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Dynamic Interlinkages Among Crude Oil, Gold, and Copper Markets: Evidence from VAR–DCC-GARCH Models

R. Madhankumar[1,*], S. Darshan[2], A. Preethi[3], Mohammed Farooq Pasha[4]

[1,2]Department of Commerce, KLE Society's Evening Degree College, Nagarabhavi, Bengaluru, Karnataka, India.
[3]Department of Commerce and Management, Center for Distance and Online Education (CDOE), Jain (Deemed-to-be University), Bengaluru, Karnataka, India.
[4]Department of Commerce and Management, Government First Grade College, Kengeri, Bengaluru, Karnataka, India.
madhan17anitha@gmail.com[1], darshan.sathyanarayana@klenagarbhabvi.edu.in[2], preethim289@gmail.com[3], farooqpasha2002@gmail.com[4]

Abstract: Risk managers and portfolio diversifiers in a financialised world understand commodity market interlinkages using the study. This study uses VAR–DCC–GARCH to assess crude oil (CO), gold (GC), and copper (HG) prices and volatility. Short-run transmission mechanisms and commodity dependence structures are represented using 2017–2023 daily futures price data, along with mean spillover dynamics, volatility persistence, and time-varying correlations. Initial diagnostics indicate that all return series exhibit unit roots, non-normality, and volatility clustering, consistent with GARCH models. Granger causality tests reveal that the copper price return predicts the crude oil return, whereas the gold price is impervious to short-run return spillovers. The VAR shows modest and asymmetric return spillovers from copper to crude oil. Impulse-response research demonstrates that cross-market shocks are ephemeral, while own-market shocks dominate return dynamics. In contrast, volatility dynamics persist and interact. Univariate GARCH estimates indicate that copper and gold exhibit significant volatility persistence, whereas crude oil shows less volatility persistence. Time-varying correlations in the DCC-GARCH are sensitive to market date shocks, indicating that commodity co-movements grow and remain robust. The study found that market uncertainty reduces state-dependent portfolio diversification gains across crude oil, gold, and copper. The findings show that volatility, not returns, drives commodity market interconnectedness. Investors and policymakers can benefit from dynamic risk management and time-varying hedging research, especially in India's rising market.

Keywords: Crude Oil; Gold and Copper; Commodity Market Interlinkages; Volatility Spillovers; Vector Autoregression; Dynamic Conditional Correlation; Augmented Dickey–Fuller; Impulse Response Functions.

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1. Introduction

*Corresponding author.

Commodity markets are an integral part of the global financial system, functioning as inputs to production, investment assets, and risk-management instruments [8]. Crude oil, gold, and copper have a special status among commodities because of their distinct yet interrelated economic roles [14]. There is hardly any doubt that crude oil is the world's most important energy source today and acts as a key driver of macroeconomic activity [15]. Furthermore, gold has acquired a reputation as a haven and a store of value [16]. Meanwhile, copper is seen as a barometer of global industrial demand and economic growth, with investors pouring money into copper prices because it is a useful commodity in modern technology, as well as in housing and construction [17]. The importance of understanding the dynamic interlinkages among these markets to investors, policymakers, and portfolio managers is considerable [18]. Over the last 20 years, commodity markets have become more financialised, with institutional investor participation and greater integration with financial markets worldwide [19].

During times of great uncertainty, such as geopolitical conflicts, disruptions to oil supplies, tightening of monetary policies, and economic slowdowns, shocks to various commodities have become far better transmitted in recent years [1]; [20]. As such, price movements and volatility in any one commodity market spill over into other markets, reducing diversification benefits and increasing systemic risk [29]; [5]. Shock in commodity markets: Crude oil-based commodities often trigger shocks that ripple through a wide variety of other commodities [2]; [21]. The rising price of oil can directly influence production costs and inflation in industrial activity, affecting metals such as copper [22]. Often, gold exhibits market behaviour that differs from that of industrial commodities [23]. During some periods of stress, gold can behave quite differently [24]. But empirical data suggest that gold's hedging capacity is not stable over time and can weaken during extreme market conditions [4]; [25]. As relationships evolve, researchers must examine not just averages but also those that change over time. Research that employs traditional empirical approaches often relies on static correlation measures or single-equation models. As a result, spillovers and correlations may be characterized as static [3]; [30].

Recent literature jointly modeled return spillovers, volatility clustering, and changing correlation structures using a multivariate time-series framework [9]; [12]. The Vector Autoregression (VAR) framework is a natural starting point for examining mean spillovers and causal linkages, while GARCH-type models are well-suited to capturing the volatility persistence and clustering typically observed in commodity returns [31]. The DCC-GARCH model is similar, in which the effect of shocks is flexible, since a shock in one asset affects the volatility of another related asset [32]. Despite the growing literature on interlinkages across commodity markets, much remains to be done [33]. To begin with, large-scale studies, such as bank stress tests, examine the entry of foreign funds [34]. These are high-level studies that will not have implications for emerging market investors [35]. As a major consumer of crude oil and a significant player in the gold and base-metal markets, India is an important economic case [36]. Additionally, earlier literature primarily delves into oil–gold or oil–metal linkages; however, fewer studies simultaneously consider oil, gold, and copper within a joint dynamic framework [37]. Another limitation is that many studies rely solely on mean spillover models or on volatility models, rather than integrating both dimensions into a coherent empirical strategy [38].

In this context, the current study explores the interlinkages between the price and volatility of the crude oil, gold, and copper markets using a comprehensive VAR–DCC-GARCH framework [39]. Using daily data from 2017 to 2023, the study first examines the statistical characteristics of commodity returns and tests for stationarity. The mean spillovers and directional predictability are examined using a VAR model and Granger causality tests, with impulse response functions tracing the effects of shocks. Volatility dynamics are modelled using univariate GARCH specifications, and the DCC-GARCH captures the time-varying correlations [40]. This study contributes to the literature in three ways. To begin with, it provides strong evidence on return and volatility spillovers across crude oil, gold, and copper within a unique multivariate framework. Also, the use of the DCC-GARCH approach highlights changing correlations over time, providing a better understanding of the stability of diversification benefits in commodities. The third contribution is India-specific and has important implications for portfolio allocation, hedging strategies, and risk management in emerging markets.

2. Review of Literature

The interdependence of commodity markets has been examined through the persistence of volatility and transmission between markets. The methodological foundation of this work starts with the evolution of conditional heteroskedasticity models [11]. The pioneering studies on volatility established that financial and commodity returns exhibit clustering and persistence, which motivated the original proposal of the ARCH framework and its later generalization in the rather simple GARCH class [6]. Due to prolonged time-varying risk modelling shocks (macroeconomic or geopolitical), causing periods of high volatility in commodities, this line of work became especially relevant. Extensions that followed claimed that volatility processes were not simply statistical artifacts but rather reflected information flows and market microstructure effects that shaped how shocks were absorbed and propagated across related assets. Following this, a large empirical literature employed GARCH-type models as a baseline for commodities, or at least as a first step, before tackling multivariate dependence. As scholars began moving beyond single-series volatility, the focus shifted from how volatile markets are to how increasingly connected they are.

In this regard, the Dynamic Conditional Correlation model made a decisive step forward by permitting correlations to evolve while keeping the covariance structure manageable [12]. Blending univariate GARCH dynamics with a correlation-updating mechanism enabled the DCC models to support a formal study of the changing co-movement that investors observe in turbulent times. It is more crucial in commodity portfolios, as one can lose the benefits of diversification precisely when risk management is needed most. In addition to the DCC approach, networks of spillover research employed multivariate time-series frameworks to quantify shocks propagating across markets. One of the most widely used benchmarks is the spillover index framework based on VAR forecast-error variance decompositions. This framework focuses on directional transmission and system-wide connectedness, rather than static association [9]. The DCC- and VAR-based spillover approaches, taken together, offer a modern empirical toolkit for studying return spillovers and volatility clustering coherently while allowing for time-varying interdependence. Within this methodological framework, crude oil often serves as the primary shock transmitter due to its macroeconomic significance. Research shows that the demand and supply shocks have differing effects on asset classes and industrial commodities. The source of price shocks matters, according to Bollerslev [7]. According to related macro evidence, oil shocks are related to the dynamics of the business cycle and inflation expectations.

Oil prices contain a lot of information about broad economic conditions. This information can spill over into metals and pro-cyclical and safe-haven assets through several channels. This macro channel is particularly important for copper, which is often interpreted as an indicator of industrial activity and global growth expectations. Consequently, several studies forecast that oil–copper connections will become even stronger under the dominance of (growth) expectations, and weaker or more unstable if supply disruptions drive (oil) movements. The relationship between oil and gold, however, has been characterised as more state-dependent and as a function of uncertainty and investor behaviour. According to Baur and Lucey [4], gold can be seen as a hedge (effective on average) and a haven (effective during market stress), and empirical evidence shows that it does not perform these roles consistently across regimes. As work further reveals, gold protection is contextual, that is, it's conditional on a measure of stress and the type of market shock considered. In other words, the gold–oil connection signs and strength flip sign according to the episode. In other words, research on broader sets of assets suggests that safe-haven characteristics are episodic and may weaken when uncertainty spreads globally (i.e., correlations increase and hedging effectiveness weakens). To sum up, it is necessary to model commodity linkages using time-varying dependence rather than long-run correlations.

The "financialization" hypothesis provides a key structural reason for stronger cross-commodity co-movements. Increased participation by financial investors and index-linked strategies can lead to greater commodity co-movement, especially during periods when portfolio flows dominate fundamentals [29]. This perspective helps us understand why correlations may rise, even between perfectly different commodities. Research finds that correlations among commodities change considerably over time and often strengthen under stress, consistent with financialization and global risk-on/risk-off behaviour [28]. This evidence supports a temporal specification in empirical analyses of oil, gold, and copper, allowing correlation and spillover measures to vary over time rather than treating interdependence as a fixed structural parameter. Studies show that the nature of uncertainty and macro-financial conditions can intensify spillovers. Research on commodity linkages in the presence of uncertainty indicates that oil price volatility transmits through the macroeconomic channel and risk sentiment. As a result, it affects other markets through expectations and precautionary behaviour. According to Sadorsky [26], commodity–financial system linkages are stronger in tumultuous times, suggesting that the measure of dependence estimated in tranquil times understates systemic co-movement (a.k.a. co-movement that matters).

The oil-shocks connection study of asset co-movement shows increased integration during periods of stress. This emphasizes that models need to incorporate both changing dependence structure and volatility persistence simultaneously. Researchers increasingly use techniques that measure changes in dependence over time to study hedging and diversification, because these interdependencies vary throughout time. According to oil–gold studies, dependence can vary across market states, producing changing hedging opportunities and, at times, short-lived diversification benefits. It is worth noting that many commodity-return distributions are non-normal, heavy-tailed, and prone to extreme events. The empirical regularity that this gives rise to is precisely why one often sees recommendations against furthering volatility models and robust inference, especially when dealing with multivariate datasets. Often, these multivariate datasets can manifest abuses of inference due to scale- and persistence-sensitivity [21]. The fact that these distributional features are not marginal for DCC-GARCH is significant. It is quite well-known that likelihood-based estimation and dynamic correlation updates are affected by heavy tails and volatility clustering. For this reason, robust standard errors and diagnostics are heavily emphasized in high-quality work. Despite their differences, two limitations stand out in oil–gold–copper interactions, despite extensive research on commodity linkages. First, much of the evidence focuses on pairwise relationships or examines commodities with widely used global benchmarks, without integrating mean spillovers, volatility persistence, and time-varying correlations within a single empirical design [27].

Next, fewer studies articulate the results for emerging-market investors who face exposure channels (import dependence, inflation pass-through, currency sensitivity) that can make commodity co-movement mean something different. These gaps motivate an integrated approach in which a VAR framework characterizes mean spillovers and directional predictability. At the same time, GARCH processes capture persistent conditional variance and DCC dynamics summarise evolving correlation structures. A combination of methods is preferred in connectedness research to achieve robustness in inference [13]; [10]. However, their individual efficacy remains open to question. The current study extends the methodological and empirical insights of prior research by jointly examining crude oil, gold, and copper returns, leveraging the VAR-DCC-GARCH framework. Our goal goes beyond static correlation and isolated spillover tests. Instead, researchers plan to identify (i) directional mean spillovers and impulse propagation using VAR-based tools, (ii) the contribution of univariate GARCH components to volatility persistence, and (iii) DCC parameters driving shock sensitivity and correlation persistence [29]; [28]. By connecting the oil- and growth-related commodity macroeconomic mechanisms, the haven arguments for gold, and the financialization-driven co-movement, this integrated review will provide a coherent basis for your empirical strategy and the investor implications for India that follow [4]; [25].

3. Methodology

3.1. Data Description and Return Construction

This research investigates the dynamic linkages among markets for crude oil, gold, and copper futures using daily data from 3 January 2017 to 27 November 2024, covering different phases of global financial distress, commodity cycles, and post-COVID normalization. Crude oil futures (WTI), gold futures, and copper futures are quoted in USD. This allows for a like-for-like comparison and avoids distortions. To eliminate non-stationarity and scale effects, prices are transformed into daily logarithmic returns given by:

$$R_t = \ln(P_t) - \ln(P_{t-1})$$

Where P_t denotes the closing price on day t. The use of log returns aligns with standard practices in volatility modelling and enables an economically meaningful interpretation of percentage changes, particularly in high-frequency commodity markets.

3.2. Initial Statistical Tests

Before estimating the model, diagnostic tests are conducted to assess econometric validity. The Augmented Dickey–Fuller (ADF) test is used to assess the stationarity of the return series, which confirms that each series is stationary at levels. Thus, they can be used directly in a VAR and GARCH framework, respectively. The descriptive statistics and Jarque–Bera tests for distributional properties reveal highly excessive kurtosis and skewness in commodity returns, like other asset classes. The ARCH–LM test is used to test for volatility clustering and conditional heteroskedasticity. The rejection of the test across all series motivates us to apply GARCH-type models to estimate volatility, in line with advanced commodity spillover studies.

3.3. Vector Autoregression (VAR) Framework

A Vector Autoregression model is used to capture mean spillovers and short-run interdependencies among the returns of gold, oil, and copper. In contrast to univariate methods, which treat one variable as endogenous and the others as exogenous, VAR treats all variables as endogenous. Hence, VAR provides each market with the flexibility to react not only to its lagged values but also to shocks in other markets. The VAR(p) model can be expressed as:

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$$

The equation represents an autoregressive model with exogenous variables, where Y is a time-series dependent variable, c is a constant term, Φ_i are coefficients on lagged values, p is the autoregressive order, and ε_t is the error term. Y_t is a vector of returns on gold, oil, and copper. Φ_i is a matrix of coefficients. ε_t is a vector of innovations with covariance matrix Σ. Information criteria (AIC and SIC) are employed to select the optimal lag length. The VAR model provides the foundation for Granger causality tests and impulse response functions (IRFs), which show how a shock originating in one commodity affects others over time.

3.4. Univariate GARCH Modeling

After the VAR estimation, the conditional variances of each commodity return are modelled using a GARCH(1,1) specification. The equation for conditional variance is. This equation suggests that the variance (σ_t^2) of time t is determined by the sum of a constant omega, the previous squared error term, and the previous time t variance, which has a t-1 time subscript. Thus, the equation of variance of GARCH (1, 1) can also be referred to as that of ARCH (1), where the error term must be normal. More complex cases can be modeled by increasing p and q:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

α reflects the presence of short-lived shocks (the ARCH effect) while β captures volatility persistence (the GARCH effect). When α+β' is close to one, this indicates long-memory behaviour. This long-range dependence characterises the behaviour of several commodity data series during periods of uncertainty. The residuals from these univariate GARCH models are used for the multivariate correlation analysis.

3.5. Dynamic Conditional Correlation (DCC-GARCH) Model

The analysis, carried out using the two-step Dynamic Conditional Correlation (DCC-GARCH) model by Engle, helps examine time-varying correlations and volatility spillovers. In the first step, estimated from the univariate GARCH (1,1) model, conditional variances, and in the second step, modeled dynamic correlations as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1}$$

Where Qt is the time-varying covariance matrix of standardized residuals, Q¯ is the unconditional covariance matrix, and θ1 and θ2 represent short-run and long-run correlation dynamics, respectively. Ensure stability with: θ_1+θ_2<1. As a result, researchers get the normalized correlation matrix. R_t is equal to D_t raised to the power of negative one-half, multiplied by Q_t, multiplied by D_t raised to the power of negative one-half. D_t is the diagonal matrix of conditional standard deviations. This framework enables the dynamic evolution of correlations between the gold–oil, gold–copper, and oil–copper markets in response to the ongoing market shocks. This feature makes it ideal to analyze commodity financialization and spillovers.

3.6. Impulse Response Analysis

Along with correlation analysis, impulse response functions (IRFs) of the VAR model are used to trace out the response of each commodity return to a one-standard-deviation shock in another market over a given horizon. IRFs are constructed to measure the size, sign, and extent of shock transmission by differentiating between transient and permanent shocks.

3.7. Econometric Rationale

The joint modeling of mean spillovers, volatility dynamics, and time-varying correlations is possible through the VAR–DCC-GARCH framework. Due to its ability to capture non-linear dependence structures and evolving risk transmission over time, this integrated approach is increasingly adopted in high-quality research on commodity and financial markets.

4. Analysis

This section presents the empirical analysis of dynamic interlinkages among crude oil, gold, and copper markets using the VAR–DCC-GARCH framework. The analysis integrates mean spillover assessment, volatility persistence, and time-varying correlation dynamics to capture both short-run interactions and evolving dependence structures across commodities. By combining impulse response analysis with dynamic conditional correlations, this section highlights how shocks propagate and how co-movements adjust under changing market conditions. The results provide economically meaningful insights into risk transmission and diversification potential within commodity portfolios, particularly from an investor-oriented perspective.

4.1. Descriptive Statistics

According to Figure 1, the sample price of oil, gold, and copper shows the way forward. The three goods show distinct yet economically significant trends, indicating their distinct roles in the economy. The gold prices exhibit a constant upward trend, especially in the last part of the sample, which is consistent with the metal's character as a store of value in conditions of uncertainty and inflation. Copper prices are quite volatile in the short term, but in the long term, they mostly head in one direction. On the other hand, crude oil prices are highly volatile, swinging sharply, suggesting they are sensitive to geopolitical events, supply interruptions, and global energy demand. Due to price divergence, researchers have plausible grounds to suspect return interaction and volatility spillover heterogeneity across markets. The daily log-return series for crude oil, gold, and copper is shown in Figure 2.

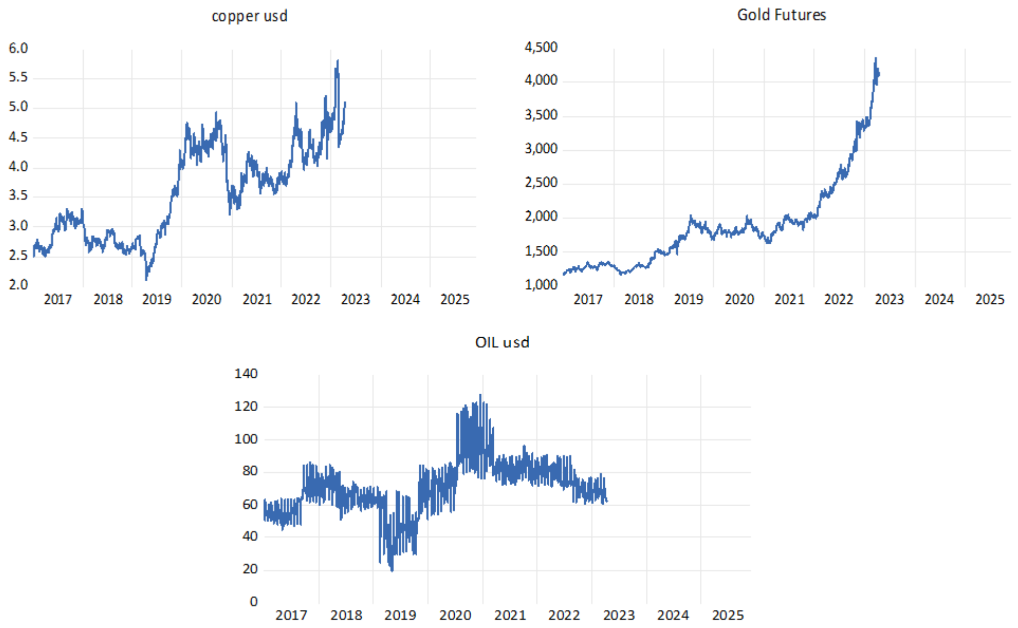

Figure 1: Price trends of crude oil, gold, and copper

The three-return series exhibits a zero mean, indicating the absence of deterministic trends before transformation and strong volatility clustering.

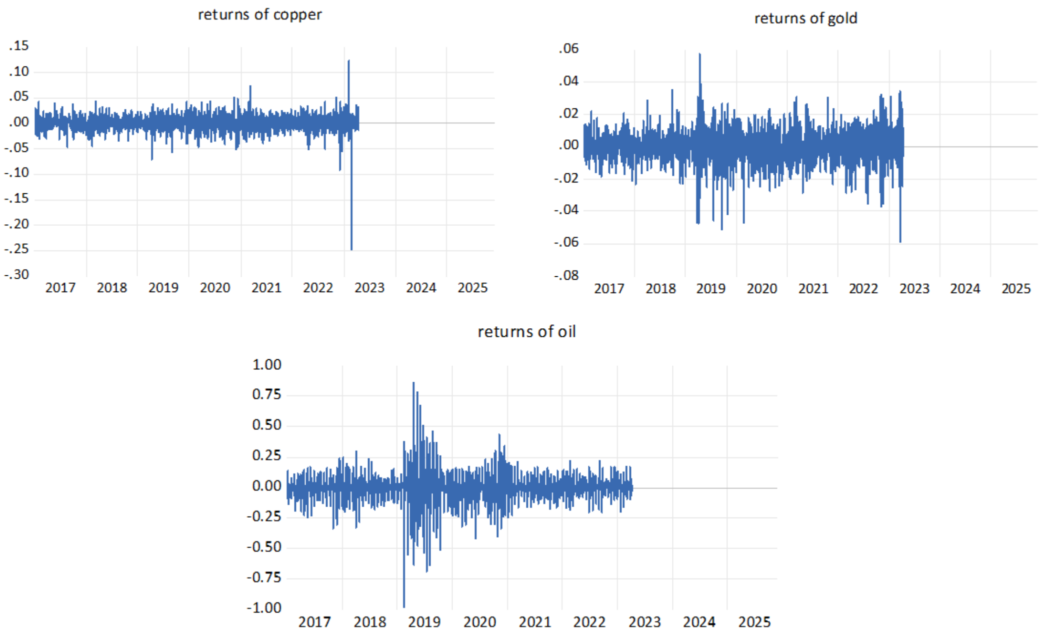

Figure 2: Daily log returns of crude oil, gold, and copper

Typically, in financial and commodities markets, there is calm after a period of high fluctuations. This is a stylized fact. Of the three, crude oil returns exhibit the highest amplitude and the most extreme observations, reflecting repeated shocks and rapid price adjustments in the market. Returns on gold appear quite stable, but intermittent spikes indicate episodes of market stress. Moreover, returns on copper exhibit moderate volatility due to the change in industrial demand expectations. Powerful empirical support for the use of GARCH-type volatility models and time-varying correlation models in later analyses is provided by the concentrations and non-normality of returns. Table 1 presents summary statistics of daily log returns for crude oil, gold, and copper over the sample period. A high-frequency financial return series is one whose means are close to zero. The average return of the three materials studied is close to zero. Of all the commodities, gold has a somewhat higher average return than copper and crude oil, suggesting that its price movements are more stable over time. Median returns are close to zero, indicating that extreme observations rather than ongoing trends drive the average return pattern. Commodities exhibit a wide range of return dispersion.

Table 1: Descriptive statistics of the selected commodities

Descriptive Statistics	RETURNS_OF_COPPER	RETURNS_OF_GOLD	RETURNS_OF_OIL
Mean	0.000314	0.000556	3.58E-05
Median	0	0.0005	0.002
Maximum	0.123	0.0578	0.864
Minimum	-0.249	-0.0591	-0.981
Std. Dev.	0.014977	0.009535	0.093421
Skewness	-1.984989	-0.309559	-0.471756
Kurtosis	39.42694	7.044274	22.04222
Jarque-Bera	128282.1	1599.316	34729.06
Probability	0	0	0
Sum	0.72	1.2743	0.082
Sum Sq. Dev.	0.514098	0.20839	20.00354
Observations	2293	2293	2293

Crude oil has the highest standard deviation, indicating it is particularly sensitive to supply shocks, geopolitical events, and changes in global energy demand. Copper and gold returns are relatively moderate in volatility. Copper is sensitive to industrial activity and growth expectations. While gold is less volatile than copper, it stabilizes BC's portfolios of commodity returns. All return series exhibit significant departures from normality, as evidenced by negative skewness and excessive kurtosis. The returns on copper exhibit pronounced left skewness, with a notably high kurtosis. The crude oil returns exhibit strong leptokurtic behaviour, indicating large price jumps during these periods. Gold excess kurtosis is less important but still significantly large. These properties indicate that more extreme movements occur than expected under normality. The Jarque-Bera statistics for all series at conventional significance levels reject the null hypothesis of normality. According to the authors, the empirical results show the existence of non-linear dynamics and heavy-tailed return distributions, which are not compatible with the constant-variance models currently used. As a result, it can be concluded that the observed statistical properties provide strong justification for employing GARCH-based volatility models and time-varying correlation frameworks to analyze spillovers and interdependencies among these markets.

4.2. Stationarity and Preliminary Diagnostics (ADF and ARCH Tests)

The daily return series for copper, gold, and crude oil are subjected to unit root tests, with the results reported in Table 2. All three commodities exhibit a unit root, which is strongly rejected at the 1% level, as the estimated ADF statistics are significantly below the respective critical values. Overall, the result suggests that the return series are stationary in levels, meaning they follow an I(0) process. This result was in line with the theory that asset returns fluctuate around a constant mean and do not trend. The stationarity of all series supports the suitability of VAR-based models for analysing mean spillovers and GARCH-type specifications for modelling volatility dynamics. This assessment ensures that spurious regression does not occur. The ADF findings would provide a solid statistical foundation for further investigation into the transmission of returns and the time-varying interdependence among the crude oil, gold, and copper markets.

Table 2: Augmented Dickey–Fuller (ADF) unit root test results

Variable	Test Form	Lag Length	ADF Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value	Stationarity
Returns of Copper	Constant	0	–48.980	–3.433	–2.863	–2.567	0.0001	I(0)
Returns of Gold	Constant	0	–49.666	–3.433	–2.863	–2.567	0.0001	I(0)
Returns of Oil	Constant	23	–13.213	–3.433	–2.863	–2.567	0	I(0)

4.3. VAR Model

The estimated VAR results of short-run mean spillovers among crude oil, gold, and copper returns are reported in Table 3. To sum up, the outcomes reveal that return interactions across these commodity markets are minimal, as most cross-market lagged coefficients are statistically insignificant. Thus, overall, lagged returns in one commodity do not systematically forecast contemporaneous returns in the others, suggesting weak mean transmission across these markets. The gold return equation indicates that their own lagged returns do not exert a statistically significant influence on any of these commodities or on copper's lagged return or on oil's lagged return. Gold returns tend to follow their own independent dynamics and are not very sensitive to short-term moves in the energy and industrial metal markets.

Table 3: VAR model mean spillovers among crude oil, gold, and copper returns

Vector Autoregression Estimates				
		Returns_Of_Gold	**Returns_Of_Copper**	**Returns_Of_Oil**
Returns_Of_Gold(-1)	Co-efficient	-0.034744	-0.041657	0.194742
	SE	-0.021	-0.03302	-0.19213
	t	[-1.65428]	[-1.26174]	[1.01359]
Returns_Of_Gold(-2)	Co-efficient	0.008613	-9.58E-05	0.224091
	SE	-0.02101	-0.03303	-0.19222
	t	[0.40990]	[-0.00290]	[1.16578]
Returns_Of_Gold(-3)	Co-efficient	0.000776	0.014637	-0.019097
	SE	-0.021	-0.03302	-0.19214
	t	[0.03693]	[0.44331]	[-0.09939]
Returns_Of_Gold(-4)	Co-efficient	-0.033708	0.029119	0.053439
	SE	-0.021	-0.03301	-0.19208
	t	[-1.60542]	[0.88221]	[0.27822]
Returns_Of_Gold(-5)	Co-efficient	-0.008293	0.031766	0.068752
	SE	-0.02099	-0.033	-0.19205
	t	[-0.39503]	[0.96254]	[0.35799]
Returns_Of_Copper(-1)	Co-efficient	-0.003819	-0.023353	0.294136
	SE	-0.01334	-0.02097	-0.12204
	t	[-0.28631]	[-1.11355]	[2.41016]
Returns_Of_Copper(-2)	Co-efficient	-0.015785	-0.011059	0.155392
	SE	-0.01336	-0.021	-0.12219
	t	[-1.18174]	[-0.52666]	[1.27167]
Returns_Of_Copper(-3)	Co-efficient	0.001733	0.032027	0.236134
	SE	-0.01336	-0.021	-0.12223
	t	[0.12973]	[1.52483]	[1.93193]
Returns_Of_Copper(-4)	Co-efficient	-0.00147	-0.00313	0.085215
	SE	-0.01337	-0.02101	-0.12229
	t	[-0.10999]	[-0.14895]	[0.69682]
Returns_Of_Copper(-5)	Co-efficient	0.008604	0.017761	-0.109783
	SE	-0.01337	-0.02102	-0.12231
	t	[0.64352]	[0.84504]	[-0.89759]
Returns_Of_Oil(-1)	Co-efficient	0.003394	-0.000475	-0.280968
	SE	-0.00229	-0.0036	-0.02096
	t	[1.48104]	[-0.13187]	[-13.4022]
Returns_Of_Oil(-2)	Co-efficient	0.000448	-0.000147	-0.338866
	SE	-0.00236	-0.00372	-0.02162
	t	[0.18948]	[-0.03944]	[-15.6707]
Returns_Of_Oil(-3)	Co-efficient	0.002713	-0.001688	-0.154917
	SE	-0.00246	-0.00387	-0.02252
	t	[1.10180]	[-0.43606]	[-6.87789]
Returns_Of_Oil(-4)	Co-efficient	-0.000293	-0.003757	-0.122558
	SE	-0.00236	-0.00371	-0.0216
	t	[-0.12398]	[-1.01227]	[-5.67430]
Returns_Of_Oil(-5)	Co-efficient	-0.002743	-0.001767	-0.061281
	SE	-0.00229	-0.0036	-0.02092
	t	[-1.19944]	[-0.49156]	[-2.92921]
C		0.000588	0.000284	-0.000357
		-0.0002	-0.00032	-0.00184
		[2.92056]	[0.89712]	[-0.19362]

This kind of behaviour has made gold insulated in terms of returns, as it often behaves like a safe-haven asset rather than a momentum commodity. On the other hand, the oil return equation shows signs of economically significant spillovers from copper. More specifically, the first lag of copper returns has a positive and statistically significant effect on oil returns. Movement in the industrial metal market was taken to have predictive information about energy prices. This connection likely arises from common macro fundamentals, such as global industrial demand and business-cycle conditions, which simultaneously drive copper and crude use. However, gold returns don't significantly affect oil returns, suggesting an asymmetric pattern of return spillovers. Ultimately, copper returns appear to be determined predominantly by their own past returns, whereas gold and oil returns are less so. Lagged copper coefficients were marginally significant for some sectors. Still, overall, the evidence suggested that copper market returns were more sensitive to sector-specific fundamentals than to feedback from precious metal or energy markets in the short run. The VAR results collectively suggest weak and selective mean spillover. This justifies further analysis on dynamic correlation and volatility transmission using the DCC-GARCH framework.

4.4. Granger Causality

The Granger causality and block exogeneity tests provide further insight into the directional return spillovers among the crude oil, gold, and copper markets. The results show that return interdependencies among these commodities are largely weak and asymmetric, and that the mean equations do not exhibit any systematic predictive relationships. The gold market does not consider the copper and crude oil return data, which do not Granger-cause gold returns, as evidenced by the Wald statistics' statistical insignificance. The findings indicate that gold returns are independent of short-term fluctuations in industrial metals and energy prices (Table 4).

Table 4: VAR Granger causality

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent Variable: Returns_Of_Gold			
Excluded	**Chi-sq**	**df**	**Prob.**
RETURNS_OF_COPPER	1.874018	5	0.8663
RETURNS_OF_OIL	5.462783	5	0.362
All	7.155752	10	0.7107
Dependent variable: RETURNS_OF_COPPER			
Excluded	**Chi-sq**	**df**	**Prob.**
RETURNS_OF_GOLD	3.49054	5	0.6248
RETURNS_OF_OIL	1.193508	5	0.9455
All	4.781585	10	0.9053
Dependent variable: RETURNS_OF_OIL			
Excluded	**Chi-sq**	**df**	**Prob.**
RETURNS_OF_GOLD	2.512267	5	0.7746
RETURNS_OF_COPPER	12.16235	5	0.0326
All	14.36386	10	0.157

These behaviours cement gold's unique status as a more autonomous asset, whose returns are less influenced by coincident dynamics in other commodity markets. Similarly, the copper market shows no Granger causality with gold or crude oil returns. The results show that no significant causality exists between copper and precious metals or energy, suggesting that market-specific fundamentals, such as industrial demand and supply-side conditions, determine copper price movements. The oil markets, however, show a remarkable difference. At conventional significance levels, researchers reject the null hypothesis that copper returns do not Granger-cause oil returns. The results indicate a one-way causation running from copper to crude oil returns, suggesting that developments in industrial metals contain predictive information about energy prices. The common drivers of global industrial activities and manufacturing demand are likely influencing both copper and oil use, suggesting a connection in that context. Regarding block exogeneity results, the three commodities exhibit limited mean spillovers, except for a copper-to-oil channel. The generally weak return causality justifies the need to go beyond mean dynamics. This provides a case for volatility-based models such as GARCH and DCC-GARCH, which capture time-varying risk transmission and co-movement across commodity markets.

4.5. Impulse Response Function Analysis

The impulse response analysis shows how commodity markets with similar characteristics react dynamically to unexpected shocks within and across markets. The reactions are flagged with confidence bands, noted over a ten-day horizon. When gold returns shift suddenly, its own market may respond sharply, only briefly. In the first period, the initial response is pronounced, but the effect soon diminishes and converges to zero in a few days. This behaviour indicates that the gold markets process information shocks efficiently, consistent with the view that gold prices do not persist strongly. Copper and oil returns' responses to gold stocks are rather low and statistically insignificant, suggesting weak cross-market transmission from the gold market in the mean equation. The copper market exhibits a strong own-response and limited influence on other markets (Figure 3).

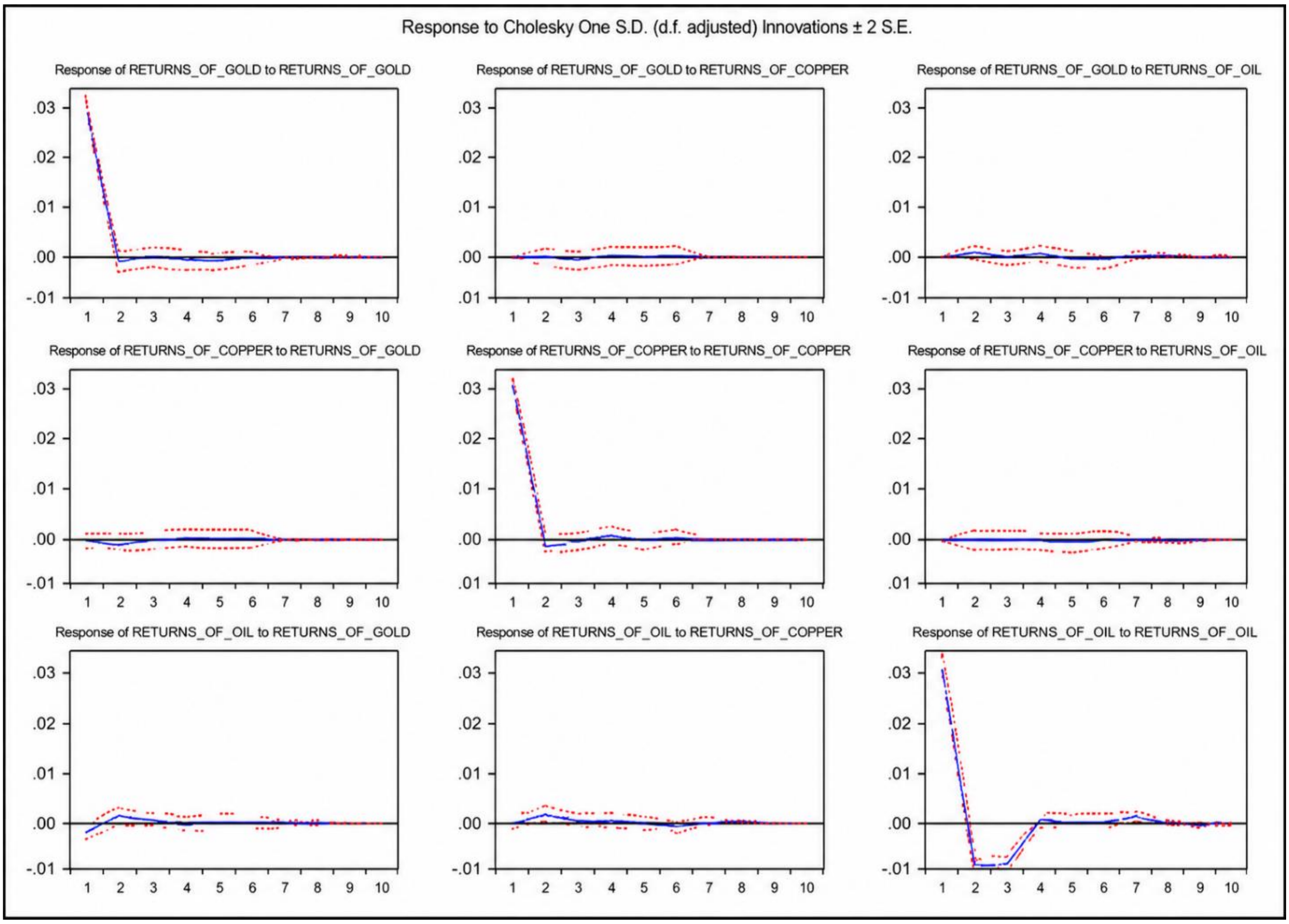

Figure 3: Impulse response function analysis

An innovation in copper returns leads to an immediate but quick adjustment, showing that the market can internalise shocks from both industrial demand and supply-side news. The impacts of copper shocks on the returns of gold and oil are minimal and may move within tight confidence bands. This implies that shocks to copper do not significantly change the returns of other commodity markets. On the other hand, shocks emanating from the crude oil market elicit stronger and longer-lasting responses, especially in oil's own returns. In the beginning, the reaction is highly negative, followed by successive corrections toward equilibrium. The endurance of oil illustrates its central role within the global system of commodity goods, of which energy price shocks have become more pronounced and enduring. The results for gold and copper returns to oil shocks are statistically weak, but the "trends" nevertheless show mild, transitory impacts, namely indirect exposure to energy-related macro conditions. In general, impulse response results suggest own-market shocks dominate return dynamics while cross-market spillovers in the mean are limited and short-lived. The convergence of responses to zero across all markets indicates the system's stability and the absence of return transmission. The findings extend the Granger causality investigation to volatility, allowing for the possibility that spillover effects operate through more time-varying risk and correlation structures.

4.6. Univariate GARCH (1,1) Estimation and ARCH Diagnostics for Commodity Returns

The estimates of copper, gold, and crude oil returns are presented in Table 5 using univariate GARCH (1,1) specifications. The ARCH (α) and GARCH (β) coefficients are significant for each series, confirming the presence of time-varying conditional heteroskedasticity. The returns on copper exhibit extremely high volatility persistence.

Table 5: Univariate GARCH (1,1) estimation and ARCH diagnostics for commodity returns

Variable	ω (Constant)	α (ARCH)	β (GARCH)	α + β	Log-Likelihood	AIC	ARCH LM (p-value)	Volatility Persistence
Copper Returns	5.78E-07***	0.02699***	0.97247***	0.99946	6489.83	-5.6579	0.2311	Very High
Gold Returns	2.23E-06***	0.05364***	0.92159***	0.97523	7555.62	-6.5875	0.2253	High
Oil Returns	0.00370***	0.44694***	0.21710***	0.66404	2438.09	-2.1239	0.8309	Moderate

The sum of the ARCH and GARCH parameters is nearly equal to one ($\alpha + \beta = 0.99946$). Thus, volatilities or shocks to volatilities do not dissipate quickly. The industrial metal market seems to remain under uncertainty due to demand-supply imbalance and macro sensitivity. The return volatility of gold also exhibits stronger persistence ($\alpha + \beta = 0.97523$), which is lower than that of copper, given that gold is an important commodity and a financial asset that absorbs shocks over the long term. In contrast, crude oil returns exhibit lower persistence ($\alpha + \beta = 0.66404$). This indicates that, though oil markets experience large, short-run shocks to volatility, the effect reverses more quickly.

Table 6: DCC parameter estimates

Parameter	Coefficient	Std. Error	Z-Statistic	p-value
θ_1 (Shock effect)	0.1569	0.0324	4.8392	0
θ_2 (Persistence effect)	0.7734	0.0557	13.8765	0
$\theta_1 + \theta_2$	0.9303	—	—	—

The ARCH LM test results indicate that there are no remaining ARCH effects in the standardized residuals. Consequently, it can be inferred that the GARCH (1,1) model captures the conditional volatility dynamics of all three commodities sufficiently. Consequently, these findings justify the further application of a multivariate DCC-GARCH framework to assess time-varying volatility spillovers and dynamic correlations among the selected markets.

Table 7: Model diagnostic

Statistic	Value
Log-Likelihood	−2677.84
Average Log-Likelihood	−1.9489
Akaike Information Criterion (AIC)	7.8777
Schwarz Criterion (SC)	7.9003
Hannan–Quinn Criterion (HQ)	7.8559
Stability Condition	Satisfied ($\theta_1 + \theta_2 < 1$)

Table 6 presents the estimated parameters of the DCC-GARCH (1,1) model, which captures the time-varying correlations among crude oil, gold, and copper returns. The shock parameter (θ_1) is positive and statistically significant. An unexpected shock in one commodity market will immediately transmit its influence on the conditional correlations with all other markets. The persistence parameter (θ_2) is much larger and significant, indicating that correlations are strongly persistent after the shock adjusts. The conclusion that $\theta_1 + \theta_2$ is less than 1 confirms that the dynamic correlation process is stable and that the DCC model is appropriate for modeling time-varying dependencies. Table 7 shows the comprehensive diagnostic statistics of the DCC model.

Table 8: Univariate GARCH (1,1) and DCC-GARCH (1,1) estimation results

Model Component	Parameter	Copper	Gold	Oil
Univariate GARCH (1,1)	ω (Constant)	5.78E-07***	2.23E-06***	0.00370***
	α (ARCH)	0.02699***	0.05364***	0.44694***
	β (GARCH)	0.97247***	0.92159***	0.21710***
	α + β	0.99946	0.97523	0.66404
	Log-Likelihood	6489.83	7555.62	2438.09
	AIC	−5.6579	−6.5875	−2.1239
	ARCH LM (p-value)	0.2311	0.2253	0.8309

The adequacy of the model is reinforced by the log-likelihood and information criteria values, as well as by the satisfaction of the stability condition for the estimated dynamic correlation. The diagnostics suggest that the DCC-GARCH specification successfully captures the joint volatility–correlation structure of selected commodity markets for the sample period. The first step in DCC estimation involves univariate GARCH (1,1) estimates, which are reported for each commodity in Table 8. The ARCH and GARCH coefficients for copper and gold returns are found to be positive and highly significant, with the sum of the volatility parameters close to unity. Volatility persistence is significant, suggesting that volatility shocks persist over time. By contrast, the conditional variance of the crude oil market shows lower persistence, suggesting faster mean reversion. The ARCH LM test statistics for all series are not statistically significant, confirming that there are no remaining ARCH effects and that the fitted GARCH models are appropriate. The findings from Tables 6-8 indicate strong volatility clustering in each of the commodity markets under consideration and time-varying, highly persistent correlations across the markets. These findings indicate the presence of evolving volatility spillovers and linkages among crude oil, gold, and copper. The findings have important implications for portfolio diversification, risk management, and commodity-based hedging in India.

5. Conclusion

Through a VAR–GARCH–DCC framework, the study inspects the price-volatility interrelationship of crude oil, gold, and copper markets over time. By using the daily data, this study integrates linear dependence, short-run spillovers, volatility clustering, and time-varying correlations in a unified framework. According to the empirical findings, the price return spillovers between these commodities are limited. In contrast, volatility spillovers are persistent and time-varying, suggesting the value of modeling higher-order dependence structures. The stationarity results indicated that all return series are mean-reverting, enabling multivariate modeling. Commodity returns are highly kurtotic and negatively skewed, according to descriptive statistics; hence, models of conditional heteroskedasticity are relevant. The VAR estimates indicated weak short-run return transmission among markets. And Granger causality results further confirmed that they mainly show a one-way influence from copper to crude, without much feedback effect involving gold. The findings suggest that price discovery in the chosen commodities occurs through indirect, asymmetric channels rather than through powerful contemporaneous return spillovers. On the other hand, the volatility analysis revealed a different story. The univariate GARCH results reveal high volatility persistence in the copper and gold markets, whereas crude oil shows lower persistence and faster volatility adjustment.

The estimates from the DCC-GARCH model give evidence that correlations are time-varying. Both the shock and persistence parameters are significant, meaning that shocks to correlations will have immediate effects but will wear off slowly. The benefits of commodity diversification are not constant, as they tend to weaken during periods of heightened market stress. The overall finding indicates that volatility spillovers, rather than return spillovers, are the main channel of connection among the crude oil, gold, and copper markets. In practice, these findings are useful to investors, portfolio managers, and policymakers. Static hedging approaches may not serve a commodity portfolio well. Indeed, the correlation structure evolves in response to global shocks. Financial risk, exacerbated by cross-commodity volatility transmission, should also be of utmost concern to policymakers and market regulators, especially during turbulent times. By jointly modeling returns, conditional variances, and dynamic correlations, this study contributes to the literature on commodity market connectedness and provides a deeper understanding of inter-market risk transmission. In future studies, researchers may propose regime-switching behaviour, examine higher-frequency data, or incorporate macro-financial variables within this framework to further examine global and domestic forces affecting commodity market integration.

5.1. Limitations and Scope for Future Studies

While this study sheds light on the interdependencies among the crude oil, gold, and copper markets, it still suffers from certain limitations that may be addressed in future studies. Initially, when daily return data is used, it does not exploit intraday information flows or high-frequency volatility transmissions. In the future, studies could use intraday or high-frequency data to examine how information is incorporated into commodity prices over shorter time horizons in busy markets. Also, the empirical framework is specified as a VAR–DCC-GARCH model under the multivariate normal assumption. While this methodology captures time-varying correlations and volatility clustering, it may understate tail dependence during extreme market events. Future research could extend to other distributional assumptions, functions such as Student-t, skewed distributions, and/or the application of copula-based modelling to capture asymmetric and nonlinear dependence structures. To begin with, the study limits itself to three important commodities, which, while economically significant, constitute only a subset of the other commodities. In future research, it may be possible to identify additional commodities, such as natural gas, agricultural products, and industrial metals, to measure spillovers and diversification across the whole set of commodities. Fourthly, the model does not capture structural breaks, policy interventions, and other macroeconomic and geopolitical variables that affect commodity prices. Using regime-switching models, time-varying parameter VARs, or exogenous macro-financial indicators can help us gain a deeper understanding of the connectedness of the commodity market in the presence of shocks. In the end, the study does not assess optimal hedges or portfolio volatility, even though it shows spillovers and dynamic correlations. Future research could focus on hedge-ratio estimation for the pricing of risky assets, risk-adjusted portfolio analysis, or the development of downside risk measures, yielding actionable findings for investment and risk management. In conclusion, mitigating these limitations would enhance the robustness of the empirical findings, leading to a better understanding of commodity market integration and risk transmission in a globalized financial system.

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