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Working Paper

Contemporaneous and Lagged #² Decomposed Connectedness:
Evidence for Stock Market Indices, Thematic ETFs, Bitcoin, Brent Crude
Oil and Geopolitical Risks

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**Contemporaneous and Lagged R^2 Decomposed Connectedness:
Evidence for Stock Market Indices, Thematic ETFs, Bitcoin,
Brent Crude Oil and Geopolitical Risks**

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Abstract

This paper applies the R^2 connectedness method proposed by Balli et al. (2023) to analyse contemporaneous and lagged connectedness between returns on several asset classes (sector ETFs, Bitcoin, stock market indices, Brent crude oil) over the period 1 January 2023 – 22 September 2025, in the presence of heightened geopolitical risk. The results indicate that contemporaneous effects dominate over lagged ones. Specifically, the Nikkei 225, the STOXX 600, and Brent oil act as net risk receivers, while Bitcoin plays a limited role as a safe haven. Conversely, the S&P 500 index appears to be the main shock emitter, followed by the Defence (ITA) and Technology (XLK) ETFs, while the Energy (XLE) ETF seems to be particularly exposed to risk. These findings provide valuable information to policymakers responsible for financial stability and to investors seeking effective portfolio diversification and hedging strategies, especially during periods of market turbulence.

Keywords: Contemporaneous and lagged R^2 connectedness; Thematic ETFs; Brent oil; S&P 500; STOXX 600; Nikkei 225; geopolitical risk

JEL Classification: C32; G11

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1. Introduction

In recent years various geopolitical developments have had a significant impact on economic and financial stability. These include the US presidential elections, the trade war between the US and China, and the conflicts in Ukraine and in Gaza, all of which can be classified as geopolitical risks that can lead to economic stagflation and financial turmoil, both at the national and at the global level (Caldara and Iacoviello, 2022). In such circumstances portfolio diversification becomes even more important for investors, who will be targeting (safe-haven) assets with lower or negative correlation with those that have been adversely affected by exogenous shocks (Baur and Lucey, 2010). In other words, such geopolitical events will prompt investors to rebalance their portfolios by seeking alternative financial instruments such as safe havens (Iwanicz-Drozdowska et al., 2021).

The recent rise of exchange-traded funds (ETFs) offers market participants a new, appealing option to access assets with flexibility, transparency, and cost-effectiveness. ETFs combine the strengths of mutual funds and stocks, providing diversification opportunities while being traded on exchanges as individual stocks. Among the various ETF categories, thematic ETFs have gained remarkable popularity thanks to their targeted approach which allows investors to align their portfolios with specific sectors, industries, or themes likely to outperform the market as a whole.

Several recent studies have examined the interdependence between traditional financial assets and thematic ETFs. For example, Kuziak and Górka (2023) showed that some energy ETFs exhibit low correlations with oil and gas prices. By contrast, using time-varying parameter copulas, which are shown to outperform static models, Naeem et al. (2020) found that energy ETFs and WTI oil prices exhibit significant positive correlations, especially during periods of market volatility. More recently, Polat et al. (2024) and Rubbaniy et al. (2024) concluded that renewable energy and ESG-linked ETFs only have weak linkages with traditional and digital

financial assets, which highlights their role as alternative assets for portfolio hedging and diversification strategies.

The present paper aims to contribute to this area of the literature by analysing the dynamic connectedness of the returns on different asset classes , namely sectoral exchange-traded funds (ETFs), cryptocurrencies, energy commodities, and major stock market indices, over the period from 1 January 2023 to 22 September 2025, in the context of the recent geopolitical developments affecting global financial markets, such as the Israel-Hamas conflict and the growing tensions between Israel and Iran, which have generated high regional uncertainty and disrupted the global oil trade. Specifically, the present study uses the R^2 connectedness approach proposed by [Balli et al. \(2023\)](#) to analyse the contemporaneous and lagged linkages between the returns on those different asset classes. Our findings yield a better understanding of the immediate impact of market volatility and of the delayed transmission of information following investment decisions, thus providing practical guidance to investors on how to adjust their strategies during periods of financial turmoil.

The remainder of the paper is organised as follows : Section 2 briefly reviews the relevant literature ; Section 3 describes the data and methodology used ; Section 4 presents the empirical results ; Section 5 offers some concluding remarks.

2. Literature Review

A growing number of studies have examined the performance of thematic ETFs relative to benchmark indices and other asset classes, such as stocks, bonds, commodities, and cryptocurrencies, particularly in the context of high market volatility ([Kuziak & Górká, 2023](#); [Naeem et al., 2020](#) ; [Ozcelebi et al., 2025a, 2025b](#); [Górká & Kuziak, 2024](#); [Olaniran et al., 2025](#)).

Da Costa Neto et al. (2019) analysed the use of ETFs in various sectors, including commodities, currencies, etc., and concluded that developed economies such as the US still prefer traditional ETF investment strategies, while emerging markets such as India and Brazil seek information-based arbitrage opportunities when investing in ETFs. Ji et al. (2024) examined the dynamic interdependence between fossil fuel, clean energy, precious metals, and real estate ETFs, using the DCC-GARCH-Copula model to measure dynamic correlations and the TVP-VAR model to analyze volatility spillovers. Their results indicate volatility linkages between clean energy and real estate ETFs. Furthermore, total connectedness between them varied over time, reaching its peak during the global COVID-19 pandemic. Yadav et al. (2022) analysed spillovers from financial to energy ETF futures carrying out Granger causality tests and estimating a DCC model for adjusted daily data from 2 April 2009 to 23 November 2020. They found significant volatility spillovers, specifically contagion effects from financial ETFs to short- and long-term energy futures, the spillovers being unidirectional or bidirectional, depending on the instruments examined. In a related study, Naeem et al. (2022) investigated dependence between energy and commodity ETFs and WTI crude oil prices, using EGARCH-Copula models. They found positive correlations between energy ETFs and oil prices, which suggests that the former can be used to manage oil price risk. Furthermore, the time-varying copulas showed significant differences between them, providing valuable insights into the hedging properties and safe haven potential of energy and commodity ETFs. Çelik et al. (2022) analysed dynamic connectedness between the realized volatilities of clean energy ETFs and implied volatilities of the energy sector, using the TVP-VAR model and GARCH asymmetric dynamic conditional correlation (ADCC) models. They found that clean energy ETFs are the main sources of volatility, with OVX generally receiving shocks rather than transmitting them. By contrast, traditional energy ETFs show more stable relationships with uncertainty indices. These results highlight the different exposure of thematic ETFs to greater uncertainty resulting

from external stress conditions and regulatory developments. More recently, [Hadad et al. \(2024\)](#) analysed the risk-adjusted performance of commodity ETFs between 2004 and 2022. They reported that these ETFs underperformed relative to US stocks but showed resilience during crises, such as the COVID-19 pandemic. They also found that changes in global commodity prices and disposable income influence their excess returns, while their risk measures (VaR and expected shortfall) indicate lower exposure to losses, highlighting their hedging potential for investors.

Other studies show that investor sentiment in the stock market influences the prices of thematic ETFs. [Yin et al. \(2025\)](#) focused on the dynamic interplay between energy ETF affordability and stock market sentiment. They found that clean energy ETFs exhibited post-pandemic resilience, their prices remaining stable even during financial crises, a feature shared by ESG ETFs as a result of increased investor demand for sustainability-focused assets. Finally, [Ozcelebi et al. \(2025a, b\)](#) analysed the contagion dynamics between technology ETFs and uncertainty indices using quadruple wavelet coherence and wavelet-quantile correlations. Their results indicate strong contagion between these markets, especially during periods of stress and greater financial instability.

3. Data and Methodology

3.1 Data and Descriptive Statistics

This study examines the dynamic connectedness between defence, energy, and technology exchange-traded funds (XLE, ITA, XLK), cryptocurrencies (specifically Bitcoin, BTC), major stock market indices (the S&P 500, Nikkei 225, and STOXX 600), the price of Brent crude oil, and the geopolitical risk (GPR) index developed by [Caldara and Iacoviello \(2022\)](#). The selected ETFs capture key sectors influencing global market dynamics which are particularly exposed to geopolitical and energy-related shocks.

The sample period goes from 1 January 2023 to 22 September 2025, encompassing 996 observations. Data on financial asset prices were obtained from [investing.com](https://www.investing.com), while Bitcoin prices were retrieved from [finance.yahoo.Com](https://finance.yahoo.com)

During the period under examination, the MENA region experienced several major geopolitical developments, including the conflict between Israel and Hamas, ongoing tensions between Iran and Israel, and Iran's acquisition of control over the Strait of Hormuz, a strategic chokepoint for global trade. These events had significant repercussions on both global and regional financial markets, as well as on crude oil prices.

For the estimation, stock returns are calculated as follows :

$$R_t^1 = \log \left(\frac{P_t}{P_{t-1}} \right),$$

where P_t stands for the stock price at time t .

Table 1. Descriptive Statistics

	Mean	Variance	Skewness	Kurtosis	JB	ADF	ERS	Q(20)	Q ² (20)
Brent	-0.025	2.369	-0.4970	6.047	425.52***	-11.222	-14.540***	25.209	45.655***
S&P500	0.0559	0.642	0.5372	25.025	20139***	-10.959	-14.869***	34.234**	46.092**
STOXX600	0.0266	0.416	-1.2088	13.574	4873.5***	-10.353	-6.9587***	27.954	51.092**
Nikkei 225	0.056	1.336	-1.0895	32.289	35726***	-9.913	-14.428***	48.223**	50.782***
Bitcoin	0.192	6.060	0.4701	7.323	810.66***	-10.179	-13.133***	17.003	21.092**
XLE	0.0002	1.369	-1.014	13.489	4727.6***	-10.685	-13.982***	30.933**	17.696**
ITA	0.0605	0.850	-0.2066	20.864	13225***	-11.102	-15.407***	30.1	12.846
XLK	0.0825	1.465	0.4580	17.869	9191.8***	-10.483	-13.909***	19.382	13.909
GPR	0.010	2530.28	0.638	5.312	599.362***	-10.284	-4.306***	169.830**	81.362***

Note: The Q(20) and Q²(20) statistics are the Ljung-Box test statistics used to test the null hypothesis of no serial correlation up to the 20th order in returns and squared returns, respectively. A 20-lag specification is chosen to capture serial dependence over a full half-year period. The Jarque-Bera statistic tests the null hypothesis that a series is normally distributed by examining its first two moments, with the statistic following a χ^2 distribution with two degrees of freedom under the null hypothesis. The

Elliott, Rothenberg, and Stock (ERS: 1996) test is a modified version of the Augmented Dickey-Fuller (ADF: 1979) test. Significance levels are indicated as follows: (***) 1%, (**) 5%, and (*) 10%.

Table 1 presents some descriptive statistics for the average daily returns of all series. All of them are positive, except in the case of the Brent oil market (-0.0257%). Bitcoin (BTC) has the highest average return (19.2%), while the GPR index exhibits the highest variance (2530.281), indicating that it is the most volatile series.

The skewness analysis shows that some stock market indices, such as the STOXX 600 (Europe) and the Nikkei 225 (Japan), as well as the energy (XLE) and defence (ITA) ETFs, exhibit negative skewness, with distributions skewed to the left. This indicates greater vulnerability to large negative returns. By contrast, the US S&P 500 index, Bitcoin, and the technology ETF (XLK) exhibit strictly positive skewness (>0), implying that their return distributions are skewed to the right, with a longer tail suggesting the potential for high returns and relatively strong resilience to geopolitical tensions. High kurtosis statistics, such as those for the Nikkei 225 (32.289) and the S&P 500 (25.025), suggest that returns are highly concentrated around the mean, with fat tails. This phenomenon is typical of markets exposed to extreme events or significant geopolitical risks. Moreover, the results of the [Jarque-Bera test \(1980\)](#) reject the null hypothesis of normality for all return series. The ADF (Augmented Dickey-Fuller) test indicates that all return series are stationary at the 1% significance level. This is confirmed by the negative values of the [ERS \(1996\)](#) test statistics.

The Ljung-Box Q(20) test, which detects autocorrelations over the first 20 lags, produces significant results for some stock indices such as the S&P 500 and Nikkei 225, the energy ETF (XLE) and the GPR index, suggesting the presence of autocorrelation resulting from persistent factors, most likely the recent geopolitical events including the ongoing conflict in the Middle East. By contrast, other financial assets, such as Bitcoin, the technology and defense ETFs (XLK and ITA), and the Brent oil price do not exhibit significant Q(20) statistics, which indicates that they are less sensitive to geopolitical shocks.

The $Q^2(20)$ test shows high persistence of volatility in the returns for global stock indices, commodities, the energy ETF (XLE), Bitcoin and the GPR index in the current geopolitical context. By contrast, no autocorrelation is found in the case of the volatility of returns on technology and defense ETFs (XLK and ITA).

Figure 1 displays the return series. Most of them appear to be highly volatile (especially Bitcoin and GPR), with a peak in the period from June 2025, which has been characterised by increased instability in financial markets linked to geopolitical factors, such as the persistent tensions in the Middle East. However, the defence (ITA) and technology sector (XLK) ETFs are relatively less volatile as a result of their lower direct exposure to shocks.

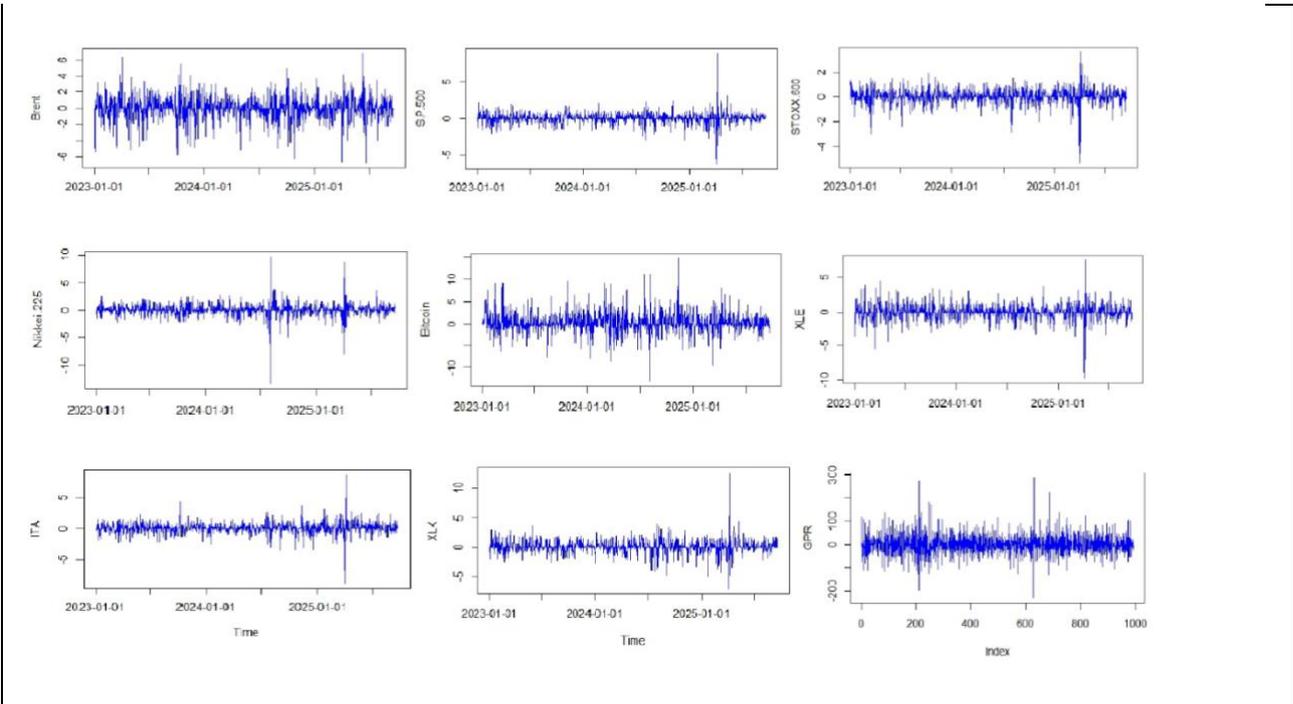


Figure 1: Returns on the series examined

3.2 Methodology

We examine linkages between sector ETFs, Bitcoin, stock market indices, Brent crude oil and geopolitical risk using Balli et al.’s (2023) R^2 decomposition connectedness analysis framework. This approach is an extension of Diebold and Yilmaz’s (2012)’s method which can distinguish between contemporaneous and lagged spillovers and thus leads to a deeper

understanding of market dynamics. Within this framework, a Vector Autoregression (VAR(p)) model is used to compute connectedness measures and to examine the relationship between the goodness-of-fit indicator and the Generalized Forecast Error Variance Decomposition (GFEVD). Building on insights from [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#), this method sheds more light on connectedness by going beyond the limitations of model-based assumptions. The optimal lag length (p) is determined using information criteria such as the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC), ensuring both parsimony and predictive accuracy of the VAR model. The model's goodness-of-fit is then evaluated and the robustness of the results is tested through cross-validation and by incorporating potential confounding variables to mitigate omitted variable bias.

In this study we use a vector autoregression (VAR(p)) model with lag length $p = 1$ chosen on the basis of the BIC statistic. Therefore the estimated model is the following:

$$y_t = \sum_{i=0}^p B_i y_{t-i} + u_t; \quad u_t \sim N(0; \Sigma) \quad (1)$$

where y_t , y_{t-i} , and u_t are $K \times 1$ vectors of de-meaned variables at time t . The matrices B_i and Σ are $K \times k$ dimensional, with the diagonal elements of B_i constrained to zero, ensuring that the variable on the left is not included in the predictors on the right. It is crucial to emphasize that the VAR model reduces to the contemporaneous R^2 decomposed connectedness framework when its order (B_i) is zero, as shown by [Balli et al. \(2023\)](#). The model can also be expressed in a matrix form as follows: $y_{k,t} = b_k x_{k,t} + u_{k,t}$,

where $x_t = (y_t; y_{t-1}; \dots \dots \dots; y_{t-i}; \dots \dots \dots; y_{t-p})$ is a vector with dimension $K(p + 1) \times 1$ and b_k is also a vector with dimension $1 \times K(p + 1)$ and zero in the k th position, respectively.

The goodness-of-fit measure of R^2 from multiple linear regression (MLR) is consistent with the sum of R^2 contributions from binary linear regressions (BLRs), provided that all of the right-hand-side variables (RHS) are uncorrelated with one another. The key to addressing this

problem is finding a transformation that converts the correlated series, where $x_{k,t}$ is similar to x_t but lacks the left-hand side (LHS) variable, into a set of orthogonal series. Principal component analysis (PCA) is an effective tool for achieving this transformation since it uses several latent factors corresponding to the count of the RHS variables. Consequently, the R^2 decomposition of an MLR is calculated as follows:

$$R_{X;X} = V\Lambda V' = CC' \quad (2)$$

$$C = V\Lambda^{1/2}V' \quad (3)$$

$$R^{2,d} = C^2(C^{-1}R_{Y;X})^2 \quad (4)$$

where V and $\Lambda = \text{diag}(\lambda_1; \dots \dots \dots; \lambda_{K(p+1)-1})$ and $R_{X;X}$ represent $[(K(p+1)-1; K(p+1)-1)]$ eigenvector matrices, eigenvalue matrices, and Pearson correlation matrices, respectively, while $R_{y.x}$ et $R^{2,d}$ are $[K(p+1)-1; 1]$ Pearson correlation and R^2 contribution vectors, respectively. More precisely, $R_{X;X}$ refers to the Pearson correlation coefficients of the RHS variables and $R_{y.x}$ to the Pearson correlation coefficients between the LHS and RHS variables. The first $K-1$ values of $R^{2,d}$ represent the contemporary R^2 contributions, while the other measures the lagged R^2 contributions. Consequently, the vector sum of $R^{2,d}$ is equal to the MLR R^2 goodness-of-fit measure. Next, one stacks the $R^{2,d}$ contribution of all K MLRs to obtain the $K \times K(p+1)$ dimensional $R^{2,d}$ decomposition matrix, $[R_0^{2,d}; \dots; R_i^{2,d}; \dots R_p^{2,d}]$.

$R_0^{2,d}$ can be interpreted as the contemporaneous spillovers ($R_C^{2,d}$) while the sum of the lagged values ($R_L^{2,d} = R_1^{2,d} + \dots + R_i^{2,d} + \dots + R_p^{2,d}$) stands for the lagged spillovers.

Compared to the connectedness approach of [Diebold and Yilmaz \(2012, 2014\)](#), $R_C^{2,d}$ and $R_L^{2,d}$ replace the scaled GFEVD matrix. This implies that the total connectedness index (TCI) is equal to the average R^2 of the k MLRs:

$$TCI = \frac{1}{K} \sum_{K=1}^K R_K^2 \quad (5)$$

As R_K^2 is within zero and unity, TCI also lies within the same range avoiding the connectedness normalization problem (Lastrapes and Wiesen (2021), Chatziantoniou and Gabauer (2021), Gabauer (2021)). Using this methodology allows us to investigate the contemporaneous and lagged TCI:

$$TCI = \frac{1}{K} \sum_{K=1}^K R_K^2 \quad (6)$$

$$TCI = \frac{1}{K} (\sum_{K=1}^K \sum_{j=1}^K R_{C,K,j}^{2,d}) + \left(\frac{1}{K} \sum_{K=1}^K \sum_{j=1}^K R_{L,K,j}^{2,d} \right) \quad (7)$$

$$TCI = TCI^C + TCI^L \quad (8)$$

where TCI^C and TCI^L represent the contemporaneous and lagged TCI, respectively. Finally, the same concept can be applied to the total directional connectedness TO and FROM others as well as the net total directional connectedness measures:

$$TO_j = \sum_{K=1}^K R_{C,K,j}^{2,d} + \sum_{K=1}^K R_{L,K,j}^{2,d} \quad (9)$$

$$TO_j = TO_j^C + TO_j^L \quad (10)$$

$$FROM_j = \sum_{K=1}^K R_{C,j,K}^{2,d} + \sum_{K=1}^K R_{L,j,K}^{2,d} \quad (11)$$

$$FROM_j = FROM_j^C + FROM_j^L \quad (12)$$

$$NET_j^C = TO_j^C - FROM_j^C \quad (13)$$

$$NET_j^L = TO_j^L - FROM_j^L \quad (14)$$

$$NET_j = NET_j^C + NET_j^L \quad (15)$$

While the TO_j (TO_j^C/TO_j^L) total directional connectedness illustrates how much of the overall (contemporaneous/lagged) variance in all LHS variables is explained by series j , the $FROM_j$ ($FROM_j^C/FROM_j^L$) total directional connectedness measures how much all RHS variables explain of the overall (contemporaneous/lagged) variance in series j equal to R^2 of the KMLR. If the $NET_j > 0$ ($NET_j < 0$), series j is considered as a net transmitter (receiver)

of shocks indicating that it can explain more (less) of the variation in others than vice versa. The contemporaneous and lagged connectedness measures can be interpreted in the same fashion.

4. Empirical Results

4.1 Averaged Connectedness Analysis

Table 2 presents the average total connectedness of returns between different assets: defence, energy, and technology exchange-traded funds (ETFs) (XLE, ITA, XLK); cryptocurrencies represented by Bitcoin (BTC); major stock market indices such as the S&P 500, Nikkei 225, and STOXX 600; the Brent crude oil price; the geopolitical risk index developed by [Caldara and Iacoviello \(2022\)](#). Tables 3 and 4 present the results of the decomposition between contemporaneous connectedness and lagged connectedness. The analysis is based on a 200-day sliding window VAR model with a lag order of one, determined according to the Bayesian Information Criterion (BIC). The latter is widely used because of its ability to balance model fit and parsimony, thus reducing the risk of overfitting. The use of short lags also allows to capture more accurately the dynamics of critical information transfers ([Lütkepohl, 2005](#) ; [Xu et al., 2019](#)). The choice of a 200-day moving window is a suitable compromise : it is long enough to guarantee stable estimates while remaining short enough to capture medium-term changes in market dynamics. This setting is also commonly adopted in the literature ([Diebold and Yilmaz, 2012](#) ; [Balli et al., 2023](#)). This approach thus makes it possible to highlight the mechanisms by which volatility and shocks spread across asset classes and to identify those that play a central role as transmitters or receivers, emphasizing the importance of transmission channels during periods of economic and geopolitical tensions.

Table 2. Average Overall Connectedness (%)

	Brent	S.P.500	STOXX.600	Nikkei.225	Bitcoin	XLE	ITA	XLK	GPR	FROM
Brent	0.37	3.41	2.09	1.03	1.19	33.59	3.40	2.83	1.06	48.60

S.P.500	1.81	0.31	6.68	2.24	3.73	6.72	15.37	52.62	0.51	89.68
STOXX.600	1.45	9.37	0.92	11.46	1.20	4.89	6.20	5.75	0.49	40.82
Nikkei.225	1.00	5.92	12.70	2.52	2.13	1.63	2.86	6.65	1.24	34.13
Bitcoin	1.28	4.70	1.16	2.02	0.86	2.04	3.04	3.24	1.60	19.07
XLE	28.68	9.13	4.31	1.27	1.71	0.34	10.86	6.07	0.62	62.65
ITA	2.37	18.39	4.49	1.23	3.43	11.57	0.62	10.29	0.77	52.54
XLK	1.63	59.10	4.84	1.90	3.14	4.28	10.50	0.43	0.47	85.85
GPR	1.12	0.76	0.48	1.49	0.99	0.53	1.05	0.57	10.45	6.99
TO	39.33	110.79	36.76	22.63	17.52	65.26	53.28	88.01	6.76	440.33
Inc.Own	39.70	111.10	37.68	25.15	18.38	65.59	53.90	88.44	17.21	cTCI/TCI
NET	-9.27	21.11	-4.06	-11.50	-1.55	2.60	0.74	2.16	0.23	55.04/48.93
NPT	2.00	8.00	2.00	2.00	3.00	5.00	5.00	6.00	3.00	

Notes : These results are obtained using a 200-day rolling-window VAR model with a lag length of order one (BIC).

Table 3. Average Contemporaneous Connectedness (%)

	Brent	S.P.500	STOXX.600	Nikkei.225	Bitcoin	XLE	ITA	XLK	GPR	FROM
Brent	0.00	2.98	1.35	0.63	0.82	32.39	2.64	2.42	0.65	43.88
S.P.500	1.62	0.00	5.99	1.27	3.57	6.45	14.74	52.33	0.27	86.24
STOXX.600	1.13	7.16	0.00	10.24	0.74	3.21	3.75	4.05	0.26	30.55
Nikkei.225	0.68	1.71	10.13	0.00	1.30	0.86	0.64	1.25	0.91	17.48
Bitcoin	0.92	4.25	0.82	1.37	0.00	1.57	2.70	2.91	0.49	15.04
XLE	28.35	8.48	3.14	0.72	1.23	0.00	10.30	5.18	0.26	57.65
ITA	2.03	17.94	3.82	0.54	2.50	10.81	0.00	9.87	0.40	47.92
XLK	1.39	58.80	4.18	1.02	2.90	3.93	9.81	0.00	0.23	82.26
GPR	0.75	0.54	0.34	1.00	0.51	0.34	0.52	0.42	0.00	4.43
TO	36.88	101.87	29.77	16.80	13.57	59.56	45.10	78.43	3.47	385.46
Inc.Own	36.88	101.87	29.77	16.80	13.57	59.56	45.10	78.43	3.47	cTCI/TCI
NET	-7.00	15.62	-0.78	-0.68	-1.47	1.91	-2.82	-3.83	-0.96	48.18/42.83
NPT	3.00	8.00	5.00	3.00	1.00	6.00	4.00	6.00	0.00	

Notes : These results are obtained using a 200-day rolling-window VAR model with a lag length of order one (BIC).

Table 4. Average Lagged Connectedness (%)

	Brent	S.P.500	STOXX.600	Nikkei.225	Bitcoin	XLE	ITA	XLK	GPR	FROM
Brent	0.37	0.43	0.74	0.40	0.37	1.20	0.77	0.40	0.40	4.72
S.P.500	0.19	0.31	0.69	0.97	0.15	0.27	0.63	0.29	0.24	3.43
STOXX.600	0.32	2.21	0.92	1.22	0.46	1.68	2.45	1.70	0.23	10.26
Nikkei.225	0.31	4.21	2.57	2.52	0.83	0.78	2.22	5.39	0.33	16.65
Bitcoin	0.36	0.45	0.34	0.65	0.86	0.47	0.34	0.33	1.11	4.03
XLE	0.33	0.65	1.17	0.55	0.49	0.34	0.56	0.89	0.36	5.00
ITA	0.34	0.45	0.67	0.69	0.93	0.77	0.62	0.42	0.37	4.62
XLK	0.24	0.30	0.65	0.87	0.24	0.36	0.69	0.43	0.24	3.60
GPR	0.37	0.22	0.14	0.48	0.48	0.19	0.53	0.15	10.45	2.56
TO	2.45	8.92	6.99	5.83	3.95	5.70	8.18	9.58	3.28	54.88
Inc.Own	2.82	9.23	7.90	8.35	4.81	6.03	8.79	10.01	13.74	cTCI/TCI
NET	-2.27	5.49	-3.28	-10.82	-0.08	0.69	3.55	5.98	0.73	6.86/6.10
NPT	0.00	6.00	2.00	2.00	5.00	4.00	6.00	5.00	6.00	

Notes : These results are obtained using a 200-day rolling-window VAR model with a lag length of order one (BIC).

It can be seen from Table 2, 3 and 4 that the average value of the total TCI for the whole dataset is 48.93%. This means that almost half of the volatility observed in the network of variables can be explained by connectedness, with 42.83% coming from contemporaneous effects and 6.10% from lagged ones. This decomposition suggests that shock transmission is much stronger in the short than in the medium term, and that it tends to intensify immediately after an event. Moreover, for all variables, the ratio remains below 100%, which implies that total connectedness largely exceeds conditional connectedness. The observed gap is mainly due to contemporaneous effects, confirming that variables react quickly and strongly to external shocks. Thus, contemporaneous connectedness dominates over lagged connectedness, indicating that the system is more sensitive to immediate impacts, while delayed effects remain limited and show no significant persistence over time.

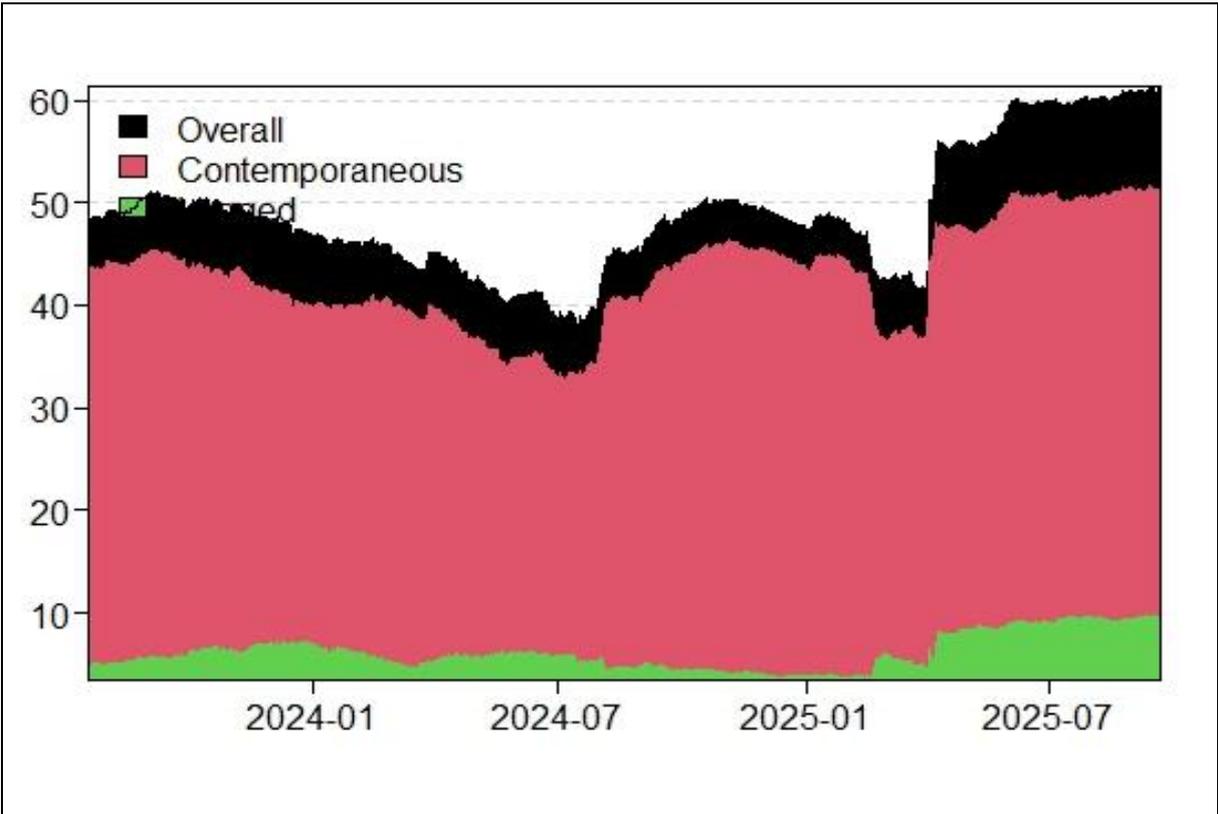
Further, concerning total directional connectedness to and from the system, as well as their net values, Table 2 shows that the S&P 500 Index (21.11%) stands out as the largest net

emitter of risk, followed by the XLE Energy ETF (2.60%). These two assets simultaneously exhibit strong transmission and high risk exposure to other markets. The Technology (XLK) and Defence (ITA) ETFs appear to be slight emitters (small positives), indicating that they transmit some volatility to other markets, but only moderately. By contrast, the Nikkei 225 (-11.50%) is the largest net receiver of shocks, followed by Brent oil (-9.27%). Bitcoin, with a slightly negative value (-1.55%), is less sensitive to shocks and could act as a relative safe haven.

4.2 Dynamic Connectedness

Next we explore dynamic connectedness. Figure 2 shows the evolution over time of total system connectedness, decomposed across energy, defence, and technology ETFs, cryptocurrencies, the Brent oil price, stock market indices, and the Geopolitical Risk (GPR) index. The black area represents global total connectedness, whilst the red one corresponds to contemporaneous connectedness, and the green one to lagged connectedness.

Figure. 2. Time Variation of Total Connectedness



Notes: The black area corresponds to total dynamic connectedness, while the red and green ones represent dynamic contemporaneous and lagged connectedness respectively.

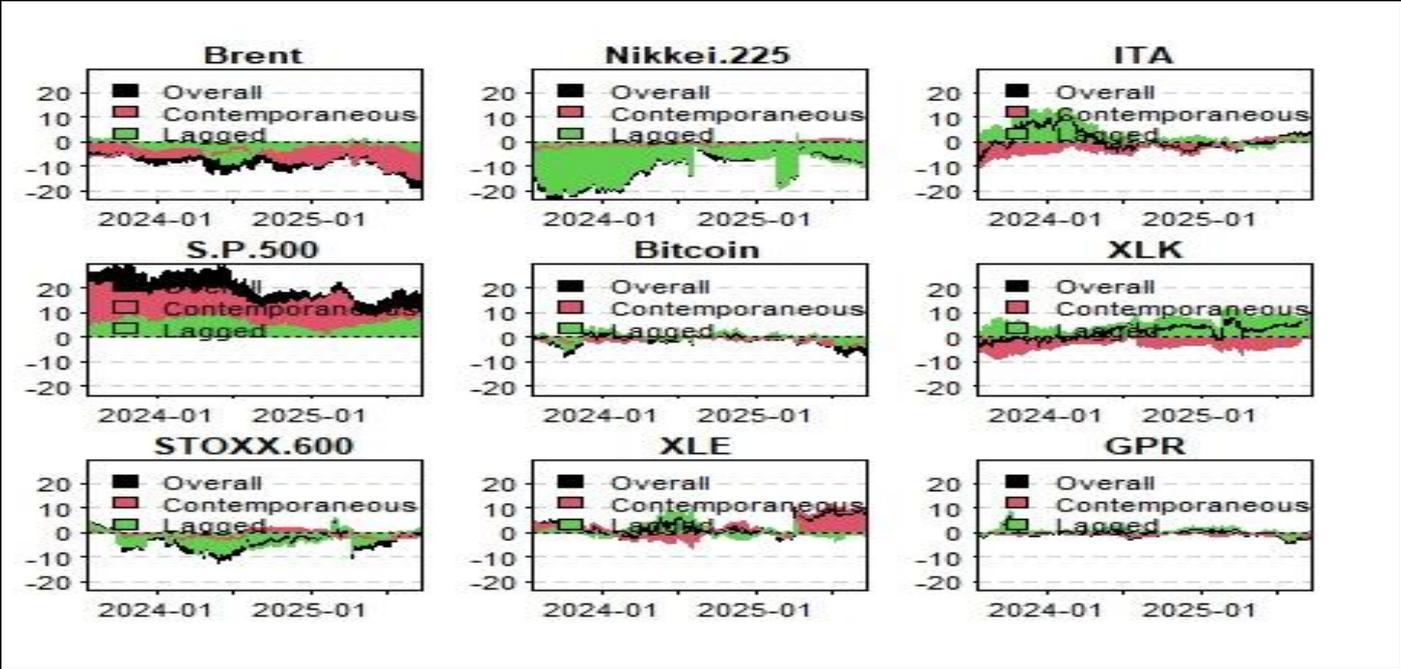
It can be seen that contemporaneous connectedness largely dominates over the entire period, indicating that shocks tend to be transmitted immediately between markets, which reflects a high sensitivity to geopolitical and economic events. Lagged connectedness remains relatively low but tends to increase slightly from 2025, pointing to some lagged effects after the initial shocks. Total spillovers (in black) exhibit an upward trend, particularly marked from the first half of 2025, when total connectedness reaches its highest levels. This pattern reflects stronger financial linkages at times of heightened geopolitical tensions resulting, for instance, from the conflict in the Middle East and the potential disruption in the Strait of Hormuz, thus highlighting the growing vulnerability of global markets to such shocks.

4.3 Net Total Directional Connectedness

Figure 3 shows the evolution over time of total net directional connectedness between the returns on the assets considered here. This measure allows us to determine, at different points

in time, which assets behave as net emitters or receivers of volatility. Decomposing this estimate into contemporaneous and lagged connectedness components highlights the propagation mechanisms of instantaneous and lagged shocks within the system. The results in Figure 3 underline the dynamic and asymmetric nature of shock transmission between different asset classes. The S&P 500 Index stands out as the main net emitter of shocks, playing a central role in the diffusion of global volatility. ETFs in the defence (ITA) and technology (XLK) sectors also appear to be emitters, but to a moderate extent, influencing only slightly the returns of the other financial assets with which they interact. Conversely, European (STOXX 600) and Japanese (Nikkei 225) stock market indices, as well as the price of Brent, behave primarily as receivers, absorbing the turbulence generated by the system during times of shocks. Bitcoin exhibits slight fluctuations, which suggests some resilience in the face of geopolitical tensions. The energy ETF (XLE) exhibits a hybrid behaviour, alternating between the roles of transmitter and receiver depending on market conditions and developments in Iran and the Middle East affecting the Strait of Hormuz. On the whole, contemporaneous connectedness dominates over lagged connectedness, which highlights the instantaneous transmission of shocks related to geopolitical events.

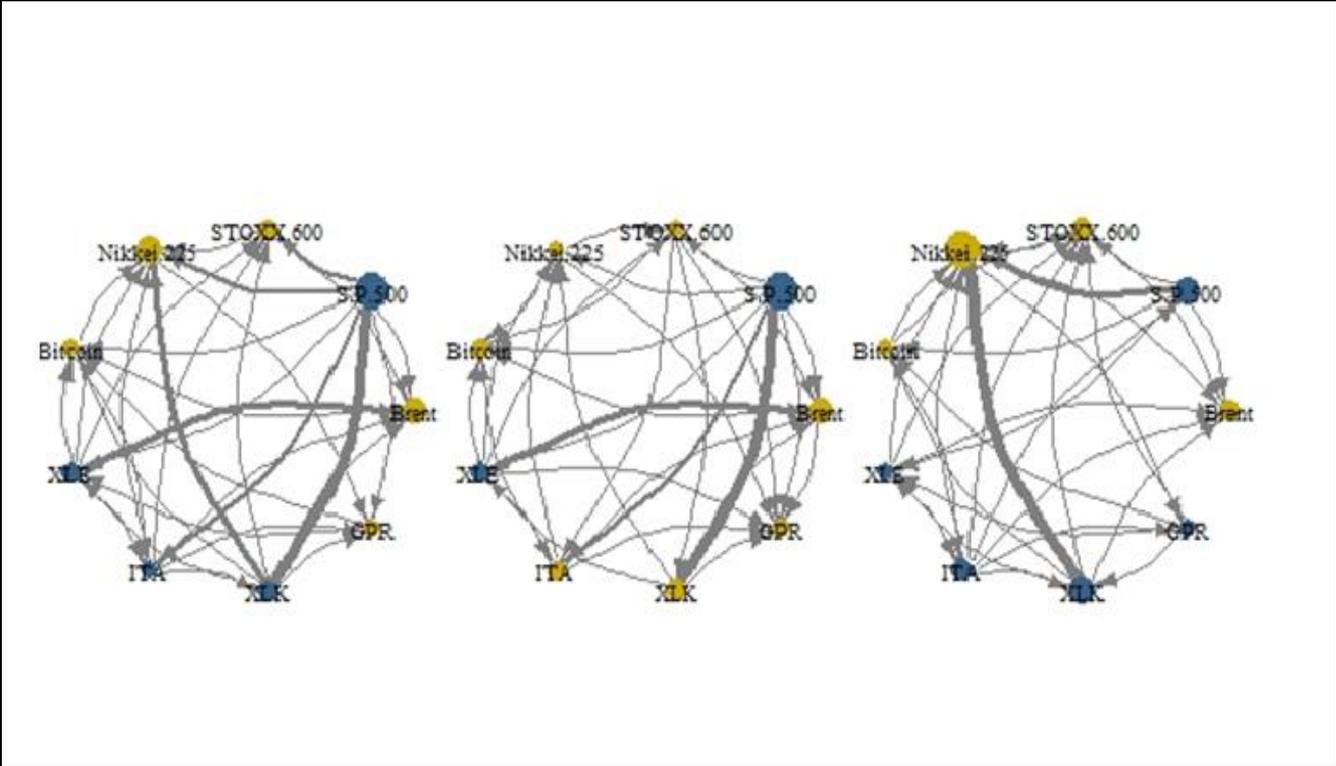
Figure 3. Net Total Directional Connectedness



Notes : The dynamic net contemporaneous and lagged connectedness are shown in red and green, respectively, while the overall dynamic Net connectedness is visualized by the black line.

Finally, Figure 4 displays pairwise net directional connectedness measures (total, contemporaneous, and lagged). Emitters are shown in blue and receivers in yellow, while the thickness of the arrows reflects the intensity of shock transmission. Stock market indices, such as the Nikkei 225, the STOXX 600, and Brent oil, behave primarily as receivers, particularly in the face of the current shocks in the Middle East. Bitcoin (BTC) also appears to be a receiver, but to a more moderate extent, with thinner arrows. Conversely, the S&P 500 Index emerges as the primary shock emitter. The Energy ETF (XLE) also acts as an emitter, especially in terms of contemporaneous effects, which reflects this sector's high sensitivity to geopolitical tensions and its role in risk diffusion. By contrast, the Defence (ITA) and Technology (XLK) ETFs exhibit hybrid behaviour : they appear to be emitters on the basis of total net directional connectedness, but seem to act as receivers in terms of contemporaneous effects, absorbing the impact of new market tensions and fluctuations in the short term.

Figure 4. Network Connectedness



Notes : Overall (Left), Contemporaneous (Centre) and Lagged (Right) Connectedness.

5. Conclusions

This paper examines connectedness between the returns on various asset classes, including sectoral exchange-traded funds (ETFs), cryptocurrencies, energy commodities and major global stock market indices over the period from 1 January 2023 to 22 September 2025, which was characterised by significant geopolitical risks in the Middle East and elsewhere. More specifically, the analysis is based on the decomposed R^2 connectedness method developed by Balli et al. (2023), which sheds light on both contemporaneous and lagged effects.

The results indicate that the dynamics of the Total Connectedness Index (TCI) are mainly driven by contemporaneous, rather than lagged, effects. Some major stock market indices, such as the Nikkei 225 and the STOXX 600, as well as the Brent oil price, exhibit highly negative contagion effects, indicating that they are net receivers. Bitcoin (BTC) displays slightly negative spillovers, is less sensitive to shocks, and appears to be a relative safe haven.

By contrast, the S&P 500 Index stands out as the largest net emitter of shocks, playing a central role in diffusing global volatility. Defence (ITA) and technology (XLK) ETFs also appear to act as emitters, but only to a moderate extent. The Energy ETF (XLE) exhibits a hybrid behaviour, alternating between the roles of emitter and receiver depending on market conditions, absorbing shocks related to the turbulence of the conflict in the Middle East and also exhibiting high exposure to other markets. Thus, in some market conditions, defence and technology ETFs can act as partial safe havens.

Future work could extend our analysis in several ways. First, longer data spans and additional assets could be examined, for instance sovereign bonds or other commodities such as gas, wheat, and gold. Further, investor sentiment could be included in the model in order to gain a better understanding of portfolio diversification in the face of geopolitical risks. Finally, other types of models such as VAR-GARCH specifications could be estimated to shed more light on both mean and volatility spillovers.

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