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The evaluation of time-varying hedging and portfolio decisions under Trump's tariff-induced volatility

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Abstract

The declaration of Trump's reciprocal global tariffs had a profound influence on global trade dynamics and triggered excessive volatility across global financial markets. The drastic imposition of tariffs has disrupted international supply chains, commodity flows, and additional risk perceptions in equity, commodity and currency markets. In this study, an asymmetric multivariate model is used to capture the negative economic shocks or policy tensions in volatility co-movements among equity (NASDAQ) and commodity markets (Gold Futures and Crude oil Futures). These estimation results are crucial in determining the dynamic hedge ratio and time-varying portfolio weight in designing effective hedging and optimal asset allocations. These indicators are important for market participants to plan their overall portfolio stability in the global trading environment.

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1. Introduction

Since the announcement of Trump's tariff policy on April 1, 2025, the global stock and commodity markets have experienced drastic volatility. This implementation has triggered heavy selloffs in stock markets and a sudden hike in safe-haven assets such as gold. Global stock markets declined drastically after the announcement due to recession fears. Commodity markets such as crude oil were under pressure due to expectations of slower global growth and possibility of retaliatory global trade actions. The projection of crude oil demand concerns intensified due to possible economic recession. On the other hand, the demand for safe-haven gold commodities has reached historical heights as global investors sought safety amid heightened global market uncertainty. Numerous studies (Kaczmarek et al.,2025; Wei et al., 2026; Nie, 2025) have documented the impact of Trump's reciprocal tariff implementation to global stock, crude oil and gold markets.

For portfolio risk management and asset allocation in stock and commodity markets, the core study focuses on the dynamic correlation between the markets, which is highly relevant for determining the hedge ratios and portfolio weights. Thus, an understanding of these markets' dynamics is very important for modelling the hedge ratio and portfolio weight allocation. The multi-market dynamics during the tariff implementation highly influence volatility, and correlation shifts may alter the hedging portfolio strategies. This includes the phenomenon of a high negative correlation between the stock market and the gold market which implies higher hedge ratios toward gold during tariff-driven turmoil. The crude oil market on the other hand becomes less important as a hedge as the global demand expectations fall in the near future.

In this study, the dynamic correlations among the markets are estimated using the asymmetric dynamic conditional correlations (ADCC)-GJR-GARCH with Student-t distributions. The DCC model is introduced by Engle (2002) and extended by Cappiello et al. (2006) into the ADCC framework. Several studies (O'Connor et al., 2015; Baur & Lucey. 2010) have been conducted to study the relationships between stock, crude oil and gold markets using the ADCC-GARCH models.

2. Methodology

Given a continuous compounded column vector of continuously compounded return, $r_t = (r_{1t}, r_{2t}, ..., r_{nt})'$ represents an *n*-dimensional vector of zero-mean asset returns at time *t* with the following expression:

$$r_t = \mu_t + H_t^{1/2} z_t, \quad a_t = H_t^{1/2} z_t \tag{1}$$

where a_t are the standardized residuals (innovations) and $\boldsymbol{R}_t$ on the other hand, represents the time-varying conditional correlation matrix. The conditional covariance matrix $\boldsymbol{H}_t$ is decomposed

as $\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t$, where $\boldsymbol{R}_t = diag\left(\boldsymbol{Q}_t\right)^{1/2} \boldsymbol{Q}_t diag\left(\boldsymbol{Q}_t\right)^{1/2}$ represents the time-varying conditional correlation matrix and $\boldsymbol{D}_t = diag\left(\sqrt{h_{1t}}, \sqrt{h_{2t}}, ..., \sqrt{h_{nt}}\right)$ is a diagonal matrix of conditional standard deviations obtained from univariate GJR-GARCH (1,1) processes with the specification $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I_{\{\varepsilon_{t-1}<0\}} \varepsilon_{t-1}^2 + \beta h_{t-1}$ where $I_{\{\varepsilon_{t-1}<0\}}$ is the binary variable. The Asymmetric Dynamic Conditional Correlation (ADCC) model (Cappiello et.al.,2006) based on Engle's model (2022), defines the dynamic correlation process as:

$$\boldsymbol{Q}_t = \left(1 - \boldsymbol{A} - \boldsymbol{B} - \boldsymbol{G}/2\right)\bar{\boldsymbol{Q}} + \boldsymbol{A}\left(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'}\right) + \boldsymbol{B}\boldsymbol{Q}_{t-1} + \boldsymbol{G}\left(\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}_{t-1}^{'}\right) \tag{2}$$

where:

- $\boldsymbol{Q}_t$ is the conditional covariance matrix of standardized residuals,
- $\bar{\boldsymbol{Q}}$ is the unconditional correlation matrix of standardized residuals,
- $\boldsymbol{\varepsilon}_t$ represents the $\boldsymbol{D}_t^{-1}\boldsymbol{r}_t$, standardized residuals,
- $\boldsymbol{\eta}_t$ represents the $\min\left(\boldsymbol{\varepsilon}_t, \boldsymbol{0}\right)$, leverage effect,
- $\boldsymbol{A}$ represents the coefficients of impact of recent shocks on correlations,
- $\boldsymbol{B}$ represents the coefficients of persistence of correlations over time,
- $\boldsymbol{G}$ represents the coefficients of the leverage effect.

For the GJR-GARCH model, we assume that the innovations of individual markets follow a skewed Student-t (Hansen, 1994; Fernandez & Steel, 1998) with $a_t \sim sstd\left(m, v, \xi\right)$, where m, v, ξ representing the location vector, degree of freedom and skewness of a distribution. The probability density function of the skewed Student-t for standardized residual is given by:

$$f(a_t) = \begin{cases} \dfrac{2c}{\xi + \dfrac{1}{\xi}}\left[1 + \dfrac{1}{v-2}\left(\dfrac{ca_t + m}{\xi}\right)^2\right]^{-\frac{v+1}{2}}, & a_t < -\dfrac{m}{c} \\ \dfrac{2c}{\xi + \dfrac{1}{\xi}}\left[1 + \dfrac{1}{v-2}\left(\xi\left(ca_t + m\right)\right)^2\right]^{-\frac{v+1}{2}} & a_t \geq -\dfrac{m}{c} \end{cases} \tag{3}$$

where *m* and *c* are normalization constants that ensure zero mean and unit variance, conforming to the following specifications:

$$m = \frac{2c\left(\xi - \xi^{-1}\right)}{\xi + \xi^{-1}} \text{ and } c = \sqrt{\frac{v}{v-2}}\frac{\Gamma\left(\dfrac{v+1}{2}\right)}{\sqrt{\pi\left(v-2\right)}\Gamma\left(\dfrac{v}{2}\right)} \tag{4}$$

When $\xi = 1$, the a_t reduces to a symmetric Student-t distribution. This distribution is divided into left and right distributions as $\frac{cz+m}{\xi}$ and $\xi(cz+m)$ inside a Student-t kernel. For estimation, two-step quasi-maximum likelihood (QMLE) procedure is commonly used where firstly univariate GJR-GARCH models are fitted to each return series. In the second step, the estimated standardized residuals are utilized to estimate the time-varying correlation structure to obtain $\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t$. Adding an additional term that captures the impact of negative shocks on correlations, the ADCC model specification is obtained. The estimation is conducted under a multivariate Student-t distribution to capture fat-tailed behavior, with the degrees of freedom parameter jointly estimated with the correlation parameters.

2.1 Application in Hedging and Portfolio Allocations

The pairwise hedge ratio between Nasdaq and either crude oil futures and gold futures is derived from the ADCC-GARCH estimations. Let $r_t = (r_{N,t}, r_{C,t})$ where $r_{N,t}$ is the Nasdaq return and $r_{C,t}$ is the commodity return (either crude oil or gold). The estimated conditional covariance matrix is

$H_t = \begin{bmatrix} h_{NN,t} & h_{NC,t} \\ h_{NC,t} & h_{CC,t} \end{bmatrix}$. Under the Kroner and Sultan (1993) framework, the optimal hedge ratio is $Hedge_t = \frac{h_{NC,t}}{h_{CC,t}}$. For instance, if an investor holds a long position in the Nasdaq and hedges it with crude oil futures, the hedge ratio is defined as

$Hedge_{Nasdaq,Oil,t} = \frac{h_{NO,t}}{h_{Oil,t}}$, with $H_t = \begin{bmatrix} h_{Nasdaq,t} & h_{NO,t} \\ h_{NO,t} & h_{Oil,t} \end{bmatrix}$. Assume that if the $Hedge_{Nasdaq,Oil,t} = 0.35$, one should short USD 0.35 of crude oil futures for every USD 1.00 long in the Nasdaq. Positive ratio suggests shorting crude oil futures, while negative ratio recommends a long position in crude oil futures. For the dynamic optimal weight allocation that minimizes portfolio variance across the three markets (Kroner and Ng, 1998), let $r_t = (r_{N,t}, r_{O,t}, r_{G,t})$, then $H_t = \begin{bmatrix} h_{NN,t} & h_{NO,t} & h_{NG,t} \\ h_{NO,t} & h_{OO,t} & h_{OG,t} \\ h_{NG,t} & h_{OG,t} & h_{GG,t} \end{bmatrix}$. The dynamic optimal allocation is written as $w_t = \frac{H_t^{-1} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}{\begin{bmatrix} 1 & 1 & 1 \end{bmatrix} H_t^{-1} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}}$ which yields dynamic weights for the Nasdaq, crude oil futures, and gold futures.

3. Empirical Study

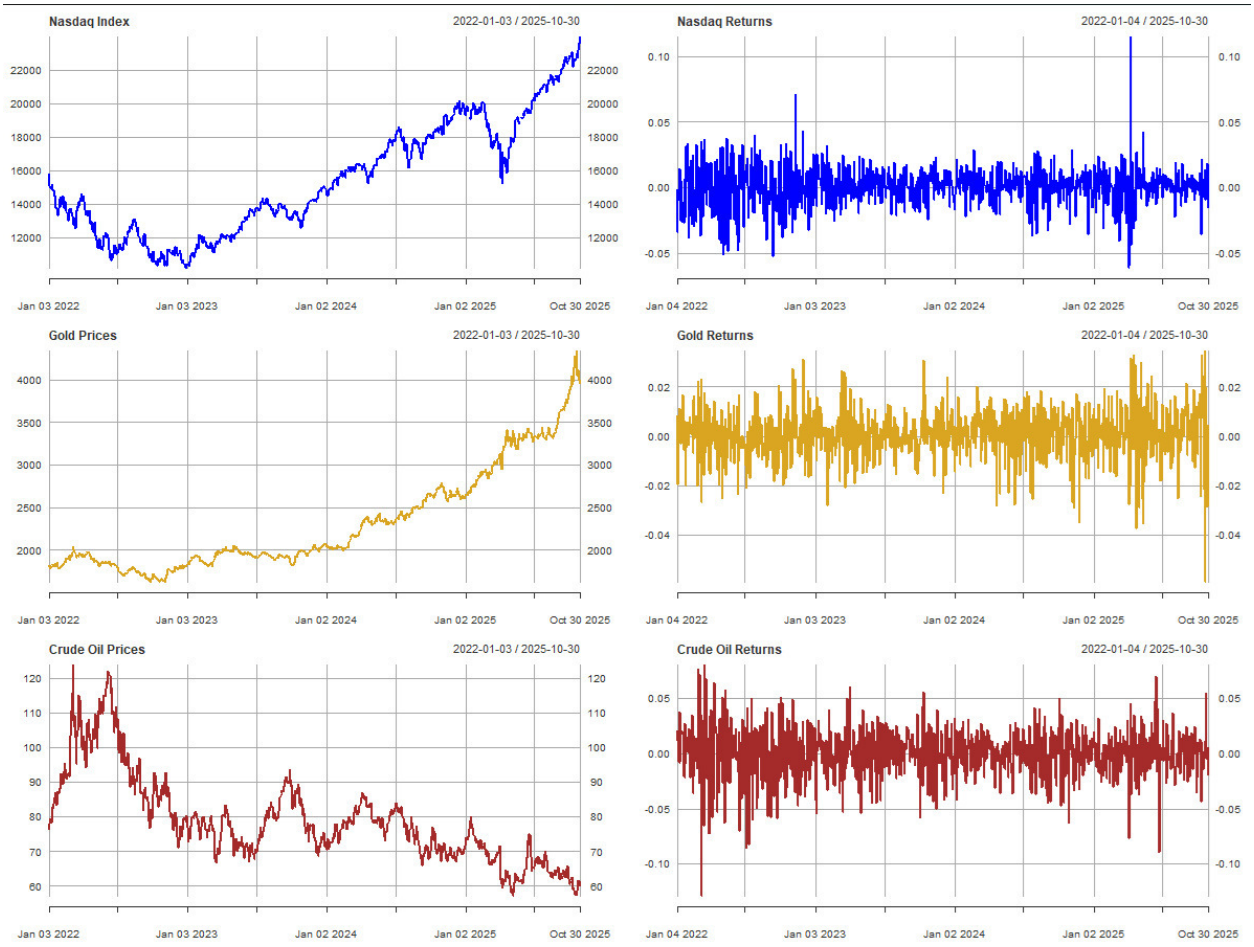

Figure 1: Price Index and Return Series for Nasdaq, gold futures and crude oil futures

Figure 1 presents the price and return series for the NASDAQ, gold futures, and crude oil futures markets. The selected dataset spans from January 1, 2022 to October 31, 2025, which includes the outbreak of the Russia-Ukraine War on February 24, 2022. The impact of this war is also discussed in our empirical analysis. To examine the influence of Trump's reciprocal tariffs in April 2, 2025, the overall dataset is divided into pre-tariff (January 1, 2022 to April 1, 2025) and during-tariff periods (January 1, 2022 to October 31, 2025). First, the NASDAQ Composite index indicates an upward trend from 14,000 points in early June 2022 to approximately 23,700 by the end of October 2025. However, after the announcement of the tariffs, the index experienced downward trend and more intense volatility. Second, gold futures as an alternative safe-haven investment (besides government bonds, currencies, and other precious metals, among others), rose from $1,800 to over $4,000 between 2022 and 2025. This reflected the increased demand for gold amid trade tensions and possibility of global inflationary pressures.

Table 1: Percentage Changes in Pre-tariff and During the Tariff Periods

	Pre-tariff Period	During-tariff Period
Market	1st Jan 2022 to 1st Apr2025	1st Jan 2022 to 31st Oct2025
NASDAQ	+27.86	+69.46
Gold Futures	+43.33	+124.33
Crude Oil Futures	–27.86	–14.14

Lastly, crude oil futures declined from approximately $70 in early 2022 to $60 by the end of 2025. It is worth noting that during the Russia-Ukraine War, the NASDAQ index declined over several months, while gold futures and crude oil futures indicated a significant rise due to risk-hedging in gold market and crude oil supply disruptions affecting Russia exports. Overall, crude oil futures exhibited a bearish trend due to oversupply and global demand shifts. In summary, the percentage changes before and after the tariff announcement are illustrated in Table 1.

3.1 Estimation Results

The multivariate GARCH estimations are conducted using the *rmgarch* package (https://cran.r-project.org/web/packages/rmgarch/index.html) in R. Table 2 illustrates the ADCC-GARCH estimation results for the three markets. For the individual NASDAQ market, the volatility persistence coefficient, β is 0.9540 before the tariff and decreases to 0.9042 during the tariff period. This suggests that shocks to the NASDAQ market became less long-lasting or persistent. The leverage effect coefficient, γ increases from 0.0688 to 0.1441, showing that the asymmetric response of volatility to negative shocks became more intense in the during the tariff period. Regarding the shape coefficient, v, there is no evidence of heavy-tailed innovation distribution in the pre-tariff period, however, it becomes heavy-tailed during the tariff period with 11.1948 degrees of freedom. The skewness coefficient reduces slightly from 0.8742 to 0.8613, suggesting a slightly stronger downside risk, which aligns with higher uncertainty and risk aversion in the during the tariff period.

For the gold market, the volatility persistence, β increases slightly from 0.8934 to 0.9289 across the two periods. Meanwhile, the ARCH coefficient, α, increases from 0.054979 to 0.119991, suggesting that volatility became more responsive to short-term shocks during the tariff period. This condition is quite similar to the NASDAQ, where the shocks to the gold market became more long-lasting or persistent. On the other hand, the leverage effect coefficient, γ is not significant in the pre-tariff period, whereas it shows a reverse leverage effect during the tariff period with a value of –0.106848. Gold behaves differently compared to stock markets because it is a safe-haven asset. The so-called "flight-to-quality" effect suggests that when the markets crash (due to bad news), investors have a higher tendency to move into gold market. Thus, the gold market provides asymmetric hedging benefits. This shows that the asymmetric response of volatility to positive shocks intensified between the two periods. Gold, as a safe-haven asset, often indicates a negative leverage effect due to its function as a hedging instrument when stock markets fall.

Table 2: Estimation for NASDAQ, Gold futures and Crude Oil futures

		Estimation	Estimation
Market	Parameter	Pre-tariff Period	During the tariff Period
NASDAQ	m	0.000437	0.000744**
	ω	0.000002	0.000004
	α	0.000000	0.000001
	β	0.954031**	0.904215**
	γ	0.068855**	0.144172**
	v	35.311278	11.194830**
	ξ	0.874195**	0.861271**
Gold futures	m	0.000584*	0.000723**
	ω	0.000003**	0.000005**
	α	0.054979**	0.119991**
	β	0.928928**	0.893422 **
	γ	-0.041822	-0.106848 **
	v	7.451501**	7.819651**
	ξ	0.904200**	0.903316**
Crude Oil futures	m	0.000196	0.000029
	ω	0.000009	0.000013**
	α	0.084917	0.093086**
	β	0.909198**	0.900382**
	γ	-0.019577	-0.030111
	v	25.535234	13.342072**
	ξ	0.830187**	0.848661**
ADDC coefficients	A	0.015514**	0.019497**
	B	0.950878**	0.934282**
	G	0.000000	0.000000
	mv	16.205093**	11.330658**

* significant at 10% level ** significant at 5% level

For skewness coefficient, ξ , the values are almost identical (0.9042 and 0.9033), suggesting that a mildly left-skewed return distribution is observed in both periods. Meanwhile, the shape coefficient, v, increases from 7.4515 to 7.8197, showing a potential shift toward a less heavy-tailed distribution and a reduction in kurtosis during the tariff period.

The crude oil market, the volatility persistence coefficient shows a slight decline from 0.9092 to 0.9004, suggesting that the market shows a shorter volatility memory. The ARCH coefficient α, is significant only during the tariff period, with a value 0.093086, suggesting a greater magnitude of shock response in volatility. The leverage effect coefficients are insignificant in both periods. The skewness coefficient also indicates a similar condition across both periods, with values of 0.8302 and 0.8487, respectively. Finally, the tail behavior approaches a normal distribution, with degrees of freedom 25.5352 and 13.3421 for the pre-tariff and during tariff periods, respectively. For the correlation dynamics among the markets, the DCC coefficients (A and B) shifted from 0.0155 and 0.9509 in the pre-tariff period and 0.0195 to 0.9343 during the tariff period, respectively. These results indicate that that conditional correlations among

NASDAQ, gold and crude oil markets became slightly less persistent, yet more responsive to shocks during the tariff period. The leverage effect coefficient, *G*, is insignificant in both periods, indicating that negative returns (bad news) do not influence the correlation dynamics. The multivariate shape coefficient, *mv* shows how likely large shocks are to occur simultaneously across the three markets, rather than focusing on individual tails. Statistically, it is denoted as the degrees of freedom of the multivariate Student-t distribution. In short, this coefficient controls joint tail thickness (kurtosis), where a smaller *mv* value implies fatter tails with more extreme observations. The finding that *mv* reduced from approximately 16 to 11 implies moderately heavier tails in the joint distribution, which suggests elevated systemic risk and tail dependence across the three markets. In other words, there are non-negligible extreme co-movements among the markets, though they are not excessively frequent. Knowing the presence of heavy tails allows researchers to avoid underestimating tail risk in portfolio analysis.

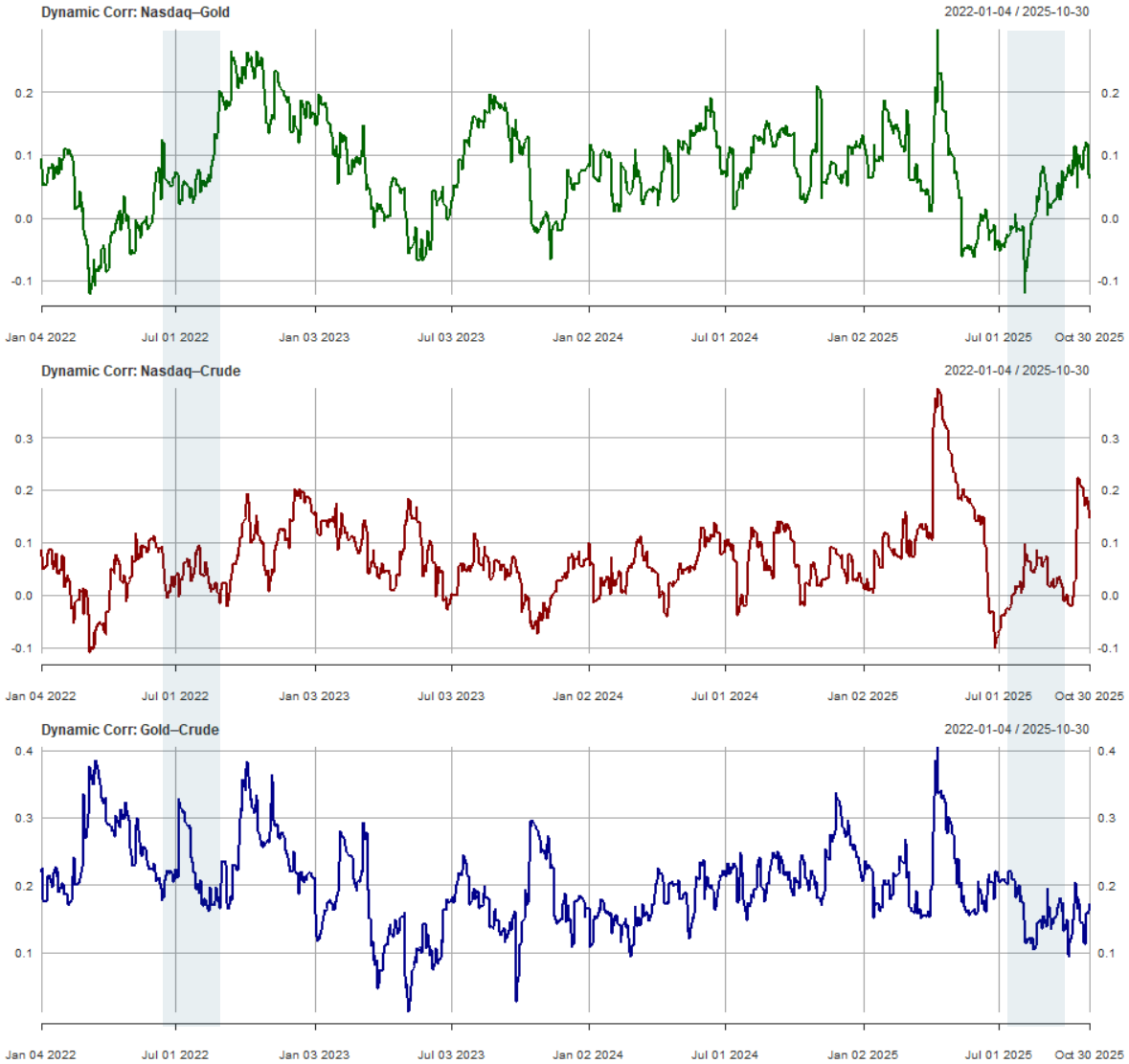

Figure 2: Dynamic Correlation between Markets

Figure 2 displays the dynamic correlations between the three markets. The dynamic correlations between the NASDAQ-Gold and NASDAQ-Crude Oil markets fluctuated between –0.100 to 0.400, illustrating how their co-movements evolved over the selected periods. On the other hand, the Gold-Crude oil relationships show a positive correlation ranging from 0.000 to 0.400. For the pre-tariff period, the dynamic correlation between the NASDAQ and Crude Oil shows weak positive interdependence (around 0.200 to –0.100), reflecting the diversification benefits of crude oil against the NASDAQ stock market. The correlations of all paired markets show a tendency to increase approximately from 0.100 to 0.400 following the announcement of Trump's tariff on April 2, 2025. This unprecedented tariff implementation by the US government may have created synchronized responses from a vast number of investors, thereby driving systemic uncertainty. These events may have contributed to the sharp rise in conditional correlations between the three markets. This also indicates that the announcement has partly lifted the conditional correlation between the three markets with reduced diversification opportunity. Finally, the joint volatility persistence of the system underscores the enduring nature of the tariff policy environment and investor risk aversion.

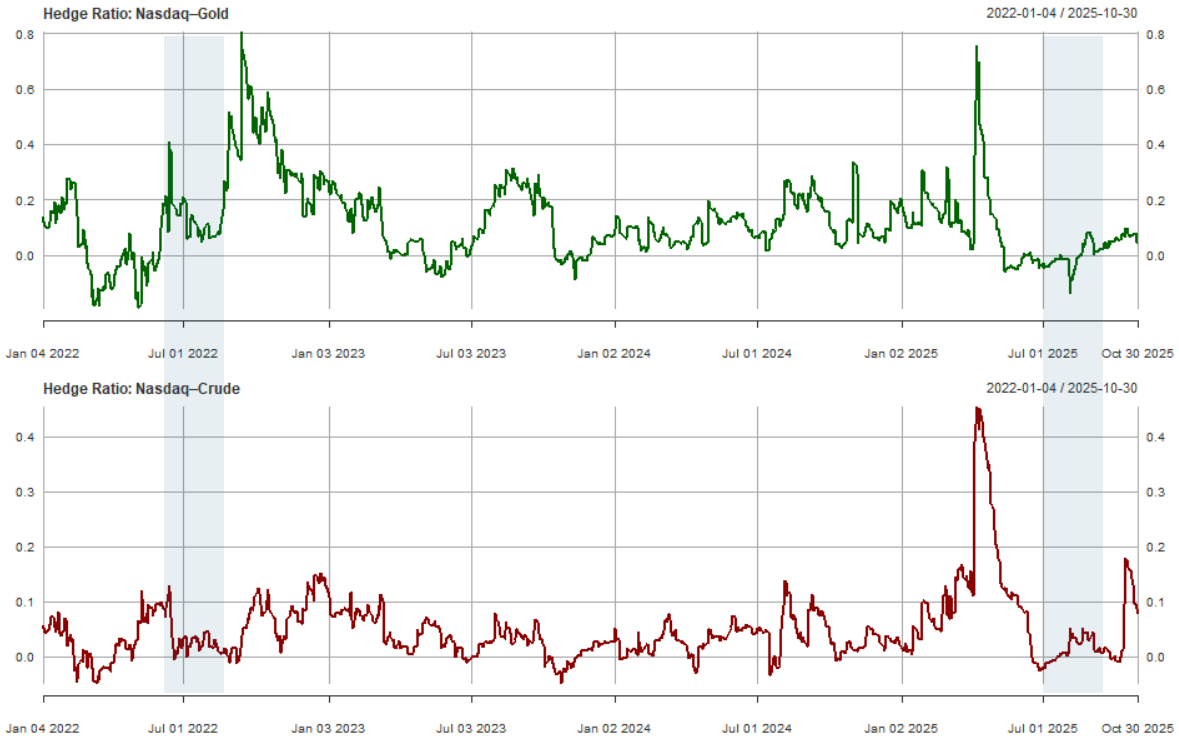

Figure 3: Dynamic Hedge Ratio Between Markets

Figure 3 illustrates the dynamic hedge ratio, H_{ij} between NASDAQ-Gold and NASDAQ-Crude Oil for the overall period. During the high speculated and volatile market conditions, this indicator demonstrates how much of one asset (the hedge asset, Gold or Crude Oil) should be held to hedge the exposure of another asset in the primary market (NASDAQ) over the three-year period. This indicator changes dynamically over time because the volatility and correlation

between the markets evolve. It is found that most of the time the dynamic hedge ratios, H_{ij} are positive (selling Gold or Crude Oil to offset NASDAQ's loss) and sometimes move to negative values (buying NASDAQ to offset Gold's or Crude Oil's losses). In short, this indicator provides useful information for investors in NASDAQ stock market on how to hedge using Gold or Crude oil to minimize portfolio variance. For NASDAQ -Crude oil, the hedge ratio was relatively stable and low (–0.05 to 0.15) in the pre-tariff period, which indicates a weak co-movement. This suggests that crude oil provides limited and inconsistent hedging effectiveness against NASDAQ movements under normal market conditions. However, the hedge ratio increased to 0.45 after the tariff was announced in April 2025. This suggests a heightened sensitivity and strong contagion between the NASDAQ and crude oil markets. It is worth noting that this spike was not persistent and was most likely driven by temporary market stress rather than structural changes in NASDAQ and Crude oil markets. After the global reciprocal tariff announcement, investors needed to readjust their hedge positions more intensively to maintain portfolio stability.

For NASDAQ and Gold market, a similar stability and low hedge ratio prevailed over the period. However, there were two time points that triggered the drastic rise in the hedge ratio, namely the Russia-Ukraine War in February 2022 and the tariff announcement in April 2025. During these two events, the correlation rose, and gold became a stronger hedge for the NASDAQ.

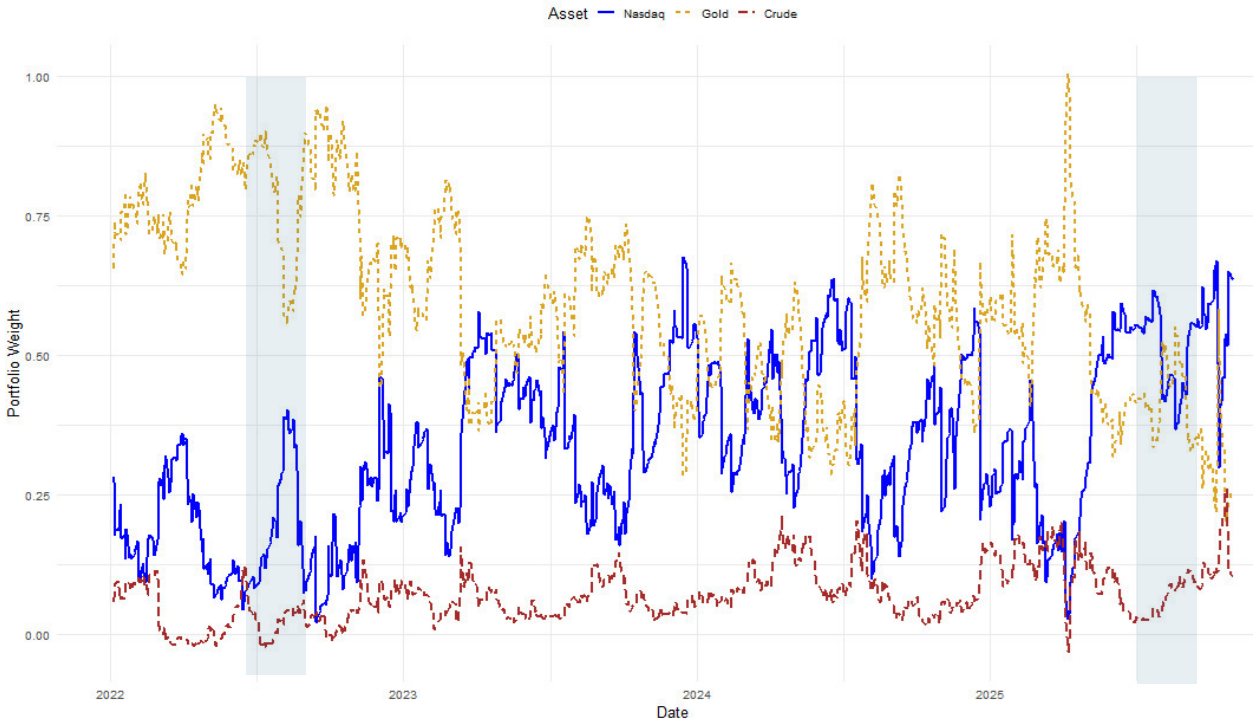

Figure 4: Dynamic Minimum-Variance Portfolio Weights for Three Markets

Figure 4 displays the dynamic portfolio weights constructed under the ADCC-GARCH volatility and correlation structures estimations, representing the optimal allocation among the NASDAQ, gold and crude Oil markets. Consistent with dynamic hedge ratio analysis, during the Russia-Ukraine War and Trump's tariff announcement, the model indicates a substantial

reallocation toward gold market, which is consistent with its safe-haven characteristics. Meanwhile, the NASDAQ was allocated a lower weight in response to elevated equity volatility. Other than during these periods, the portfolio allocations among the three markets were relatively balanced with moderate and stable risk levels. Overall, the gold market maintained the highest weight among the assets, whereas crude oil held the lowest weight over the period. After the two important events, the weights for the three markets gradually reverted as market risk stabilized, which implies the importance of dynamic portfolio rebalancing under different market conditions.

4. Conclusions

This study uses the ADCC-GARCH model to evaluate the interdependence among the stock, gold, and crude oil markets under the geopolitical (the Russia-Ukraine war) and tariff policy (Trump's tariff) shocks. It is found that during these two events, the dynamic correlation and hedge ratios showed substantial increases, implying strong market co-movements and contagion effects. An intensive transmission of shocks across stock and commodity markets is revealed with heightened volatility persistence and reduced diversification opportunities.

The empirical study also found that gold demonstrated its safe-haven characteristic with high portfolio weight during the turbulent periods, whereas crude oil proved to be the weakest diversification asset. In summary, this study provides valuable insights for investors to understand cross-market portfolio optimization and risk management strategies under high uncertainty and crisis conditions.

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