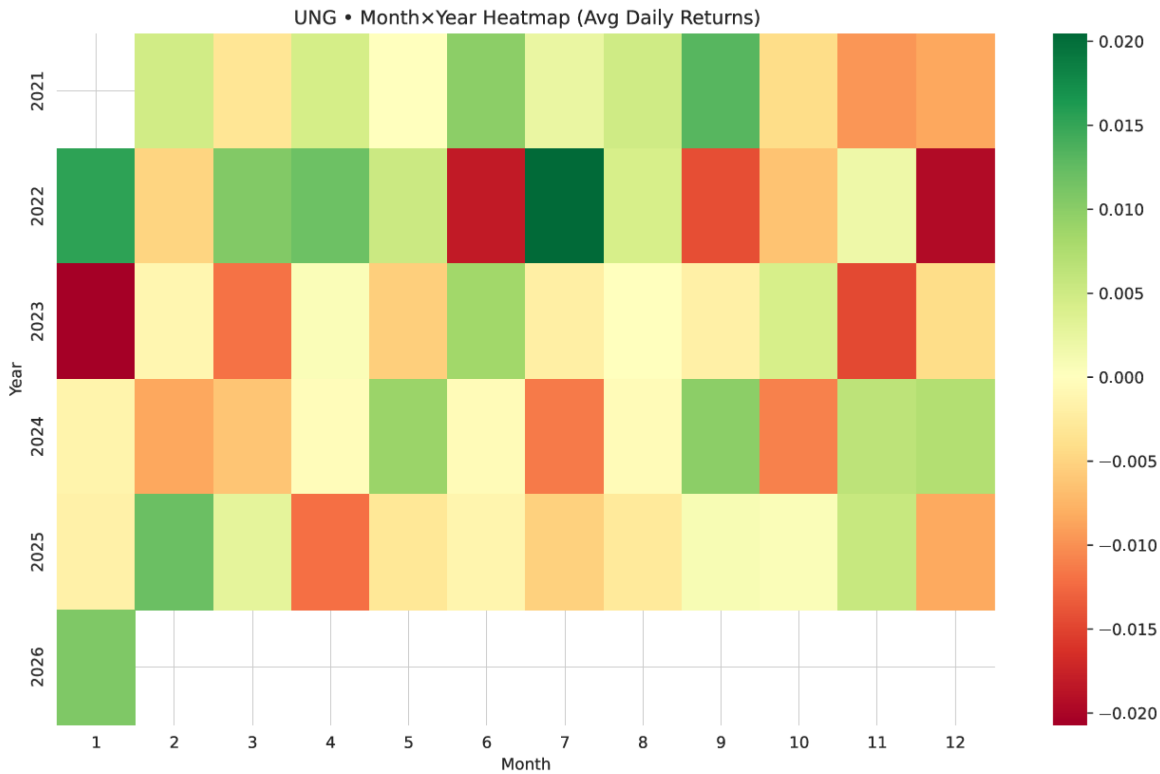

UNG • Monthly Returns
Average (mean)
Daily log return
Month (1–12)
+0.0014
-0.0037
-0.0015
+0.0007
+0.0012
-0.0002
+0.0005
+0.0012
+0.0015
-0.0034
-0.0023
-0.0067

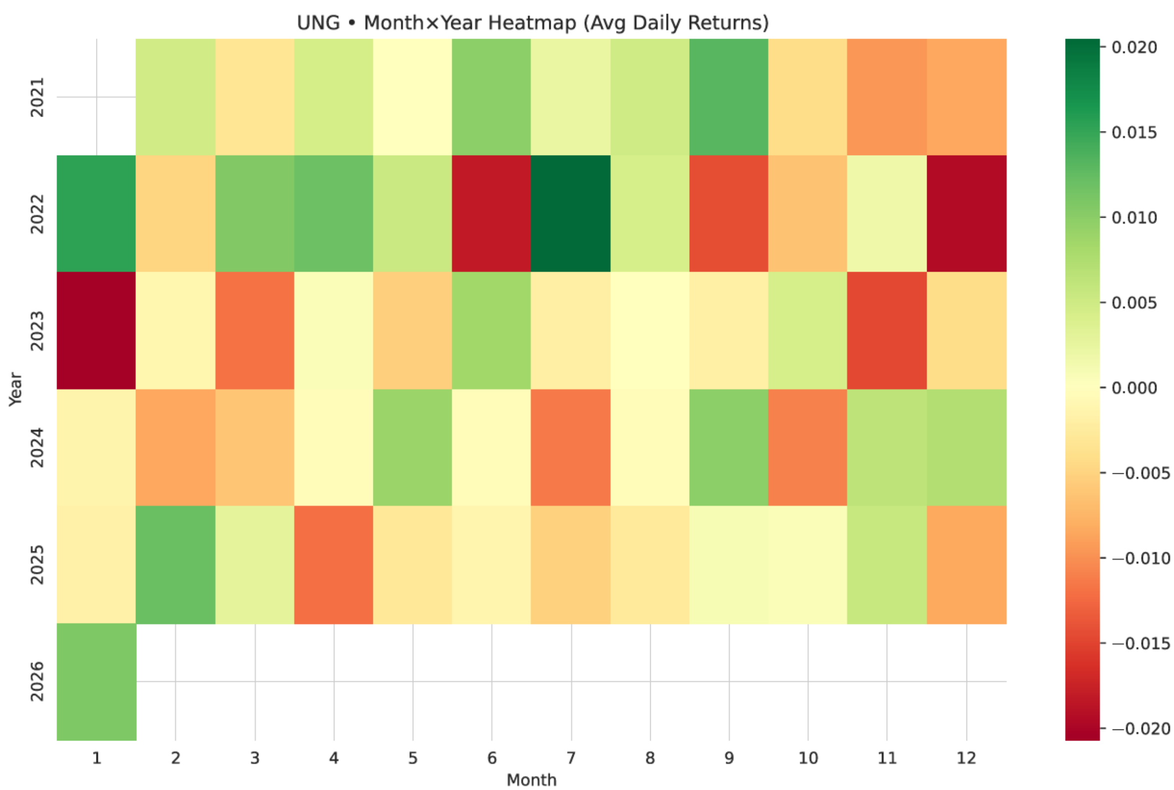


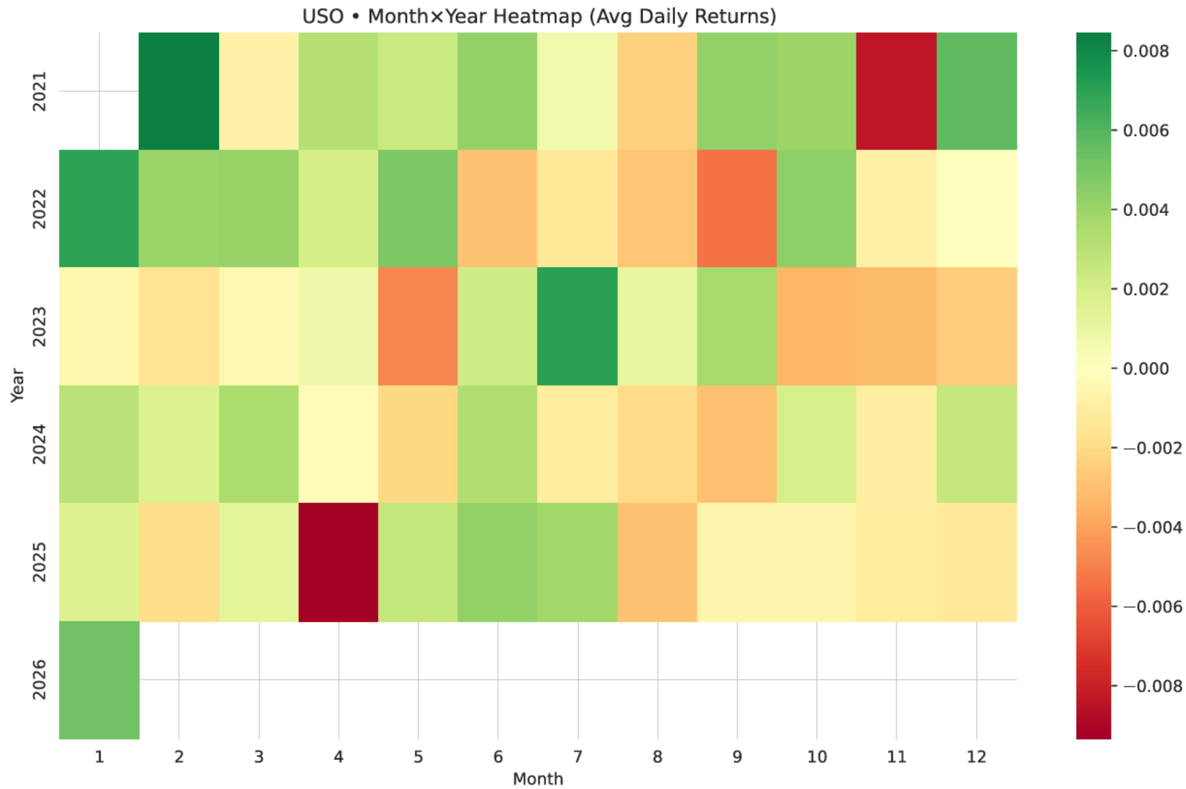
Seasonal Effects- Monthly returns by year

The heat-map plots of average monthly returns by year highlight recurring seasonal patterns in the commodity ETFs. Because February 2026 contained only a few trading days, it was excluded to avoid distorting monthly comparisons. Across the datasets, the return patterns reinforce the seasonal tendencies evident in earlier analyses, while also reflecting broader market disruptions. For example, UGA, UNG, and USO each exhibit occasional large positive returns in 2022 following the Russian invasion of Ukraine, accompanied by substantial negative returns during the same period which is consistent with heightened volatility clustering driven by geopolitical shocks.

For UNG, the heat maps also show pronounced variability during the winter heating season, with noticeably stronger swings in both directions, aligning with the sensitivity of natural gas markets to temperature, inventory management, and extreme weather events. USO shows a notable large negative return in April 2025, corresponding to U.S. tariff announcements that created significant short-term market pressure. These annual-monthly patterns help illustrate how seasonal demand cycles interact with unexpected macroeconomic events, providing both context for historical volatility and potential signals for identifying future trading opportunities.

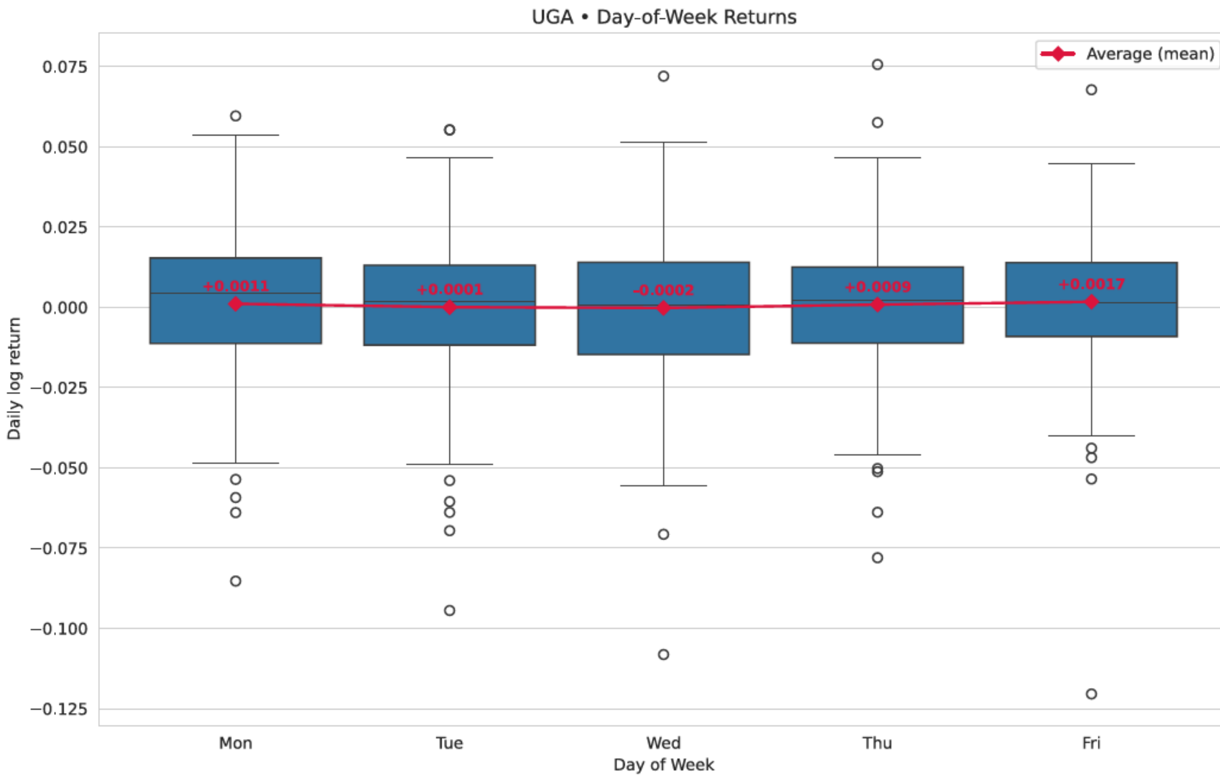

UNG • Month×Year Heatmap (Avg Daily Returns)
Year
2021
2022
2023
2024
2025
2026
Month
1 2 3 4 5 6 7 8 9 10 11 12
0.020
0.015
0.010
0.005
0.000
−0.005
−0.010
−0.015
−0.020

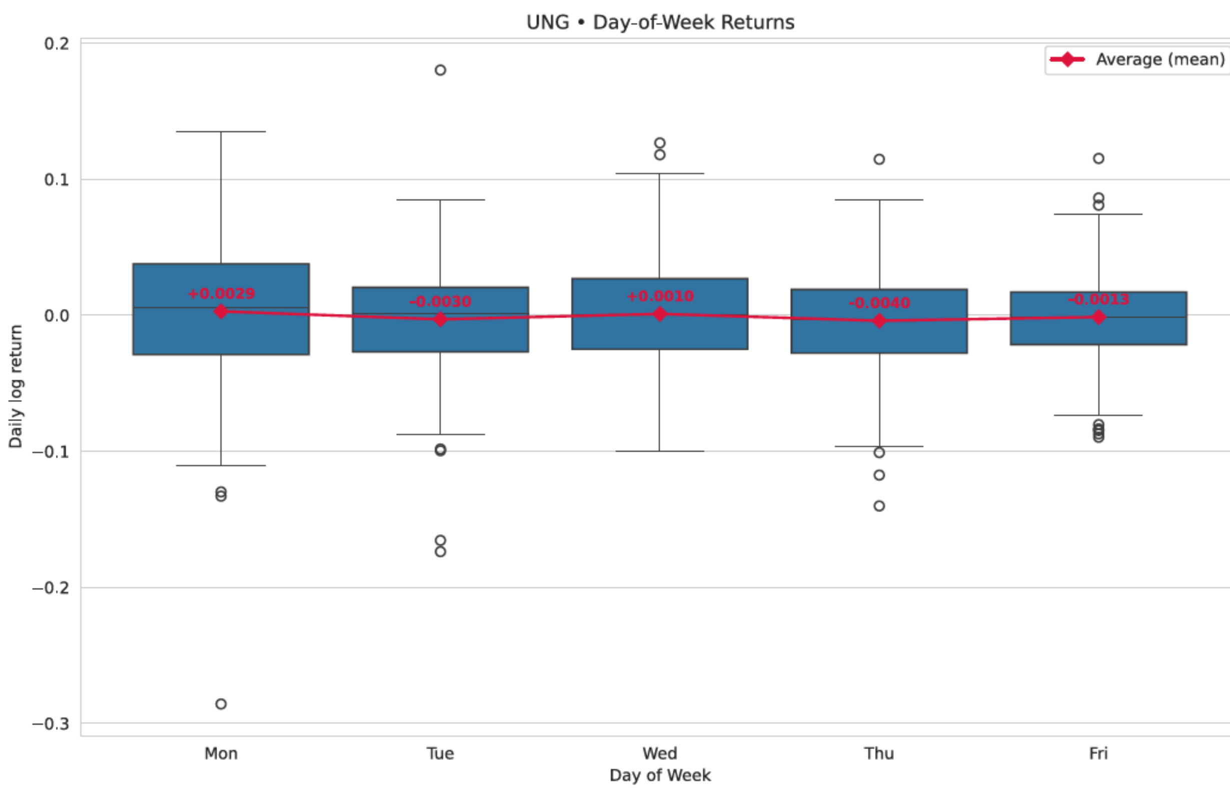

UNG • Month×Year Heatmap (Avg Daily Returns)
Year
2021
2022
2023
2024
2025
2026
Month
1 2 3 4 5 6 7 8 9 10 11 12
0.020
0.015
0.010
0.005
0.000
−0.005
−0.010
−0.015
−0.020

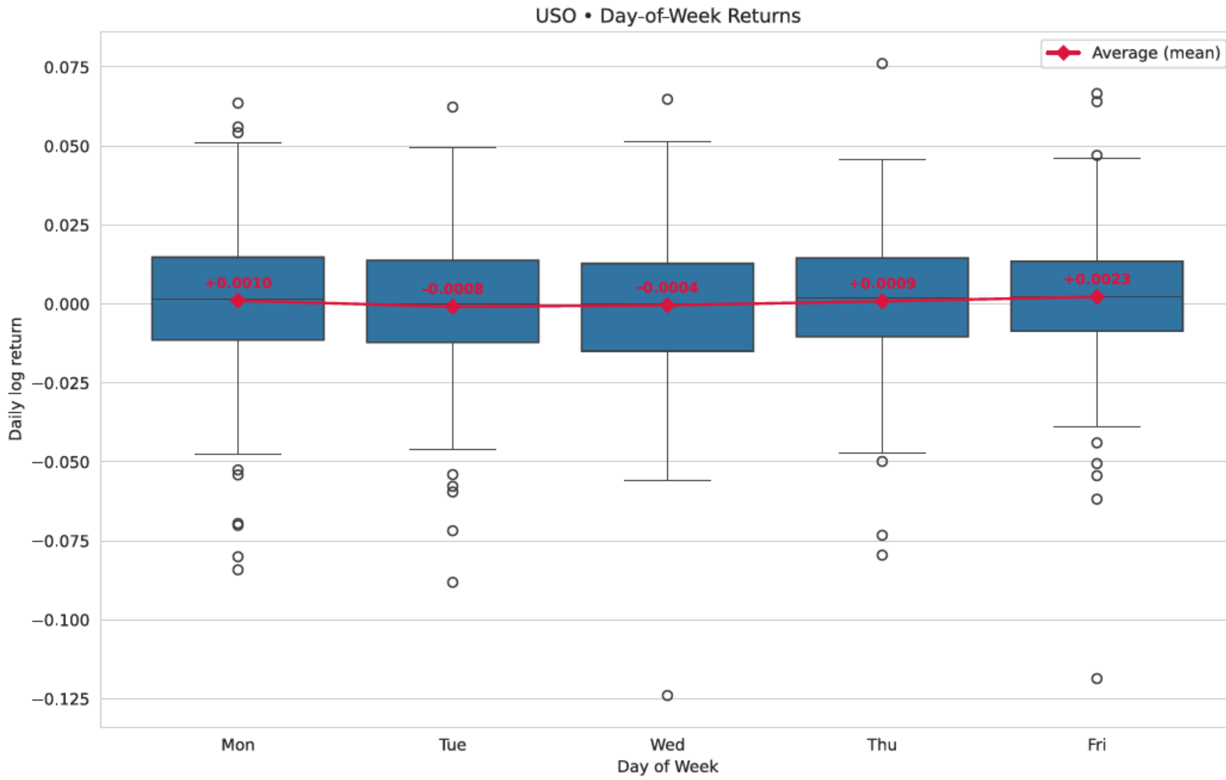


Timing Effects- Returns by day of the week

The following plots show box plots of returns by day of the week. Consistent with Taylor's findings, there doesn't appear to be any significant differences in average returns across weekdays, and any apparent variations are small relative to overall market noise. Taylor noted that day-of-the-week patterns can occasionally introduce minor distortions such as weak Monday effects or slight calendar-driven shifts, but these influences tend to be subtle and unstable over time. In line with this, a few modest patterns emerge in the ETF data, including slightly positive mean returns on Mondays, with the effect being more pronounced in the UNG natural-gas series.


UGA • Day-of-Week Returns
Average (mean)
Daily log return
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
+0.0011
+0.0001
-0.0002
+0.0009
+0.0017
Mon
Tue
Wed
Thu
Fri
Day of Week


UNG • Day-of-Week Returns
Average (mean)
Daily log return
0.2
0.1
0.0
−0.1
−0.2
−0.3
+0.0029
-0.0030
+0.0010
-0.0040
-0.0013
Mon
Tue
Wed
Thu
Fri
Day of Week


USO • Day-of-Week Returns
Average (mean)
0.075
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
Daily log return
+0.0010
-0.0008
-0.0004
+0.0009
+0.0023
Mon
Tue
Wed
Thu
Fri
Day of Week

Conclusions

This analysis of UGA, UNG, and USO confirms that energy commodity ETFs exhibit the key stylized facts of financial time series as outlined by Taylor (2005). Across all three funds, price levels follow a random-walk-like process, with daily returns showing near-zero autocorrelation and no consistent predictive structure. However, volatility clustering is clearly present, as evidenced by significant autocorrelation in both absolute and squared returns. Return distributions deviate meaningfully from normality, displaying heavy tails and mild negative skewness. Both UGA and USO show each of these results in the trends. UNG shows similar results and stands out for its heightened volatility and pronounced seasonal effects, especially during winter months, reflecting the underlying natural gas market's sensitivity to weather and storage dynamics.

Seasonal and calendar-based analyses reveal subtle patterns, such as stronger returns during the summer driving season for UGA and USO, and heightened winter volatility for UNG. However, these effects are often overshadowed by macroeconomic and geopolitical events, such as the 2022 Russia–Ukraine conflict and the 2025 U.S. tariff announcements, which introduced significant short-term volatility across all three ETFs.

Overall, the findings reinforce the importance of incorporating volatility-aware models and risk management strategies when analyzing or investing in energy commodity ETFs. These instruments provide valuable exposure to commodity price movements but require careful consideration of their structural features, such as roll yield and futures curve dynamics, which can materially impact performance. Because of these reasons the ETFs are not well setup for long term buy and hold investment strategies.

Keywords

Energy ETFs, UGA, UNG, USO, Financial Time Series, Stylized Facts, Volatility Clustering, Random Walk, Heavy-Tailed Distributions, Autocorrelation, Seasonality, Futures Markets, Roll Yield, Contango, Backwardation, Taylor (2005), Commodity Markets, Risk Management, Time Series Analysis

Bibliography

Taylor, Stephen J. 2005. *Asset Price Dynamics, Volatility, and Prediction*. Princeton, NJ: Princeton University Press.