
Global risk transmission in GCC markets

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Abstract

This study analyses the transmission of global risk across global markets (MSCI US, Brent crude oil, and MSCI Gold) and the Gulf Cooperation Council (GCC) region from January 2009 to November 2024. The study uses a dual econometric framework: first, calculating extreme downside risk with a DCC-GARCH model, and then capturing the direction and magnitude of risk spillovers with a TVP-VAR model. The analysis helps determine how the relationships between these indices evolve during periods of global financial crises and uncertainty. Results show that GCC markets are highly vulnerable to external shocks and predominantly net recipients of risk. The US market emerges as the strongest net transmitter of volatility, especially during periods of crisis. Brent crude oil serves as both a transmitter and a receiver of risk, while gold serves as a shock absorber and remains a safe-haven asset. Robustness checks using alternate specifications confirm the reliability of these findings.

Keywords: Global markets; GCC markets; Tail risk; Time-varying connectedness; DCC-GARCH; TVP-VAR; Volatility transmission; Emerging markets.

JEL Classification: C32, C58, G01, G15, F36

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1. Introduction

Global financial stability has been extremely fragile in recent years as markets react instantaneously to shocks. Modern financial systems operate as highly interdependent networks, and incidents like the pandemic show how volatility in one node can instantly spread across global markets. This interdependence is particularly pronounced between global financial markets and energy markets. When oil prices fall, fiscal balances in oil-dependent economies strain; rising gold prices signal a collective move to safety; and shocks to equity markets affect liquidity worldwide. These interactions show that the stability of these economies relies heavily on the dynamics of financial markets. Within this fragile structure lie the GCC markets that are influenced by both oil and global capital flows. Analyzing these markets offers a unique perspective on how global risk affects emerging, oil-dependent economies.

The growing interconnectedness of global markets has caused shocks to rapidly propagate from major markets, thereby affecting asset prices and volatility worldwide, and the stock markets of the GCC are no exception. However, unlike most other economies, these oil-rich nations are exposed to two distinct types of risk. In addition to the financial market turbulence that affects all economies, they are also vulnerable to fluctuations in the commodity market due to their



dependence on oil production. Understanding global risk transmission into the GCC markets is important not only for investment decisions and policy-making, but also for international portfolio stability, as GCC markets are becoming a larger part of global indices.

A comprehensive understanding of global risk transmission and its economic impact depends on the concepts of volatility spillovers and dynamic connectedness, which are central to explaining how risks propagate across markets. In financial econometrics, a substantial portion of the literature shows co-movement in volatility across markets and that shocks arising in one market are transmitted to others. Multivariate GARCH models allow us to study time-varying conditional correlations and volatility spillovers (Bollerslev, 1986; R. Engle, 2002). Engle's dynamic conditional correlation (DCC) framework, for instance, has become a standard method for capturing the dynamic connectedness among different assets. In emerging markets, it is well documented that volatility shocks from developed markets or commodity markets are often strongly transmitted to local markets. For example, Guesmi and Fattoum (2014) studied the positive co-movement of oil prices and stock markets during global shocks. They concluded that oil, unlike gold, is not a safe haven during turmoil. Likewise, studies done in emerging Asian and BRICS markets also report significant volatility transmission from major global players (e.g., Bouri et al., 2017). In the GCC context, studies confirm that global oil volatility, US market volatility, and even geopolitics have spilled over into GCC markets. Alqahtani and Chevallier (2020) and Mensi et al. (2016) each observed strong volatility transmission into the GCC markets. These studies further confirm the influence of financial and commodity-driven shocks in the region. However, there is no comprehensive study analyzing global equity, oil, and gold markets and their influence on GCC. This gap motivates the present study, which uses MSCI US, Brent oil, and MSCI Gold indices as proxies for global risk factors to examine their impact on GCC stock markets.

The GCC's economic and financial significance makes it an ideal setting for studying global risk transmission. Oil revenues are a major source of funding for both government budgets and corporate activities. At the same time, GCC markets have also been expanding and becoming more exposed to the global markets. While this has established a strong global presence for these markets, it also means external shocks can quickly affect them. Factors such as trade openness, financial market liberalization, and large investments abroad have made the GCC more interconnected with the global economy (Alotaibi & Mishra, 2017). Given this context, the current study uses three major global indices as proxies for risk: the MSCI US stock index, Brent crude oil, and the MSCI Gold index. These proxies capture different aspects of how global factors affect this region, and together they help us better understand the global transmission of risk across GCC markets.

Despite the extensive literature on volatility spillovers and connectedness in the GCC region, several important gaps remain to be addressed. Firstly, many of the previous studies are narrow in scope. They either focus on a single external factor that transmits risk across the region, or on only a select few GCC markets and their relationship with a single global factor. Secondly, several limitations exist in previous studies. A significant number of studies use rolling-window techniques or constant-parameter models that may not fully capture volatility dynamics. Third, many empirical studies on the GCC's global interconnectedness focus on specific events. Several of the frequently cited papers use data that ends in the early or mid-2010s, thereby excluding critical events. The literature is only just beginning to study a longer range of period for the GCC region.

This study aims to address the above gaps by providing a comprehensive analysis of global risk transmission across GCC stock markets using advanced econometric techniques. The core research question we aim to address is how volatility shocks from major indices transmit to GCC equity markets and vice versa, and how these relationships may have evolved over time. To address this, we measure the dynamic correlation between GCC stock markets and the chosen global indices to identify periods of heightened interconnectedness. Once isolated, we try to quantify the magnitude and direction of volatility spillovers to differentiate between the net transmitters and net receivers of risk. We then compare the dynamics of these periods with those of tranquil periods to see how external shocks affect this region. Based on this analysis, we draw implications for portfolio diversification, risk management, and policies in the GCC region. To achieve these objectives, we use a two-step analysis that uses two advanced econometric frameworks in tandem. We first use the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to measure risk and identify volatility periods at the 5% VaR. Next, we use a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to capture the dynamic nature of connectedness between these indices. This combination addresses the potential shortcomings of each model and provides a holistic view of risk transmission in the region.

The contributions of this research are both empirical and methodological, with significant implications for academics and policymakers. Unlike prior studies that examine one or two factors, we simultaneously examine the influences of US equity, oil, and gold on the GCC stock markets, and vice versa. To our knowledge, very few studies have simultaneously examined the impact of MSCI US, Brent crude oil, and gold on MSCI GCC using a DCC-GARCH-TVP-VAR framework, and this study aims to contribute to that emerging strand of the literature. Our study also covers all major events that could affect GCC markets since their liberalization. By identifying the extent of shock transmission, this study will help policymakers and regulatory authorities better understand how to safeguard financial stability in this region. Using this clear map of risk flow, regulators can better anticipate systemic vulnerabilities and develop strategies to mitigate contagion risk before it destabilizes markets.

The rest of this paper is organized as follows. Section 2 details previous studies in this regard and the rationale for our chosen set of indices. Section 3 outlines the econometric methodology used to visualize risk and quantify directional connectedness. In Section 4, we present the descriptive statistics and diagnostics. Section 5 presents the empirical results, reporting VaR-based tail-risk dynamics and directional spillovers and discussing their implications. Section 6 offers robustness checks using alternative lag selections and estimation windows to validate the results. Finally, Section 7 concludes with the main findings, policy implications, and directions for future research.

2. Literature review

The concept of volatility spillover has been extensively studied to understand and quantify the propagation of shocks across markets. Hamao et al. (1990) first uncovered significant interconnectedness across major international markets- New York, London, and Tokyo, with New York being the major transmitter of risk. They used an Autoregressive Conditional Heteroskedasticity (ARCH) framework to observe how the degree of this linkage intensified specifically during the 1987 stock market crash. Their studies laid the foundation for research on volatility spillovers and risk transmission. Most of the extensive research on this phenomenon has been conducted using ARCH and GARCH models proposed by Engle (1982) and Bollerslev

(1986). Since then, multivariate extensions of GARCH models have helped deepen the analysis of market interconnectedness and volatility spillovers.

Early studies on GCC financial markets began confirming the presence of interconnectedness by the mid-2000s. For example, Hammoudeh and Choi (2007) provided initial evidence that shocks in global oil markets are significantly transmitted to GCC stock markets. They used a GARCH framework to show that uncertainty in oil prices was the major cause of market volatility in the GCC region. Similarly, Al Janabi et al. (2010) used a VAR-GARCH model to examine return and volatility spillovers between major markets, including the US and GCC markets. They observed that international diversification failed for GCC investors during periods of market stress, as market correlations increased sharply. Building on this foundation, Abuzayed and Al-Fayoumi (2021) extended this observation to the COVID-19 period and found significant, intensified spillovers from crude oil prices to GCC stock returns during the pandemic. This shows that the influence of oil in these regions, previously identified in earlier studies, remained economically significant.

Recent literature on GCC markets reveals how global and regional shocks were modeled using advances in financial econometrics. Foundational multivariate volatility models serve as the basis for much of this research. For example, the constant-correlation multivariate GARCH (CCC-GARCH) by Bollerslev (1990) and the BEKK-GARCH by Engle and Kroner (1995) were among the early frameworks that helped understand interconnectedness and volatility spillovers across markets. Engle (2002) later introduced a DCC model, which became popular to capture time-varying correlations among assets. In parallel, Diebold and Yilmaz (2009, 2012) developed another approach to quantify spillovers using vector autoregressions. They proposed a connectedness index based on generalized forecast-error variance decompositions from a VAR model. While studies using this framework have found it particularly useful, the original methodology relies on a rolling-window VAR estimation with an arbitrary window length. To overcome this limitation, Antonakakis et al. (2020) introduced the time-varying parameter VAR (TVP-VAR) models that treat spillovers as dynamic, thereby better capturing them during abrupt changes. Since then, many studies have adopted a framework that combines GARCH and TVP-VAR models to track financial contagion in real time (e.g., Gabauer & Gupta, 2018; Shahzad et al., 2023). Many studies done in the GCC region have used these models to understand how global factors drive stock volatility in these markets. For example, Arouri et al. (2011) used a VAR-GARCH approach to study significant bidirectional return and volatility transmission between oil prices and GCC stock indices. Awartani and Maghyereh (2013) used the Diebold-Yilmaz spillover index to further examine this relationship and found that risk transmission is bidirectional, with oil predominantly serving as the risk transmitter. Al-Yahyaee et al. (2019) examined this further by examining a range of commodity markets that could transmit risk into the GCC region. Arouri and Fouquau (2009) found significant responses to oil shocks in Qatar, Oman, and the UAE, but the response was muted in Bahrain, Kuwait, and Saudi Arabia. They attributed these differences to differences in economic structures and diversifications. Ziadat and AlKhouri (2022) studied volatility spillovers across GCC markets and confirmed the region's sensitivity to external shocks. Yousaf et al. (2022) showed that both the magnitude and direction of spillovers between GCC markets and global factors changed significantly between normal and crisis periods. From a geopolitical perspective, Shahzad et al. (2023) documented that geopolitical risk drives connectedness between commodity and financial markets, as GCC markets are exposed to both oil and global equity cycles. Most recently, Hanif et al. (2026) examined how GCC equity markets

interact with US and European debt markets. They highlighted the region's growing integration with global fixed-income systems beyond the traditionally studied equity and oil channels.

More recently, Al-Fayoumi et al. (2023) incorporated a TVP-VAR connectedness framework to analyze the impact of oil price shocks on the GCC equity markets. They found that demand-side shocks generated the strongest spillovers. Kapar et al. (2024) used frequency-domain TVP-VAR connectedness to study spillover dynamics within the GCC region. They found that crisis periods significantly increased spillovers across regions, and that the UAE and Qatar were dominant risk transmitters within the bloc. Younis et al. (2025) examined the connectedness among energy, gold, and GCC stock markets across multiple crisis episodes and concluded that the GCC region predominantly remained a net receiver.

Despite the extensive literature on volatility spillovers and connectedness in the GCC region, several gaps remain. First, many of the previous studies have a narrow focus. Our study explicitly addresses this issue by simultaneously examining spillovers from three major global indices into GCC markets. Second, until recently, research has focused either on major assets or safe-haven assets. These two assets have not been studied together and therefore lack a holistic perspective, which our study aims to provide. Third, advanced econometric techniques, such as those used in our study, have not been applied to this market to date. Fourth, most previous studies have covered specific crisis periods, whereas ours covers all of them. By using a larger range, we also observe the evolving nature of volatility through time that other studies have failed to capture. Finally, while it is evident that the GCC markets are globally integrated, the extent of this integration remains a matter of debate. Our study aims to quantify the degree, direction, and intensity of this global interconnectedness, specifically during periods of financial stress and uncertainty. Motivated by these gaps, we use three major risk proxies – a global equity index (MSCI US), an oil benchmark (Brent crude oil), and a safe-haven asset (gold)- and examine them simultaneously within a unified framework. We use a dual methodology to conduct this study: the DCC-GARCH model and a TVP-VAR spillover index model. The DCC-GARCH (calculated at 5% VaR) helps us identify periods of intense volatilities, which the TVP-VAR model then quantifies how shocks to one market contribute to volatility in others at each point in time.

Based on the evidence above, we present two testable hypotheses. Given the structural dependence of GCC economies on oil revenues and the documented dominance of US equity markets as global risk transmitters (Diebold & Yilmaz, 2012; Hamao et al., 1990), we hypothesize that:

H1. GCC markets act as net receivers of risk across the full sample period.

Given that prior studies consistently documented how spillover intensity rose sharply during periods of financial stress (Antonakakis et al., 2020; Yousaf et al., 2022), we hypothesize that:

H2. Risk transmission into GCC markets intensifies significantly during global crisis periods.

To our knowledge, this is one of the few studies to consider this particular combination of markets and factors in one unified volatility analysis for the GCC with an extended sample period. Our results will shed light on whether GCC's global connectedness has been growing and help isolate the dominant transmitters of risk.

3. Data and methodology

This study examines the transmission of shocks into the GCC equity markets by using the MSCI GCC Composite index as a regional benchmark. This index aggregates the performance of GCC markets, capturing regional movements while controlling for differences in individual market structures. The chosen sample period spans January 2009 to November 2024 and covers all major global crisis episodes, enabling the analysis to efficiently capture risk transmission. The global sources of risk are factored in using MSCI US and Brent Crude Oil as proxies, while MSCI Gold is used to assess whether it is a true safe-haven for investors. The analysis is conducted in two steps. In the first stage, the DCC-GARCH model (Engle, 2002) is applied to estimate tail risk at 5% VaR. In the next step, a TVP-VAR framework is used to measure the directional and net volatility spillovers among the chosen risk proxies. This dual approach helps us understand how shocks originating in the US equity, oil, and gold markets are transmitted to and from the GCC equity market. It reveals not just the strength of these linkages but also how they vary across different global crisis periods. The following subsections describe each framework in detail, offering a comprehensive understanding of how global shocks are transmitted to and absorbed by the GCC equity markets.

3.1. GARCH-based dynamic conditional covariance

To examine the time-varying conditional volatility, the two-step DCC-GARCH model by Engle (2002) is used. Each return series is pre-filtered using a univariate AR(1) mean specification. Univariate GARCH (1,1) models are estimated for each series, and the standardized residuals are then used to model the dynamic conditional correlations. The DCC-GARCH(1,1) model can be written as follows:

$$y_t = \mu_t + \epsilon_t \quad \epsilon_t | F_{t-1} \sim N(0, H_t), \quad (1)$$

$$\epsilon_t = H_t^{\frac{1}{2}} u_t \quad u_t \sim N(0, I) \quad (2)$$

$$H_t = D_t R_t D_t \quad (3)$$

where F_{t-1} represents all information available up to $t - 1$. y_t , μ_t , ϵ_t and u_t are $N \times 1$ -dimensional vectors representing the analyzed time series, conditional mean, error term, and standardized error term, respectively. R_t , H_t and $D_t = \text{diag}(h_{11t}^{\frac{1}{2}}, \dots, h_{NNt}^{\frac{1}{2}})$ are $N \times N$ matrices representing the dynamic conditional correlations, time-varying conditional variance–covariance matrices, and the time-varying conditional variances.

At the first stage, D_t is created by estimating a Bollerslev (1986) GARCH model for each series. Based on the study of Hansen and Lunde (2005), one shock and one persistency parameter are assumed:

$$h_{ii,t} = \omega + \alpha \epsilon_{i,t-1}^2 + \beta h_{ii,t-1} \quad (4)$$

At the second stage, the dynamic conditional correlations are computed as follows:

$$R_t = \text{diag}(q_{iit}^{-1/2}, \dots, q_{NNt}^{-1/2}) Q_t \text{diag}(q_{iit}^{-1/2}, \dots, q_{NNt}^{-1/2}) \quad (5)$$

$$Q_t = (1 - a - b) \bar{Q} + a u_{t-1} u'_{t-1} + b Q_{t-1} \quad (6)$$

where Q_t and \bar{Q} are $N \times N$ dimensional positive-definite matrices which represent the conditional and unconditional standardized residuals' variance–covariance matrices, respectively. a (α) and b (β) are nonnegative shock and persistency parameters, satisfying $a + b < 1$ ($\alpha + \beta \leq 1$). As long as $a + b < 1$ is fulfilled, Q_t and hence R_t are varying over time, otherwise this model would converge to the CCC-GARCH model, where R_t is constant over time.

3.2. Time-varying parameters vector autoregression (TVP-VAR)

After estimating tail risk using the DCC-GARCH framework, we examine risk transmission between the stocks using the TVP-VAR approach. The integration of time-varying parameters into the VAR framework was first introduced by Primiceri (2005) and later expanded by Nakajima (2011). The optimal lag order of the TVP-VAR model is fixed at 1, following Antonakakis et al. (2020) and Koop and Korobilis (2014). This prevents over-parameterization and facilitates a smoother transition, allowing the model to capture the dynamic nature efficiently. For this study, we utilize the TVP-VAR model as proposed by Antonakakis et al. (2020). The TVP-VAR estimation framework based is described in the following steps:

$$z_t = B_t z_{t-1} + \mu_t \quad \mu_t \sim N(0, S_t) \quad (7)$$

$$vec(B_t) = vec(B_{t-1}) + v_t \quad v_t \sim N(0, R_t) \quad (8)$$

Let z_t and z_{t-1} represent $k \times 1$ dimensional vectors corresponding to the tail risk at time t and $t - 1$, respectively, with μ_t as the associated error term. The matrices B_t and S_t are $k \times k$ dimensional and characterize the VAR model with time-varying parameters. The vectors $vec(B_t)$ and v_t are $k^2 \times 1$ dimensional, and R_t is a $k^2 \times k^2$ dimensional matrix. Following the methodologies established by Koop et al. (1996) and Pesaran and Shin (1998), the generalized forecast error variance decomposition (GFEVD) can be employed to reformulate the TVP-VAR as follows.

$$z_t = \sum_{i=1}^p B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \quad (9)$$

where A_{jt} are the $k \times k$ time-varying moving average coefficient matrices

The directional connectedness from j to i can be estimated as:

$$\Psi_{ij,t}^g(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (\tau_i A_t S_t \tau_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (\tau_i A_t S_t A_t' \tau_i)^2} \quad (10)$$

$$\hat{\Psi}_{ij,t}^g(H) = \frac{\Psi_{ij,t}^g(H)}{\sum_{j=1}^k \Psi_{ij,t}^g(H)} \quad (11)$$

The expression $\sum_{j=1}^k \hat{\Psi}_{ij,t}^g(H) = 1$ and $\sum_{j=1}^k \hat{\Psi}_{ij,t}^g(H) = k$ outlines the criteria for the generalized forecast error variance decomposition (GFEVD). In this context, H refers to the forecast horizon where $H = 10$ days, and τ_j is a selection vector that is 1 at the j^{th} position and 0 at all other positions. The shock that variable i provides to the other variables j , termed as total directional connectedness and referred to as *TO others* is then computed as follows:

$$C_{i \rightarrow j, t}^g(H) = \sum_{j=1, i \neq j}^k \hat{\Psi}_{ij, t}^g(H) \quad (12)$$

TO others represents the total directional connectedness that a particular variable transmits to all other variables within the network. This measure reflects the degree to which a variable impacts the overall network. Additionally, the shock variables are assessed when the variable i receives directional connectedness from a variable j , which is referred to as *FROM others* and is calculated as follows:

$$C_{i \leftarrow j, t}^g(H) = \sum_{i=1, i \neq j}^k \hat{\Psi}_{ji, t}^g(H) \quad (13)$$

FROM others signifies the total directional connectedness that a variable receives from all other variables in the network, indicating the extent to which the variable is influenced by the network. To analyze the overall impact of a variable, such as other GCC stock markets, we can calculate the *NET* total directional connectedness by subtracting Equation (13) from Equation (12), which provides insights into the dynamics of the variable's influence.

$$C_{ij, t}^g(H) = C_{i \rightarrow j, t}^g(H) - C_{i \leftarrow j, t}^g(H) \quad (14)$$

NET refers to the net total directional connectedness, which is determined by subtracting *FROM others* from *TO others* for each variable. This value helps to identify whether a variable acts as a net transmitter (if positive) or a net receiver (if negative) of risk within the network. Lastly, the *total connectedness index (TCI)*, serving as an indicator of market interconnectedness, is calculated as follows:

$$C_{ij, t}^g(H) = \frac{\sum_{j, i=1, i \neq j}^k \hat{\Psi}_{ij, t}^g(H)}{\sum_{j, i=1}^k \hat{\Psi}_{ij, t}^g(H)} = \frac{\sum_{j=1, i \neq j}^k \hat{\Psi}_{ij, t}^g(H)}{k} \quad (15)$$

4. Descriptive statistics

The statistical characteristics are more than just summary properties; they reveal structural market behaviors, systemic fragility, and potential asymmetries in shock propagation that may be obscured in standard volatility models. The descriptive statistics in Table 1 summarize the distributional characteristics of daily log returns for four indices: MSCI US, MSCI GCC, Brent crude oil, and MSCI Gold indices. The statistics include the mean and variance of returns, skewness, kurtosis, normality (Jarque–Bera, JB), stationarity (Elliott–Rothenberg–Stock, ERS), and autocorrelation metrics (Ljung–Box Q-statistics for returns and squared returns over 10 lags). These measures help us understand the statistical behavior and dynamics of each index.

To begin with, the GCC index exhibits a relatively higher mean (0.018) than the other indices. This indicates comparatively stronger daily returns over the full sample period. From a risk standpoint, variance levels across the four indices provide critical insight into market uncertainty. Variance is highest in Brent (4.736) and Gold (4.230), indicating that they are highly volatile commodities. In contrast, the GCC's variance (0.939) is lower than that of the US (1.315). This contradictory combination of higher returns and lower volatility may suggest that GCC markets are not globally volatile in a conventional sense but rather react sharply to regime shifts. Skewness and kurtosis statistics confirm that all series are non-normally distributed, left-skewed,

and heavy-tailed. The skewness in GCC returns is highly negative (-2.254). This indicates a higher likelihood of large negative returns. The kurtosis levels further support this. The GCC market shows extreme kurtosis (41.381), well above Brent's (15.739), indicating sharp market movements. Brent oil's kurtosis is also high (15.739), but not as high as GCC. The JB test confirms the non-normality of return distributions across all indices with highly significant values ($p < .01$) for each. The ERS test confirms the stationarity of returns across all indices, as evidenced by significantly negative ERS values. Autocorrelation tests based on the Ljung–Box Q-statistic at 10 lags indicate limited autocorrelation across all markets. Kendall's rank correlation reveals weak yet statistically significant links. The US and Brent exhibit the highest correlation (0.211), while the GCC exhibits low correlations with all three indices. These statistics confirm that traditional linear models may severely underestimate systemic risk in GCC markets. This combination of high skewness, extreme kurtosis, volatility clustering, and weak but crisis-sensitive correlations shows that GCC equity returns are not only non-normal but also nonlinear, asymmetric, and regime-switching. These stylized facts support our decision to use an integrated DCC-GARCH-TVP-VAR framework.

It is also worth noting that these distributional properties are not uniform across time. The chosen sample period includes both calm and extreme market stress. During crisis periods, GCC markets are expected to have higher kurtosis and pronounced negative skewness as extreme negative returns become more frequent. This regime-dependent behavior motivates the use of a DCC-GARCH model to capture how conditional correlations shift across regimes, while the TVP-VAR framework models the direction and magnitude of spillovers. This combination of high skewness, extreme kurtosis, volatility clustering, and weak but crisis-sensitive correlations shows that GCC equity returns are not only non-normal but also nonlinear, asymmetric, and regime-switching. These stylized facts support our decision to use an integrated DCC-GARCH-TVP-VAR framework.

Table 1. Descriptive Statistics and Kendall Rank Correlation Coefficients

Variables	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(10)	Q2(10)
US	0.0047	1.315	-0.628***	14.210***	21142.014***	-36.841	-0.018	167.747
GCC	0.018	0.939	-2.254***	41.381***	248155.454***	-8.377	-0.038	64.692
Brent	0.007	4.736	-0.932***	15.739***	27544.908***	-10.813	-0.008	11.425
Gold	0.007	4.230	-0.086**	5.739***	1251.592***	-15.834	-0.019	65.369
Variables	US		GCC		Brent		Gold	
US	1.000***		0.087***		0.211***		0.144***	
GCC	0.087***		1.000***		0.084***		0.064***	
Brent	0.211***		0.084***		1.000***		0.142***	
Gold	0.144***		0.064***		0.142***		1.000***	

Notes: This table summarizes the distributional properties of daily log-returns for four indices: MSCI US, MSCI GCC, Brent crude oil (Brent), and MSCI Gold. Reported metrics include mean and variance of returns, skewness, kurtosis, and test statistics for normality (Jarque–Bera, JB) and stationarity (Elliott–Rothenberg–Stock, ERS), as well as Ljung–Box Q-statistics for autocorrelation in returns [Q(10)] and in squared returns [Q²(10)] over 10 lags. ***, **, * denote significance at 1%, 5%, and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; and ERS: Elliott et al. (1996) unit-root test.

5. Empirical results

In this section, we present a comprehensive empirical analysis of global risk transmission in GCC equity markets. We analyze the tail risk dynamics for each index, map spillover metrics

using connectedness networks, capture the evolution of total tail connectedness over time, evaluate time-varying net tail connectedness to identify net transmitters and receivers of shocks, and finally conduct robustness checks to ensure our findings are not sensitive to specific model choices.

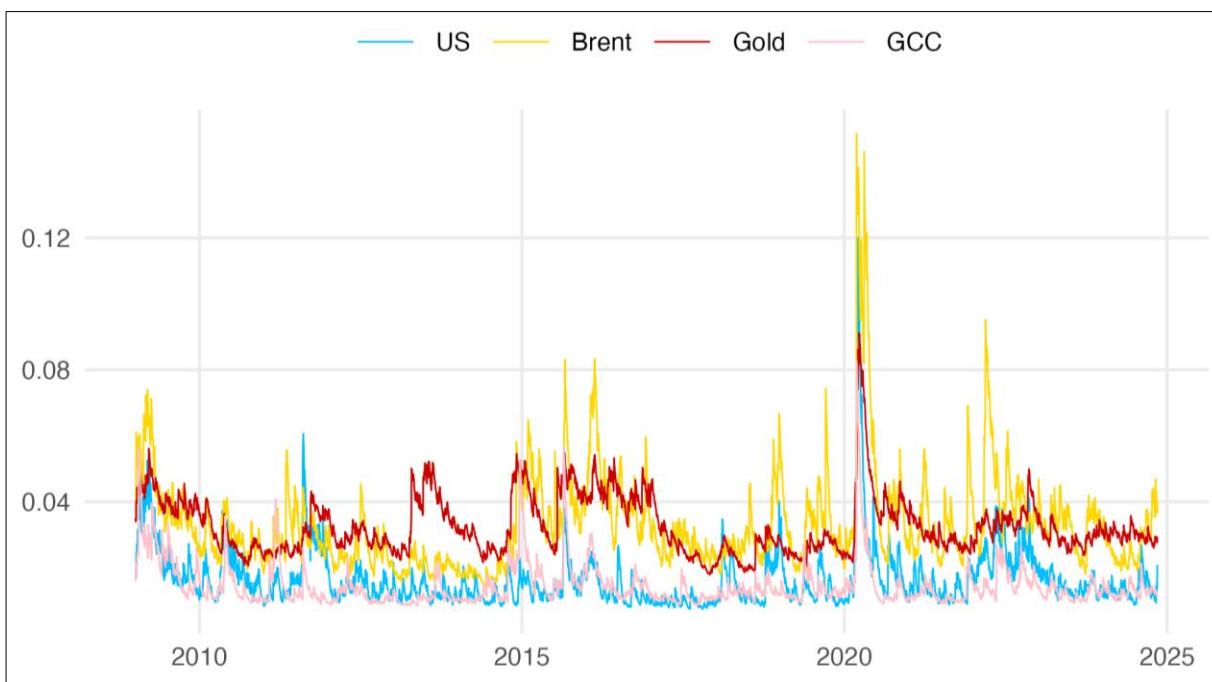


Figure 1. Tail risk

Notes: This figure plots the time series of tail risk estimates for the US, the GCC, Brent crude oil, and Gold from 2009 to 2025. Each line represents the risk measure for each market, allowing a comparison of their fluctuations across time. The y-axis indicates the magnitude of tail risk, and the x-axis tracks the evolution over the chosen sample period. Distinct peaks appear at different intervals, with some markets showing sharper movements than others. The figure helps observe the co-movement between these markets at different intervals.

5.1. Tail risk dynamics

The first step in our analysis is to quantify each index's tail risk using a DCC-GARCH model (Engle, 2002). We estimate 5% VaR for each index's log-returns, capturing extreme downside risk at each point in time. These VaR graphs have been generated for two main reasons. First, they allow us to identify and visualize periods of elevated tail risk and to see how they coincide with global crises or geopolitical tensions. These include events such as the 2008 financial crash, the 2014–2016 oil price decline, the COVID-19 pandemic, and the 2022–2023 energy shock. Second, they help us understand how each market behaves, particularly how the GCC reacts under global volatility. This provides the basis for understanding the nature and sensitivity of each market before we analyze spillovers between them using the TVP-VaR framework in the next sections.

Figure 1 presents the time-series plot of 5% VaR for all four markets from 2009 to 2024. The plot reveals how tail risk clusters around periods of major crises. The first spike is during the global financial crisis between 2008 and 2009. The plot reveals a sharp increase in correlations between these markets, especially between Brent oil and gold. While the US and GCC markets also show elevated risk levels, their correlation is moderate compared with that of the US and GCC markets. The GCC markets were only just beginning to become globally integrated, so the volatility spillovers remained low. The 2014-2016 oil price collapse is a clear indication of GCC's

growing globalization. As Brent crude oil fell from around \$100 to \$30, the correlation between the MSCI GCC index and Brent increased instantly. This period exposed GCC’s economic vulnerability to economic shocks as revenues declined, fiscal deficits widened, and investor confidence weakened. Just as the regions were beginning to recover from this shock, the COVID-19 pandemic hit, affecting markets to the point of changing the previous levels of stability.

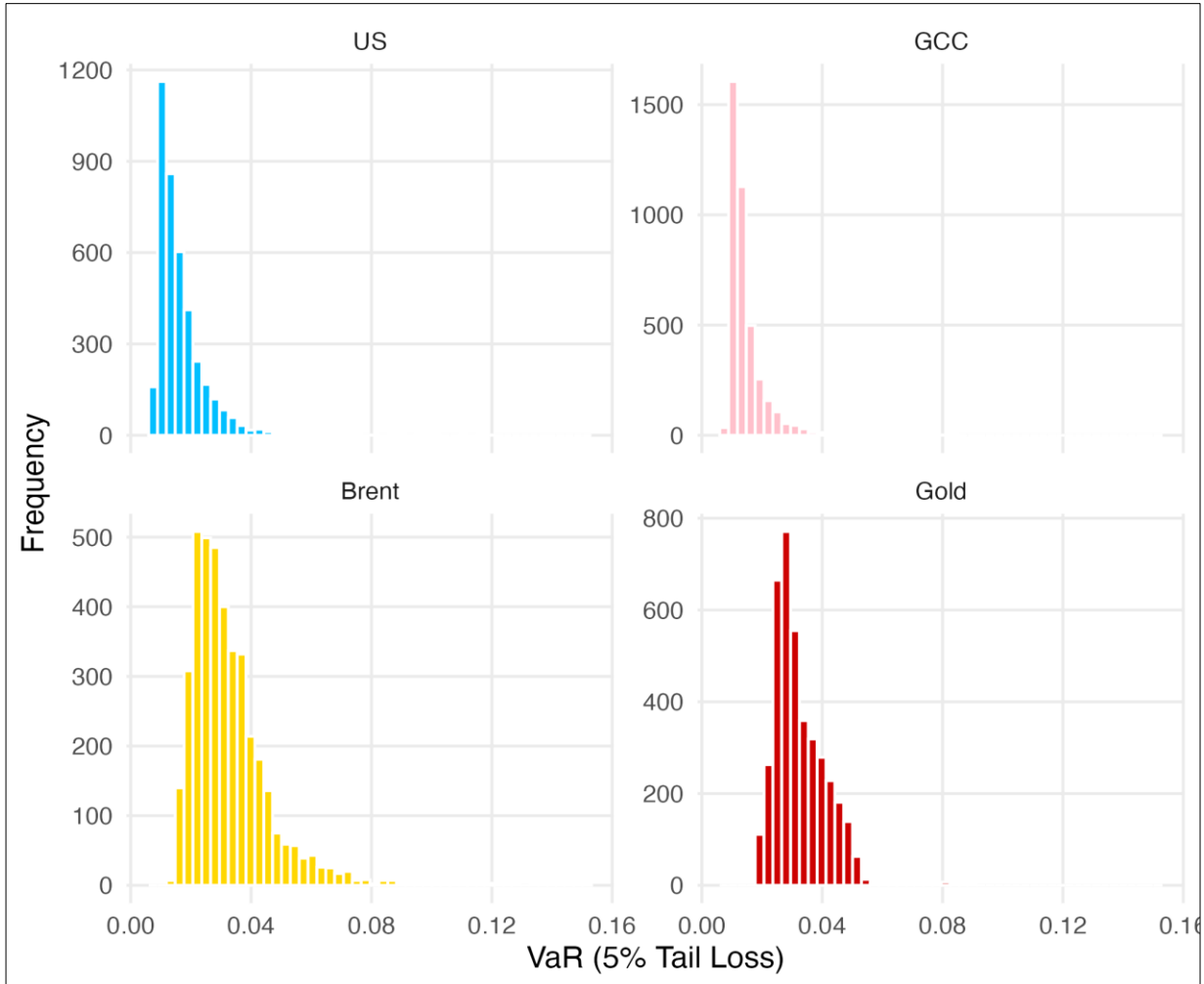


Figure 2. Histogram representation

Notes: The histograms show the empirical distribution of 5% VaR estimates for the four markets. The x-axis represents 5% VaR (tail loss at the 5% quantile) while the y-axis shows frequency counts. Each panel isolates one market and displays its range, central mass, and tail-loss distribution, making it easier to compare VaR levels, skewness, and distribution.

Figure 2 shows the distribution of these 4 markets. The US market distribution is concentrated around 0.02 to 0.04. This means that in the worst 5% scenario, US equities tend to lose 2-4% of value. The short tail indicates that the extreme losses beyond 6-8% are rare. The distribution of GCC markets is also concentrated, but because they are heavily linked to oil, their tail risk can spike dramatically when oil prices move. The Brent distribution is wider, indicating higher tail risk. Because of its strong positive correlation with the GCC markets, the GCC markets also tend to oscillate between moderate and high tail risks. Gold’s distribution is centered. It is tighter than Brent but wider than GCC, reflecting that losses do happen and that it has moderate volatility.

Together, these figures tell us that while all markets exhibit elevated tail risk during market distress, the nature and severity of that risk differ significantly across asset types. The US market is highly diversified and mature, and therefore tends to experience short but sharp tail-risk episodes. The GCC is an emerging market, so extreme events tend to have persistent effects, increasing risk. Brent oil shows violent, recurrent tail-risk spikes, while gold remains mostly stable, with minimal tail losses. Having established each market's individual tail risk behavior, we now analyze how these risks interact and propagate across markets using the TVP-VAR spillover framework.

5.2. Tail-connected networks

Here, we use a TVP-VAR model to capture the dynamic nature of spillovers and connectedness as proposed by Antonakakis et al. (2020). The generalized forecast error variance decompositions (GFEVD) used in this framework help us quantify the percentage of each market's forecast variance attributable to shocks from other markets. This provides a clear picture of which market is the transmitter and receiver of risk. The results are quantified in Table 2 and visualized in Figure 3.

Table 2 presents the spillover matrix. The diagonal cells measure the share of a market's own variance, while the off-diagonal cells measure cross-market spillovers. The last column indicates the total percentage of risk received from other markets, while the last row represents the total percentage of risk transmitted to other markets. The MSCI US index emerges as the strongest net transmitter of risk with a positive NET value of +6.19%. The US market clearly contributes more to the volatility than it receives. This aligns with the findings of Diebold and Yilmaz (2012) and (Pericoli & Yilmaz, 2024), who identified the US as the dominant global transmitter of risk. The US transmits 23.69% of its volatility to other markets, while only 17.50% is due to external shocks. In contrast, the GCC market is a net receiver of tail risk with a NET value of -2.42%. It transmits 12.11% of volatility to other markets and receives 14.53% of total volatility. The US transmits 7.01% of volatility to the GCC, and Brent transmits 5.04%. This confirms prior literature on the sensitivity of GCC markets and their nature to be NET receivers during a global crisis, documented by Alqahtani and Chevallier (2020), and it also supports our hypothesis. The GCC's sensitivity to both equity and commodity markets is solely due to its economic model. The economy relies heavily on oil exports and dollar-pegged monetary regimes, which increases the GCC's sensitivity to global events. Brent crude oil with a NET connectedness of -0.29% is balanced. It transmits 19.14% of tail risk while receiving 19.43%. Oil price volatility is known to be both a cause and consequence of macroeconomic shocks, and its dual nature is seen here (Arouri et al., 2011; Hussain & Rehman, 2022). Brent contributes more to GCC's tail risk, underscoring the GCC economy's reliance on oil. Gold is a moderate NET receiver (-3.48%) and transmits minimal risk. It carries 16.52% of risk and transmits 13.04%, which aligns with its role as a safe-haven asset during times of crisis, as analyzed by Mensi et al. (2016).

These spillover dynamics are illustrated in Figure 3. Nodes represent markets, and the lines represent the strength and direction of spillovers. The US is positioned at the center, with thick arrows pointing to Brent, Gold, and the GCC. This shows its dominant role as the transmitter. Brent influences GCC, highlighting the Gulf economies' reliance on oil dynamics. The GCC node is mostly on the receiving end of risk. Gold is loosely connected with thinner arrows, emphasizing its passiveness. These findings empirically support the central idea of this research that the GCC markets are highly sensitive to global shocks from both financial and commodity markets.

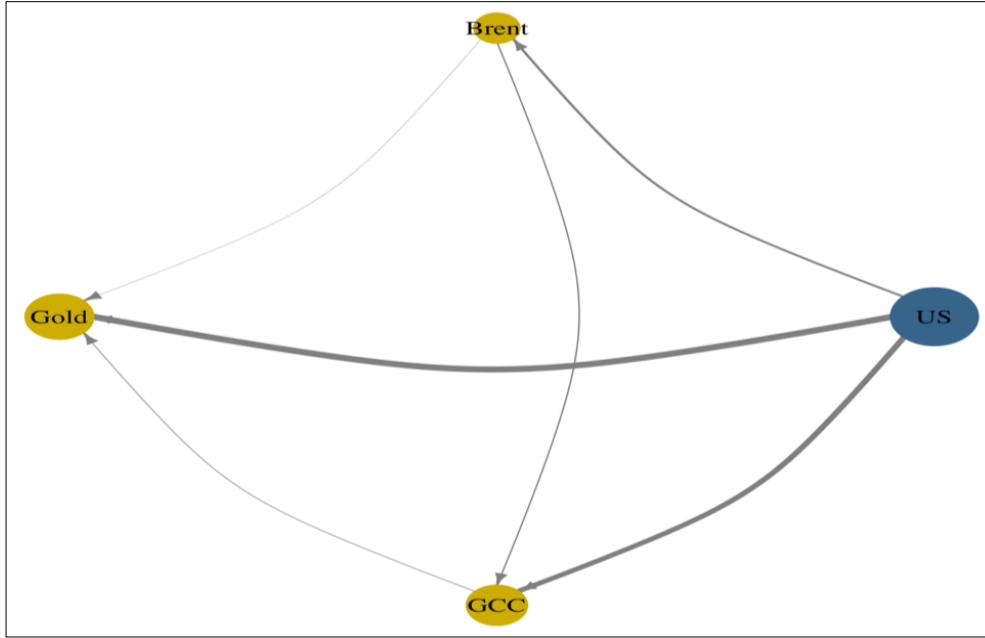


Figure 3. Network spillovers

Notes: The network diagram shows the directional spillovers of tail risk among markets. Each node represents a market with its size reflecting its importance within the system. Arrows indicate the direction of spillovers, while the thickness of the lines shows the magnitude of transmission. This figure helps visualize the net transmitters and receivers of risk and understand the dynamics of their relationships.

5.3. Time-varying total tail connectedness

The portion of the study shows the dynamic evolution of TOTAL tail-connectedness across markets, as estimated by the DCC-GARCH-TVP-VAR model with GFEVD. Unlike the static view, the average spillovers in Table 2 and Figure 4 help visualize market-wide connectedness over time. It captures the intensity of fluctuations in response to global shocks. Figure 4 shows the trajectory of total connectedness and reveals that tail-risk interdependence is dynamic and highly sensitive to external shocks. This observed behavior closely aligns with the findings of Antonakakis et al. (2020) and (Diebold & Yılmaz, 2014). These spikes are especially notable during key events: the 2008–2009 global financial crisis, the 2014–2016 oil price collapse, the 2020 COVID-19 pandemic, and the 2022–2023 geopolitical and energy crisis.

Table 2. Average pairwise spillover

	US	GCC	Brent	Gold	FROM
US	82.50	4.78	8.06	4.67	17.50
GCC	7.01	85.47	5.04	2.48	14.53
Brent	9.01	4.53	80.57	5.89	19.43
Gold	7.67	2.81	6.04	83.48	16.52
TO	23.69	12.11	19.14	13.04	67.99
NET	+6.19	-2.42	-0.29	-3.48	

Notes: This table aggregates the connectedness measures over the entire sample period. The upper-left 6×6 block is the percentage of forecast variance of each market (rows) explained by shocks from each source market (columns), averaged over time (from the TVP-VAR FEVD). Diagonal entries are own-market contributions, and off-diagonals are cross-market spillovers. The last column, “FROM,” shows the total spillovers received by each market from other markets. The last row, “TO,” shows the total spillovers each market transmits to others. The NET row is the difference (TO – FROM) for each market, and represents net spillover over the sample. NPT indicates the persistence ranks.

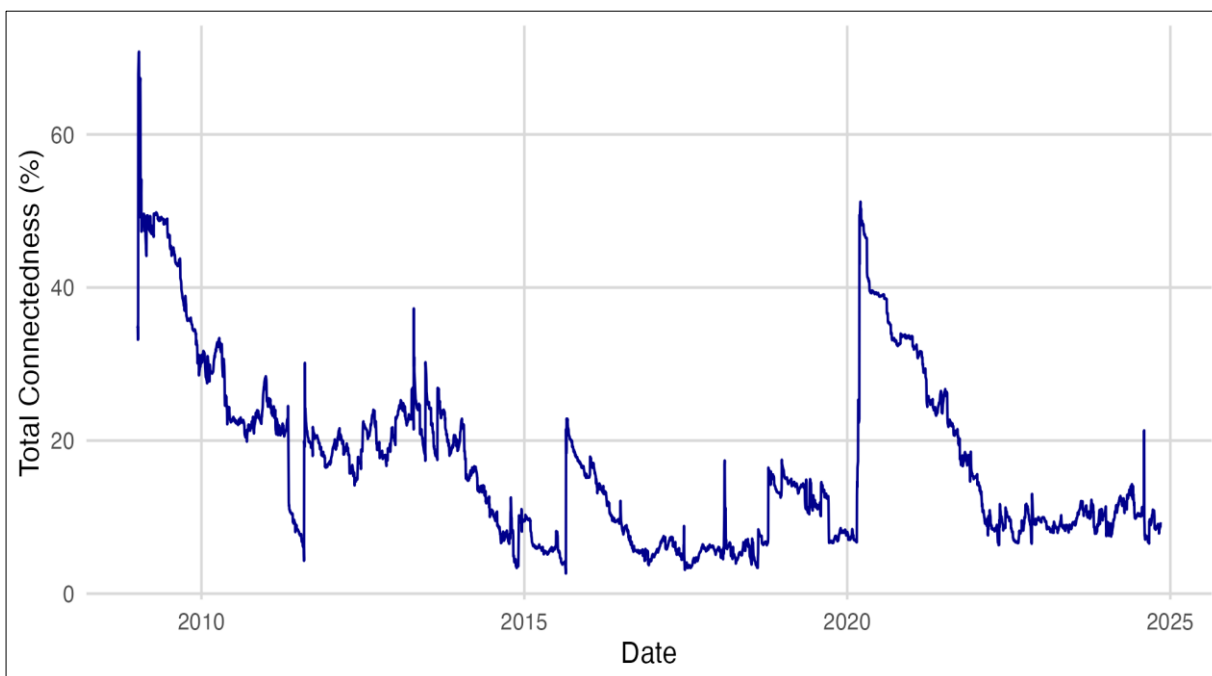


Figure 4. Time-varying TOTAL spillovers

Notes: This figure shows the dynamic total connectedness index for extreme downside risk in GCC equity markets. It is estimated using a time-varying parameter VAR model applied to the markets' 5% VaR series. The total spillover index quantifies the proportion of total forecast error variance that can be attributed to other markets. It shows that extreme-risk interconnectedness between these markets is dynamic and that systemic shocks trigger spikes in volatility spillovers. The effects of these spillovers after periods of turmoil depend on the degree of interconnectedness between these markets.

Figure 4 reveals several consistent themes. First, TOTAL connectedness is not constant. It fluctuates significantly over time, especially during periods of heightened market stress. Second, interdependence tends to rise sharply during crises and does not immediately return to pre-crisis levels. This persistence in elevated connectedness has also been documented by Gabauer and Gupta (2018), who observed the lasting impact of systemic shocks. Yousaf et al. (2022) made a similar observation, specifically in the GCC context, noting that spillover magnitudes remained elevated even during the recovery phase following the COVID-19 pandemic. Third, these trends imply that tail risks are systemic rather than localized. The GCC - a region that is economically tied to both oil and US markets- is particularly exposed to this risk. This structural vulnerability was highlighted by Alotaibi and Mishra (2017). These studies showed that GCC's global exposure made it significantly sensitive to global shocks and that it tends to absorb risk during these periods.

5.4. Time-varying net tail connectedness

This section presents the time-varying NET directional spillovers. While previous sections addressed the magnitude and intensity of connectedness, the NET connectedness focuses on whether a market is a transmitter or receiver of risk shocks. Figure 5 shows the NET dynamic tail-connectedness for each market. This figure visualizes whether a market transmits more risk than it receives or vice versa. The US index exhibits positive net values, especially during periods of global crisis. Notable spikes in 2008–09, early 2020, and 2022–23 confirm the US's role as a systemic transmitter of tail risk. The Brent crude oil index reveals a more complex pattern. During oil-centric crises, Brent becomes a conduit of risk, particularly for oil-reliant economies like the GCC. However, Brent also displays negative NET connectedness. These periods coincide with

shocks originating in equity markets rather than in commodity markets. This highlights the dual role of Brent as both the transmitter and receiver of risk, a finding confirmed by the analyses of Arouri and Fouquau (2009) and Awartani and Maghyereh (2013).

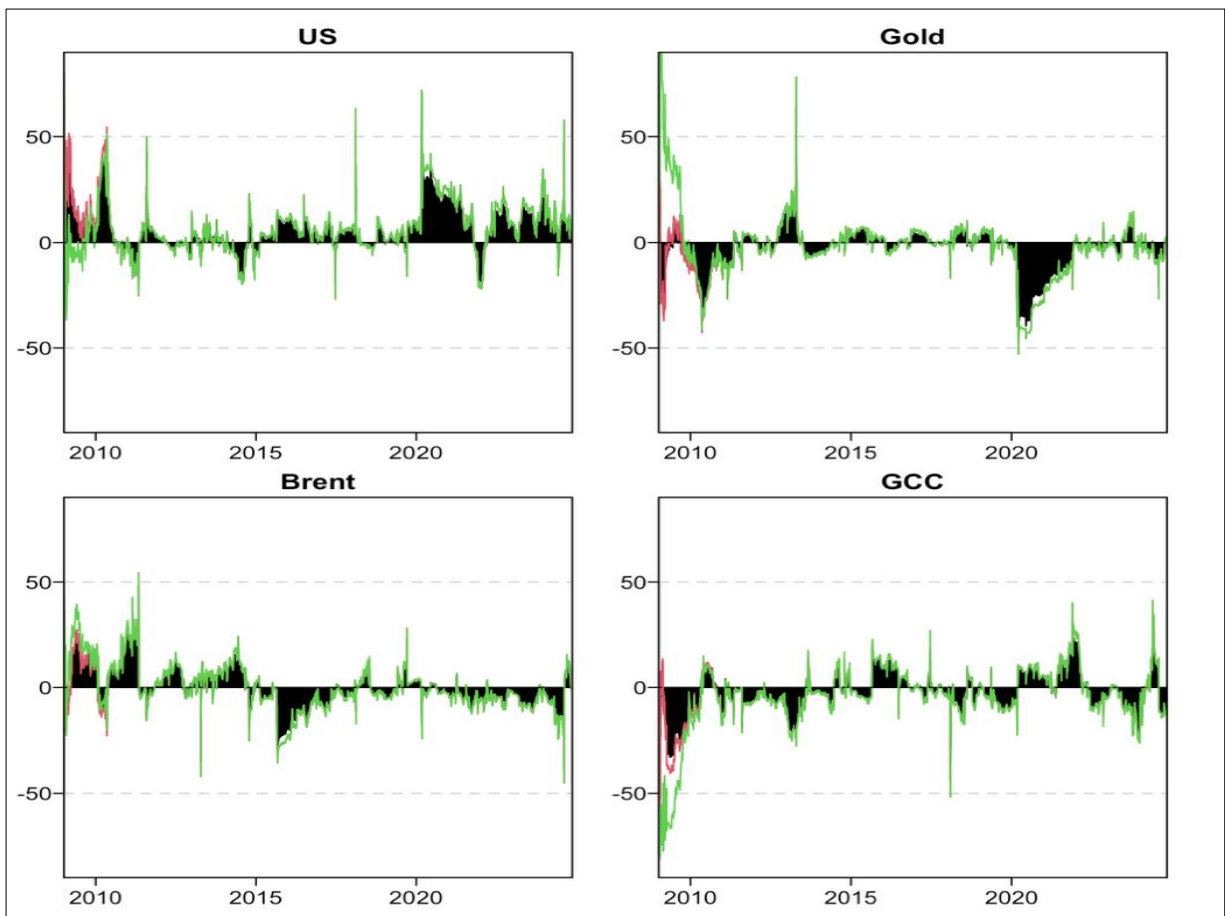


Figure 5. Time-varying NET spillovers

Notes: This figure shows the net tail-connectedness of each market. Each panel shows the time series of net contributions to spillovers, where positive values indicate periods when a node is a net transmitter of tail risk, and negative values indicate periods when a node is a net receiver.

The Gold index consistently has either negative or near-zero net connectedness. Even during periods of high volatility, Gold does not exhibit strong spillover effects. It is characterized by its nature to absorb risks but not transmit them. This empirical observation supports the findings from Mensi et al. (2016). The GCC index seems to be the most vulnerable of the four markets. Across most of the sample, it exhibits negative NET connectedness. This shows that it is constantly influenced by external markets more than it influences them. Its strongest negative dips coincide with major global events and crises. This suggests that this economy remains systemically reactive rather than proactive during these periods. The data also reveals episodes of positive NET connectedness, which could be attributed to localized oil booms. These periods, however, are short and of low magnitude. This finding supports the studies by Ziadat and AlKhouri (2022) and Al-Yahyaee et al. (2019), which confirmed GCC's sensitivity to shocks and its status as a net recipient of risk from commodity and equity markets. This also directly supports both the hypotheses of our study.

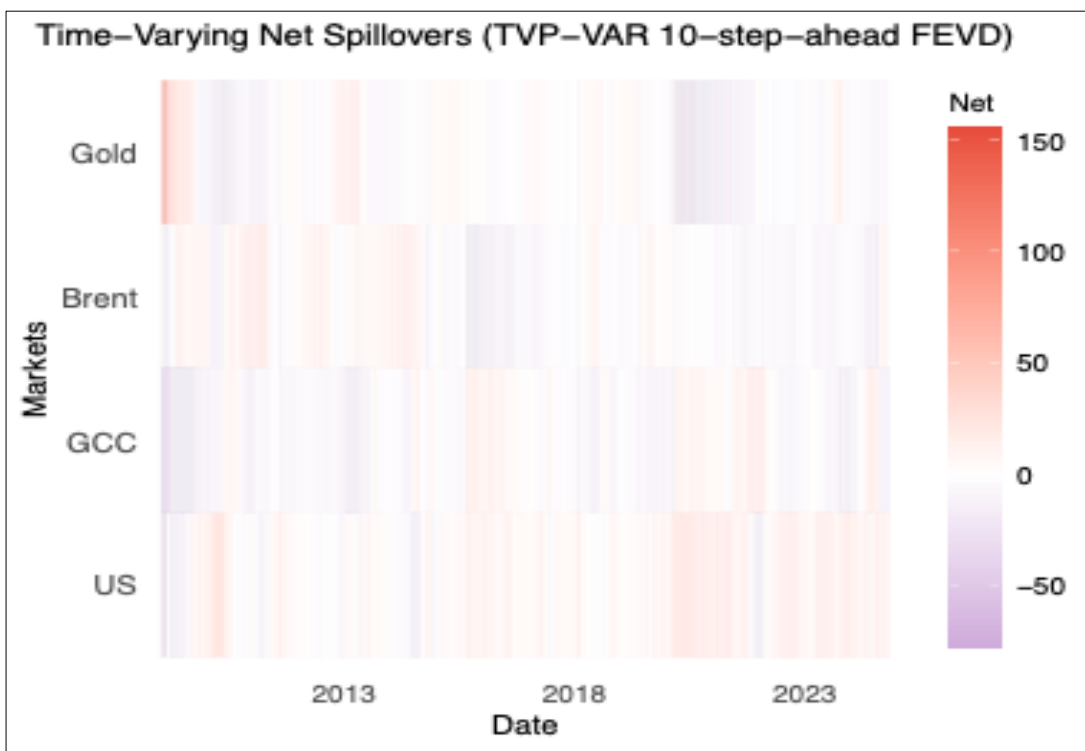


Figure 6. Heatmap of net spillovers

Notes: This figure presents a heatmap of time-varying net directional spillovers for each market across the full sample period. Each row corresponds to a market, and the intensity of the color indicates the strength of net spillovers at each time point. Warmer tones indicate periods of net transmission, while cooler tones indicate net risk reception.

Figure 6 provides a heatmap of NET spillover and its directionality. The color intensity tells us the strength and direction of net spillovers for each market. The US consistently appears in warm tones because it usually conveys a sense of risk. Brent oscillates between warm and cool phases, while Gold remains consistently cool. The GCC's heatmap row is mostly in blue, reinforcing the theory that it is a NET receiver of risk. These patterns help us understand how global markets respond in times of crisis and how they influence the GCC market.

6. Robustness

To ensure the reliability and validity of our empirical findings, we perform a series of robustness checks by altering model specifications and then comparing the results with our original analysis. These tests are done to confirm that the dynamics observed in the models are not sensitive to particular assumptions. Figure 7 presents the first robustness test, which re-estimates the Total Connectedness Index (TCI) using a rolling-window VAR rather than the TVP-VAR framework. Connectedness is calculated by estimating a standard VAR model using a 250-day rolling window. The result is a time series of total connectedness, analogous to that shown in Figure 6. This confirms that our earlier results are not driven by the choice of model but reflect existing systemic risk interdependencies. Figure 8 provides a robustness check of the time-varying total spillovers across markets using different information criteria (SIC, AIC, HQ) in the TVP-VAR model. The black, red, and blue lines represent estimates using the SIC, AIC, and HQ criteria, respectively. The overlapping lines prove that our results are not sensitive to any of the changes and that the overall trend of NET transmitters and receivers remains unchanged. No new spikes appear, and

none of the major spikes disappear. This confirms that the window length does not affect the conclusions.

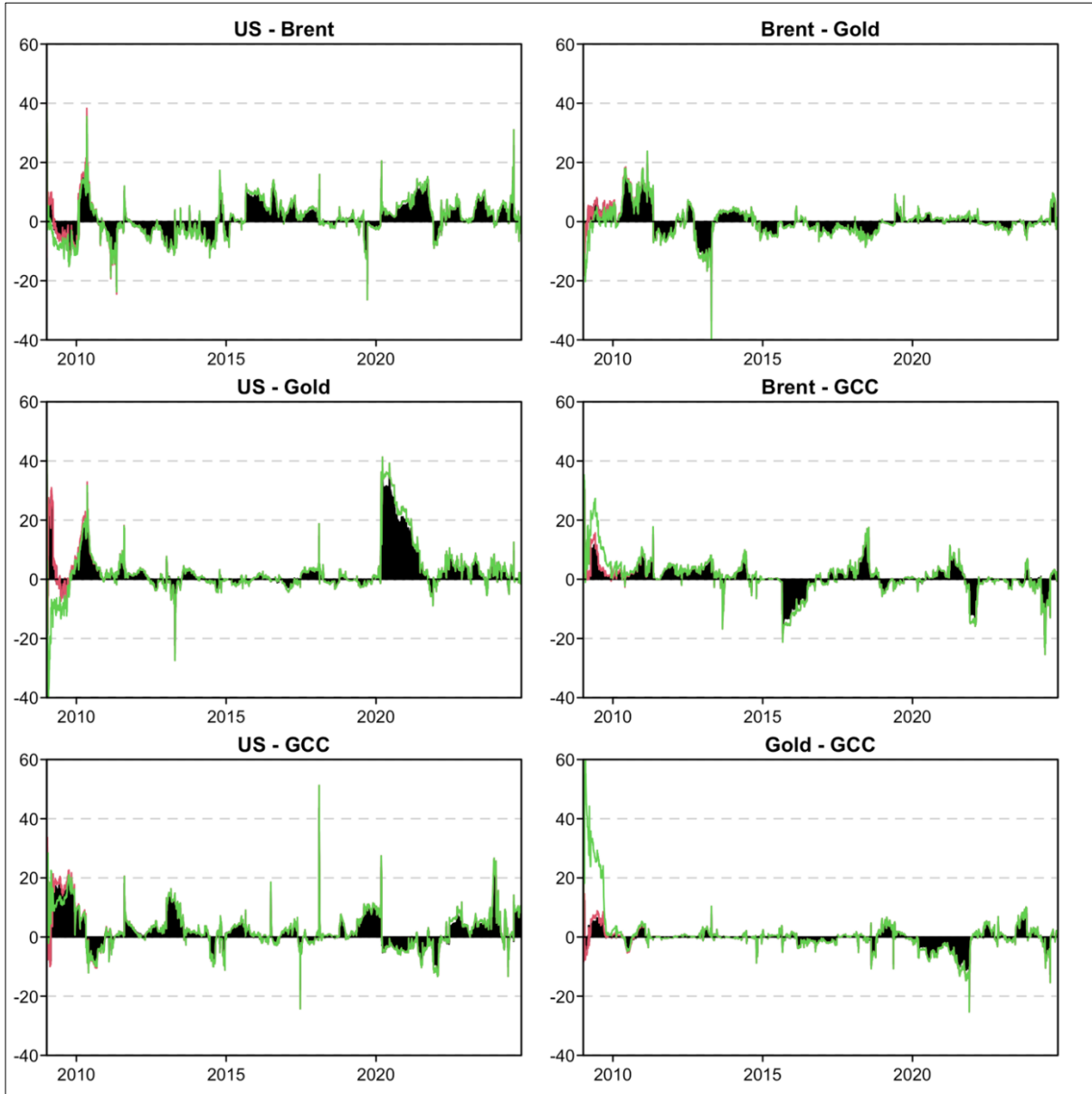


Figure 7. Time-varying pairwise spillovers of the markets

Notes: This figure provides a clear picture of the bilateral spillover relationships by showing how the influence between specific market pairs evolves over time. Instead of a single static value, this figure provides a dynamic pairwise spillover metric that captures the changing intensity and direction of risk transmission between two markets. This figure highlights the importance of a time-varying spillover framework for capturing dynamic spillovers in this region. It captures transient shifts that help identify which market is the major driver of risk at any given time.

Our net transmitter/receiver classifications also remain unchanged across both the window specifications, reaffirming the robustness of our original approach. Our robustness checks validate the reliability of our main findings. Irrespective of the lag length or window size, the figures generated are similar to those in the main body of the paper. This confirms that GCC economies are structurally vulnerable while the US and Brent continue to influence the markets in this region.

Having validated the findings, we have effectively reinforced the empirical narrative that global risk transmission to the GCC is a persistent phenomenon and provided a comprehensive and robust picture of the interconnectedness between GCC markets and global indices.

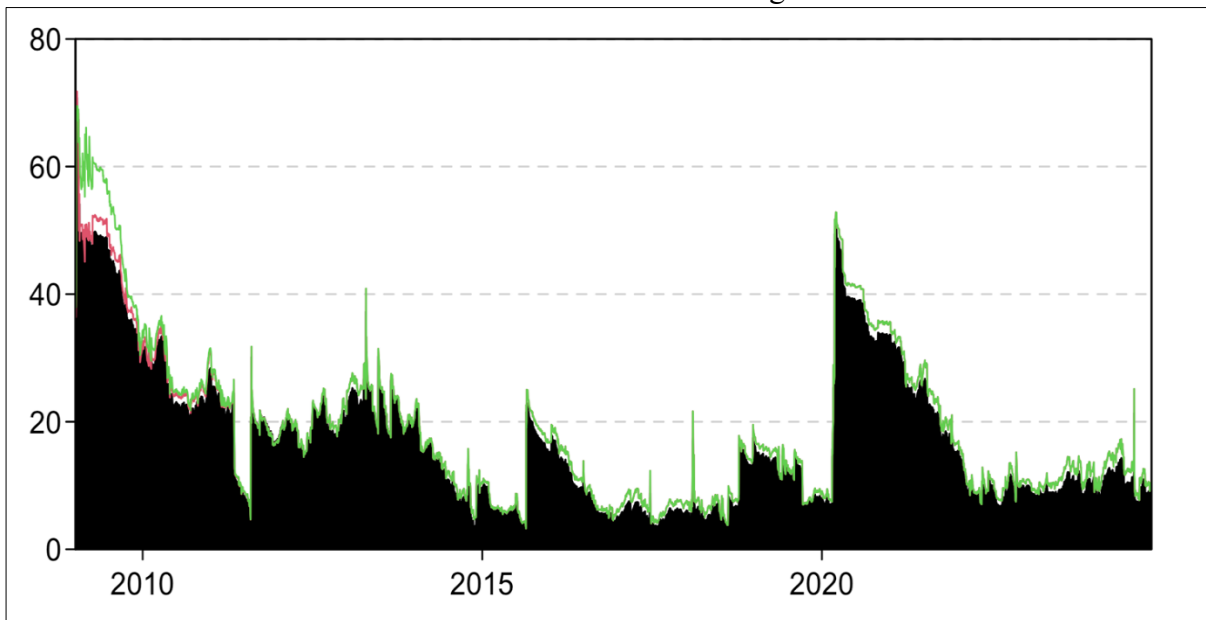


Figure 8. Time-varying TOTAL spillovers - Robustness

Notes: This figure tests the robustness of the estimated total spillover index (Figure 3) by comparing results across different model specifications. The total tail-risk connectedness measure is recalculated using alternative lag selection criteria (AIC (red) and HQ (green), in addition to SIC (black)) to configure the TVP-VAR model. While the magnitudes may vary slightly, the oscillations remain nearly identical across all 3 criteria. This confirms the robustness of the used framework.

7. Conclusion

This study uses a DCC-GARCH-TVP-VAR framework to analyze global risk transmission among the US, Brent, Gold, and GCC equity markets from January 2009 to November 2024. The analysis yields four core findings. First, GCC markets are predominantly net receivers of risk, with a *NET* connectedness value of -2.42% . This confirms our hypothesis *H1* and shows the structural vulnerability of these markets to external shocks. Second, the US market is the dominant net transmitter of risk ($+6.19\%$), and the rate of transmission intensifies sharply during a crisis, confirming our hypothesis *H2*. Third, Brent crude oil plays a dual role, transmitting and receiving risk depending on whether the originating shock is commodity- or equity-driven. Fourth, gold consistently receives risk and acts as a shock absorber, empirically confirming its role as a safe-haven asset.

This study aims to add value to investors, policymakers, and academic researchers seeking to learn more about this market. For investors, we hope our findings highlight how systemic risks from US markets and Brent crude oil affect this region. This will enable them to make informed choices about portfolio diversification. For policymakers, this study provides evidence of GCC's vulnerability to global shocks. Given that the US is a dominant source of risk transmission, especially during crisis periods, GCC regulators would benefit from monitoring US equity volatility indicators as part of their early-warning infrastructure. On the portfolio side, gold's status as a safe-haven asset suggests that sovereign wealth funds could use it as a hedging instrument when US or oil-market stress is high. Most importantly, GCC should not be treated as a bloc, and

there should be proper coordination across regions, as well as region-specific policies. For example, Saudi Arabia's oil linkages and the UAE's diversified financial sector would require tailored policy frameworks rather than a uniform policy applied across the region. Saudi Arabia's oil dependence means its markets are more sensitive to Brent shocks and would therefore benefit from countercyclical capital buffers tied to oil price movements. The UAE, with its comparatively diversified financial sector, is shaped more by global equity sentiment than oil alone, and regulatory thresholds in the region should reflect that. At a theoretical level, these findings suggest that structural factors continue to limit full market integration and also affect how these economies respond to economic shocks.

This study, however, is not without its limitations. While we focus on major global indices (US, Brent, and Gold). We exclude regional shocks and factors that may also influence spillovers within the GCC. Estimating connectedness with a relatively small sample of 4 markets could limit generalizability. Future research could include additional global factors such as geopolitical risk indices, the VIX, and sovereign bond spreads to yield a clearer picture of risk transmission. Regional indices could also be considered to differentiate between global and regional spillovers. Similarly, analysis could also include sovereign bond markets to get the complete picture of financial vulnerability in the region. Machine learning methods and high-frequency data could also be used to detect early warning signals of systemic risk that the current models may overlook.

In conclusion, this study contributes to the growing literature on global risk transmission in the GCC region. It not only showcases the market's sensitivity to external shocks but also provides a reliable framework that can help investors and academics. As the global economy grows more volatile and interdependent, understanding the global influence on emerging and resource-dependent markets like the GCC becomes not just relevant but essential.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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