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An investigation of the frequency dynamics of spillovers and connectedness among GCC sectoral indices[☆]

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ABSTRACT

We examine intra-regional patterns of return and volatility spillovers between economic sectors of GCC over the period from 2007 to 2021 at different frequencies. First, we investigate the connectedness of sectoral equity returns and volatilities by applying TVP-VAR frequency connectedness method and explore the different patterns and magnitudes. Second, we explore possible determinants of sectoral equity return and volatility spillovers. We identify that spillovers are regime dependent increasing their intensity during turmoil periods such as 2007–2008 crisis, 2014 oil price crash and 2020 COVID-19 pandemic. The level of contagion is the highest in the financial sector and the lowest in the energy sector. In general, while Bahrain stock market is segmented from other markets in many sectors, Saudi Arabia is losing its dominance position to UAE and Qatar to transmit shocks to other countries. In line with the literature, the liquidity and profitability positions significantly affect the extent of the spillovers which are highly dispersed across sectors. Particularly, the sectors that have high leverage tend to transmit the shock rather than absorb. Our findings confirm the heterogeneity of sectoral spillover returns and volatilities, thereby suggesting that portfolio managers can monitor the magnitude of the spillovers by controlling the financial performance of the firms and guide their investment decisions accordingly at different time horizon.

1. Introduction

Financial markets have recently witnessed several episodes of extreme uncertainty and volatility that have generated renewed interest among portfolio managers, policymakers and academics in understanding the nature and extent of linkages across various equity markets. Several empirical studies, pioneered by Bekaert and Harvey (1997), Ng (2000), Fratzscher (2002), Baele (2005), Kim et al. (2005), and Yilmaz (2010), examine the integration between national equity markets. These studies find a substantial rise in the degree of equity market integration worldwide, thereby reflecting a high correlation between local and global market returns. All these studies conclude that the degree of financial integration between markets increases further and local market returns are going to respond more strongly to common shocks.

Given such a scenario, investors are actively in search of potential markets that can provide attractive returns along with diversifying risk, particularly when developed and emerging markets are in turmoil. From that perspective, equity markets of oil-rich

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Gulf Cooperation Council (GCC) countries offer investors with enhanced portfolio diversification opportunities (Balli et al., 2013). There is significant relationship among different GCC stock markets due to their parallel economic structure, diversification goals, geographic proximity, harmonization of the regulations and policy coordination to achieve the declared goal of the GCC becoming a unified regional economic bloc. However, due to their frontier or newly emerging market status and unique economic structures, they are not fully integrated with the developed markets as represented by the United States and European markets (Marashdeh & Shrestha, 2010).

There is an interest in the literature to explore integration in the GCC equity markets. By utilizing data from 1999 to 2005, Yu and Hassan (2008) report evidence of segmentation of stock markets in the GCC union. Alkulaib et al. (2009) argue that the UAE stock market leads all other markets in the region due to the significant growth of UAE's equity market, and its positioning as the main financial hub in the Middle East. By focusing on integration in the UAE stock markets, Kapar et al. (2020) demonstrate the integration within three national stock exchanges in the UAE by applying vector error correction model. Hammoudeh and Aleisa (2004) find that the Saudi market has the highest linkages with other GCC countries whereas Kuwait has the lowest. According to Awartani et al. (2013), the dominance of the Saudi market in the GCC bloc is due to its higher market capitalization and liquidity. Aloui and Hkiri (2014) investigate both the long-term and the short-term dependence among the six GCC stock markets from 2005 to 2010. Using the wavelet technique, they reveal an intensified level of co-movements among GCC financial markets during the subprime crisis. By including COVID-19 era, Ziadat and AlKhouri (2022) reveal a substantial increase in the connectedness of returns and volatilities in the GCC bloc during high stress periods, especially marking a historical high during COVID-19. Alotaibi and Mishra (2017) show wide ranges in the degree of integration for GCC stock markets and attribute these differences to trade openness, financial market development, turnover, and oil revenue. Charfeddine and Al Refai (2019) show volatility spillover effects between Qatar and the other GCC countries which intensified during Qatar Blockade in June 2017. Chowdhury (2020) examines how stock market sentiment in GCC stock markets may spillover to affect sentiments in other markets in the region using DCC model. They reveal that Kuwait and Qatar stock markets are segregated from other markets in the region, while Saudi Arabia and the UAE markets are well integrated indicating a contagion effect especially during stock market panic. Yousaf et al. (2022) examine bivariate VAR-asymmetric-BEKK-GARCH model to examine returns, asymmetric volatility spillovers, and time-varying correlations among GCC stock markets and five global factors (Islamic stocks, oil, gold, bonds, and real estate) from 2004 to 2021. Spillovers strengthen in both the return and variance during post GFC and the COVID-19 periods. Gold serves as a hedge/safe haven in crisis or non-crisis episodes, whereas bonds, Islamic stocks, and real estate assets are diversifiers for GCC investors in stressful periods.

Exploring the behaviour of GCC equity markets at sectoral level is relatively under-researched. Balli et al. (2013) examine spillover effects of local and global shocks on GCC-wide sectoral equity returns. They find that GCC-wide sector returns have asynchronous responses to global and regional shocks. Including GCC-wide sectoral returns, Balli et al. (2021) investigate spillovers from regional and global equity markets to sectoral equity indices for several different regions/countries. They find that the regional and global markets spillovers on sector equity indices are highly dispersed across different markets resulting from differences in the liquidity and financial positions of the sectors. The aim of this study is to bring clarity to the issues of the main intra-regional sectoral transmissions within the GCC by providing a more comprehensive and updated analysis.

Towards this end, we examine intra-regional patterns of return and volatility spillovers between economic sectors of GCC stock markets over the period from 2007 to 2021. There is a strong justification for focusing on the spillover at the sectoral level. As Moerman (2008) stated, industry-based diversification yields more efficient portfolios than country-based diversification. International portfolio investors who seek more attractive risk–return trade-offs in their portfolios go beyond investing in aggregate equity market indices and explore investment opportunities in sectors that best suit the state of the global economy and their investment objectives (Balcilar et al., 2015). The sectors themselves offer another dimension of diversification as they cover different aspects of the macroeconomy such as energy, basic materials, industrials, banking, investment, real estate, telecommunication and utilities. We focus on return spillovers to measure the general market level while volatility spillover to measure market risk.

Our study contributes to the literature in the following ways. First, the study unravels the nature and extent of return and volatility spillovers across economic sectors which is important for portfolio managers, investors and policymakers. Understanding the nature of the linkages between various sectors of GCC markets is important for investors who may be seeking to achieve cross-sectoral diversification benefits. Moreover, by examining the magnitude and direction of return and volatility spillovers across sectors, this study can help policymakers identify the factors contributing to the overall aggregate risk in the markets. Second, when investors implement risk management plans or make investment decisions, only focusing on a fixed investment horizon is not sufficient due to the differences of multiple economic agents interacting in financial markets. Hence, we estimate the return and volatility spillovers at different frequencies such as 1–5 days, 6–22 days and 23-infinite days for investors that differ in preferences, beliefs, risk tolerances, aims, and levels of information assimilation. Lastly, despite the existence of a significant number of studies that have been conducted on spillovers of sectoral equity in various markets globally, relatively few researchers have sought to identify the determinants of these spillovers except Balli et al. (2021). We enhance this by investigating the determinants of return and volatility spillovers at different frequencies to give insight for investors with different investment horizons and goals.

We identify that spillovers are regime dependent increasing their intensity during turmoil periods such as 2008–2009 global financial crisis, 2014 oil crisis and early 2020 COVID-19 pandemic. In the GCC region, the level of contagion is the highest in the financial sector, followed by industrials and telecom sectors that lowers the diversification opportunities. Network analysis reveals that Saudi Arabia's influence on other GCC markets are getting weaker, while UAE and Qatar stock markets are becoming more dominant in the GCC region with regards to transmitting the shocks to other markets. In line with Balli et al. (2021), we find that the liquidity and profitability positions are highly affecting the extent of the spillovers which are highly dispersed across sectors and frequencies. Particularly, the return spillovers decrease with high profitability and asset size in the short term. Both return and volatility spillovers increase with high leverage over the long term. Hence, our findings confirm the heterogeneity of sectoral spillover returns and volatilities. Portfolio managers can monitor the sensitivity of fundamental market movements to spillovers and guide their investment decisions accordingly.

The rest of the paper is organized as follows. Section 2 describes the data used for our empirical analysis. Section 3 explains the empirical model and the methodology. Section 4 presents the findings and Section 5 concludes the paper with a summary of the main results and proposals for further research. Tables and figures are collected in an Appendix.

2. Data description

This study covers sectoral equity indices of six GCC countries (Saudi Arabia, UAE, Qatar, Oman, Kuwait and Bahrain) and GCC regional sectoral equity indices. The dataset is obtained from DataStream (Thomson Reuters Eikon) for the period from 1 January 2007 to 9 November 2021. The start date of the research period is chosen to ensure that majority of the sectoral indices have available data and to capture important events in GCC economies such as 2007–2008 financial crisis, 2009 Dubai debt crisis, 2014–2015 oil price decline, 2017 Qatar blockade and 2020 global COVID-19 crisis. Sectoral equity indices include Basic Materials, Consumer Discretionary, Consumer Staples, Energy, Financials, Industrials, Real Estate, Telecom and Utilities sectors. These sectors are chosen according to Thomson Reuters Business Classification System (TRBC). Weekly data is used to avoid spurious spillover effects arising from non-overlapping trading hours. A week is defined as going from Wednesday to Wednesday to account for different trading days within GCC countries.[1] For each index, weekly return is calculated as the natural logarithmic first difference of the weekly closing price multiplied by 100.

Furthermore, in line with the previous literature, we also consider the variables that measure liquidity and financial position of the sectors included in our analysis. The list of variables considered in the cross-section analysis includes: (i) the sector market capitalization ratio ($MCAP_{sector}$) which measures as each sector's market value of equity divided by the market value of equity of entire GCC region, (ii) net debt, which is calculated as: short-term debt + long-term debt - cash and liquid securities that is an indication of a business's ability to payoff all of its debts using only its available cash and highly liquid assets called cash equivalents, (iii) interest coverage ratio, which indicates a sectoral market's profit from its operations to meet its interest obligations, (iv) profit/asset measures profit of the sector divided by total assets owned by sectoral equity markets, (v) EV/EBITDA is a ratio that compares a company's Enterprise Value (EV) to its Earnings Before Interest, Taxes, Depreciation & Amortization (EBITDA), (vii) net profit margin is the profitability ratio of the sectoral markets, (viii) total assets refers to the total amount of assets owned by sectoral equity markets. This later dataset contains quarterly data from first quarter of 2007 to third quarter of 2021 in US dollars which is also extracted from DataStream (Thomson Reuters Eikon).

Table 1 provides the mean and standard deviation of the weekly returns of country/regional sectoral indices. As shown in Table 1, the highest average of the weekly returns based on aggregate indices is 0.149% for Qatar and the lowest is 0.055% for Bahrain. Based on sectoral indices, consumer discretionary index offers the highest return in Saudi Arabia, Qatar and Bahrain. In UAE and GCC, consumer staples index offers the highest return and in Kuwait, average weekly return is the highest in the energy index. UAE and Kuwait consumer discretionary indices and GCC real estate index offer negative returns for investors. In the second section of Table 1, the standard deviation of returns is given as a measure of volatility. The highest standard deviation is observed in Saudi Arabia aggregate index and the lowest in Bahrain aggregate index. Each country/region's returns on sectoral indices display a greater level of volatility than the return on respective aggregate index except a few cases. This is in line with the expectation since aggregate indices are more diversified than sectoral indices.

Table 2 provides the mean and standard deviation of the weekly volatilities of country/regional sectoral indices. As shown in Table 2, there is variability in volatility levels across industries and countries. According to regional GCC index, financial and industrial sectors have the highest volatility; telecom, utilities and basic materials sectors have the lowest volatility. The Augmented Dickey and Fuller (1978) test also illustrates stationarity of the return and volatility series and confirms satisfactory modelling conditions.

Table 3 provides an overview of statistics relating to the financial and liquidity variables from the panel data model. As shown in Table 3, sectoral market capitalization ranges between 0.000005 and 0.80 with an average value of 0.069. This indicates that sectoral markets in GCC countries vary in terms of their market capitalization. Net debt/asset ratio changes between −0.42 and 0.69. Hence, while some sectors have high liquidity to pay their debt with cash and cash equivalents,[2] some sectors have low liquidity to pay back their short and long-term debt when it is due. Interest coverage ratio varies between −0.36 and 9.32 which indicates that some sectors have negative EBIT(Earnings before Interest and Tax) and may have difficulty to cover their interest expense. For this ratio, we expect a higher(lower) value is positive(negative) indicator for company's liquidity position. Profit/Asset ratio varies between −0.19 and 0.27 with a mean value of 0.05. EV/EBITDA changes between 2.09 and 62.16. The average profit margin is 15.80% ranging between −165.97% and 387.01%. Hence, there are some GCC sectors with a very low profitability. The data sample is varied with respect to sectoral size, as proxied by total assets. The average total asset is 163 million and vary between 16,837 and 3.07 billion. To sum up, it is clearly visible that financial and liquidity ratios of the sectors are highly dispersed in the region.

[1] GCC countries have different working days during the considered period. For instance, in Saudi Arabia, weekend days changed from Thursday/Friday to Friday/Saturday in June 2013. In the UAE, weekend days changed from Friday/Saturday to Saturday/Sunday in January 2022. Hence, Wednesday is one of the common day that all GCC stocks markets are operating.

[2] The negative values in debt/asset ratios is originated from the fact that cash and equivalents are higher than the debt.

Table 1
Descriptive statistics for the return of examined indices based on weekly data for the period from 1 January 2007 to 9 November 2021.

	Saudi Arabia	UAE	Qatar	Kuwait	Oman	Bahrain	GCC
Mean of the Returns							
Basic Materials	0.152				0.093	0.090	0.069
Financials	0.112	0.090	0.139	0.062	0.090	0.052	0.101
Energy			0.174	0.316	0.038		0.189
Industrials	0.129	0.105	0.167	0.089	0.003	0.029	0.138
Real Estate	0.025		0.100	0.061		0.103	−0.023
Telecom	0.141	0.210	0.0006	0.014	0.056	0.120	0.128
Utilities	0.191	0.023	0.192		0.003		0.096
Consumer Staples	0.178	0.536	0.352	0.164	0.369	0.106	0.337
Consumer Discretionary	0.232	−0.112	0.361	−0.128	0.117	0.126	0.118
Standard Deviation of the Returns							
Basic Materials	4.215				3.083	3.182	3.334
Financials	3.359	3.289	3.282	2.527		1.566	2.408
Energy			4.188	5.327	3.121		5.100
Industrials	3.022	4.432	3.747	3.371	2.944	2.757	3.125
Real Estate	4.153		5.558	2.915		2.996	4.070
Telecom	3.387	3.059	3.614	4.155	2.993	2.246	2.680
Utilities	3.360	5.478	3.788		2.005		3.566
Consumer Staples	3.534	4.629	3.475	4.602	2.510	2.336	2.595
Consumer Discretionary	3.677	5.160	3.321	3.980	1.841	1.471	1.982
Unit Root Test of the Returns							
Basic Materials	−26.933				−25.790	−22.197	−29.335
Financials	−27.266	−27.990	−27.506	−27.295	−29.589	−24.068	−26.414
Energy				−32.750	−28.582		−24.322
Industrials	−28.204	−28.105	−29.259	−25.995	−25.914	−27.514	−27.968
Real Estate	−28.728		−24.655	−28.358		−26.995	−27.057
Telecom	−29.580	−29.816	−30.746	−30.492	−29.739	−26.645	−30.815
Utilities	−27.250	−28.564	−33.859		−28.801		−31.507
Consumer Staples	−30.599	−26.891	−27.578	−24.928	−26.035	−27.608	−20.409
Consumer Discretionary	−19.018	−23.568	−22.211	−21.639	−19.471	−22.630	−18.667

3. Empirical model

The empirical model used in this study consists of two steps: firstly, we follow TVP-VAR connectedness approach, extended joint connectedness and TVP-VAR frequency connectedness to estimate the spillovers and secondly, we develop a panel regression of gravity model to study the determinants of such spillovers.

3.1. TVP-VAR connectedness approach

This section first introduces the initial methodology of Diebold and Yilmaz (2012) and then explain the TVP-VAR connection method. Using the Bayesian information standard (BIC), we approximate a TVP-VAR design with a lag period of order one:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \textstyle\sum_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \tag{2}$$

where Y_t as well as Y_{t-1} are vectors of $N\times 1$ dimension endogenous variables; ε_t is a dimensional decay term $N\times 1$ with a time varying variance–covariance matrix $N\times N$, $\sum_t$; β_t is the $N\times N$ matrix of VAR coefficients; v_t is an $N^2\times 1$ intercept vector with $N^2\times N^2$ dimensions of the time varying variance–covariance matrix, R_t; $vec(\beta_t)$ is a vectorization of β_t.

TVP-VIMA model is structured as follows: $y_t = \sum_{h=0} N_{h,t}\varepsilon_{t-1}$ where $N_0 = I_Z$ and ε_t denotes symmetric white noise, where $Z\times Z$ varies Matrix time covariance $E\left(\varepsilon_t \varepsilon_t'\right) = \sum_t$ varies with time. Therefore, the L-step prediction error is as follows:

$$\varphi_t(L) = y_{t+L} - E(y_{t+L} \mid y_t, y_{t-1}, \ldots) = \sum_{l=0}^{L-1} N_{l,t}\varepsilon_{t+L-l} \tag{3}$$

A matrix of forecast error covariance be able to be recorded as below:

$$E\left(\varphi_t(L)\varphi_t'(L) = N_{l,t}\Sigma_t N_{h,t}'\right), \tag{4}$$

The suggested structure counts on Pesaran and Shin's (1998) L-step in advance generalized forecast error variance decomposition (GFEVD). The GFEVD, $gST_{ij,t}$, stands for an effect of a shock originating from variable j on variable i and also can be written as

Table 2
Descriptive statistics for the volatility of examined indices based on weekly data for the period from 1 January 2007 to 9 November 2021.

	Saudi Arabia	UAE	Qatar	Kuwait	Oman	Bahrain	GCC
Mean of the Volatilities							
Basic Materials	3.737				8.944	16.772	0.411
Financials	4.304	62.436	4.137	3.385	2.076	17.901	33.304
Energy				10.164	32.735		9.001
Industrials	3.105	99.786	61.383	37.911	37.197	3.805	40.574
Real Estate	0.493		2.490	0.833		0.879	3.497
Telecom	0.055	0.853	0.346	0.635	0.068	0.154	0.348
Utilities	0.412	0.158	11.728		0.588		0.577
Consumer Staples	12.291	666.363	33.166	8.604	2.285	7.112	4.292
Consumer Discretionary	14.343	7.846	8.878	4.962	1.676	1.177	3.791
Standard Deviation of the Volatilities							
Basic Materials	6.093				18.680	150.655	0.322
Financials	5.512	171.938	5.376	6.193	3.162	32.305	64.347
Energy				12.970	62.076		6.007
Industrials	3.452	173.29	74.508	66.756	96.721	4.123	57.970
Real Estate	0.558		5.383	1.735		1.853	7.885
Telecom	0.047	0.767	0.339	1.040	0.127	0.221	0.403
Utilities	0.345	0.227	10.039		0.787		0.702
Consumer Staples	12.970	3,130.983	25.325	11.843	3.650	14.416	5.875
Consumer Discretionary	15.297	4.229	8.458	4.115	1.592	0.409	2.768
Unit Root Test of the Volatilities							
Basic Materials	−7.619				−1.881	−26.613	−1.682
Financials	−8.731	−6.022	−5.301	−5.604	−8.836	−3.456	−6.202
Energy				−5.936	−4.655		−8.368
Industrials	−6.132	−3.969	−3.610	−9.039	−5.811	−4.812	−3.960
Real Estate	−4.406		−13.140	−7.121		−4.171	−6.463
Telecom	−3.769	−9.440	−4.169	−2.322	−6.223	−10.702	−2.490
Utilities	−5.624	−3.619	−3.742		−12.751		−3.115
Consumer Staples	−5.809	−6.685	−1.787	−11.631	−9.942	−14.107	−10.532
Consumer Discretionary	−8.045	−3.479	−7.312	−4.609	−8.224	−9.235	−7.159

Table 3
Descriptive statistics for the examined sectors are based on weekly data for the period from 1 January 2007 to 9 November 2021.

	Mean	Standard deviation	Minimum	Maximum
Sectoral Market Capitalization Ratio	0.069	0.13	0.000005	0.80
Net Debt/Asset	0.15	0.18	−0.42	0.69
Interest Coverage Ratio(%)	0.14	0.54	−0.36	9.32
Profit/Asset	0.05	0.04	−0.19	0.27
EV/EBITDA	10.77	6.32	2.09	62.16
Profit Margin(%)	15.80	21.76	−165.97	387.01
Total Assets	163,000,000	442,000,000	16,837	3,070,000,000

follows:

$$\varphi_{ij,t}^{gen}(L) = \frac{E\left(\varphi_{i,t}^{2}(L)\right) - E\left[\varphi_{i,t}(L) - E\left(\varphi_{i,t}(L)\right)\varepsilon_{j,t+1,\ldots,}\varepsilon_{j,t+1}\right]^{2}}{E\left(\varphi_{it}^{2}(L)\right)} \tag{5}$$

$$= \frac{\sum_{l=0}^{L-1}\left(e_i' N_{lt}\Sigma_t e_j\right)^2}{(e'\Sigma_t e_j)\cdot\sum_{l=0}^{L-1}\left(e_i' N_{lt}\sum_t N_{lt}' e_i\ \right)} \tag{6}$$

$$gST_{ij,t} = \frac{\varphi_{ij,t}^{gen}(L)}{\sum_{j=1}^{L}\varphi\ _{ij,t}^{gen}(L)} \tag{7}$$

where e_i represents the ×1 unselected vector that has one in the ith position, and $\varphi_{ij,t}^{gen}(L),(L)$, which is a symmetric reduction in variance from denotes the forecast error of variable i due to the shock state of variable j in the future.

$\sum_{j=1}^{Z}\ \varphi_{ij,t}^{gen}(L) \neq 1$ normalizes to one, which gives the value $gST_{ij,t}$. We collect these metrics as follows:

$$X_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}, \tag{8}$$

$$X^{gen,to}_{i\rightarrow\bullet,t} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}. \tag{9}$$

We then present the total net directional connectivity: $X^{gen,net}_{i,t} = X^{gen,to}_{i\rightarrow\bullet,t} - X^{gen.\ from}_{i\leftarrow\bullet,t}$. If $X^{gen,net}_{i,t} < 0(X^{gen,net}_{i,t} > 0)$, variable i implies a net receiving (sending) shock. This means that variable i is controlled by other variables in the network.

Total Connectivity Index (TCI) is also presented that clarifies the network within the network. TCI can be defined as follows:

$$gST_t = \frac{1}{z}\sum_{i=1}^{Z} X^{gen.from}_{i\leftarrow\bullet,t} = \frac{1}{z}\sum_{i=1}^{Z} X^{gen,\ to}_{i\rightarrow\bullet,t} \tag{10}$$

where higher level network overflow has greater value.

Finally, the spillovers of the net pairwise directions can be represented as:
$X^{gen,net}_{i,t} = gST^{gen,to}_{ij,t} - gST^{gen,\ from}_{ij,t}$. If $X^{gen,net}_{ij,t} > 0$, which implies that row i has a stronger influence over row j.

3.2. Extended joint connectedness approach

The $gST_{ij,t}$ and $jST_{ij,t}$ are assumed:

$$X^{jnt.from}_{i\leftarrow\bullet,t} = \sum_{j=1,i\neq j}^{Z} jST_{ij,t}, \tag{11}$$

$$X^{jnt,to}_{\bullet\leftarrow i,t} = \sum_{j=1,i\neq j}^{Z} jSTji,t, \tag{12}$$

$$jSI_i = \frac{1}{z}\sum_{i=1}^{Z} X^{jnt.from}_{i\leftarrow\bullet,t} = \frac{1}{z}\sum_{i=1}^{Z} X^{jnt,to}_{i\rightarrow\bullet}.$$

To generalize a scaling approach, we used Lastrapes and Wiesen (2021) approach where the scaling factor differs for each order as follows:

$$\eta_i = \frac{X^{jnt.from}_{i\leftarrow\bullet,t}}{X^{gen,from}_{i\leftarrow\bullet,t}} \tag{13}$$

$$\eta = \frac{1}{z}\sum_{i=1}^{Z}\eta_i \tag{14}$$

Our scaling and the one derived from the joint connectivity method are the same; the method that we have chosen which offers greater suppleness since each row has its very own scaling element. Ultimately, the complying with activities need to be coded:

Lastly, we estimate:

$$jST_{ij,t} - \eta_i gST_{ij,t}, \tag{15}$$

$$(2)\ \ jST_{ii,t} = 1 - X^{j\ jnt,from}_{Z},$$

$$(3)\ \ X^{jnt,to}_{i\rightarrow\bullet,t} = \sum_{j=1,j\neq i}^{Z} jST_{ij,t}.$$

At last, permitting the scaling parameter to differ by row enables to calculate the net total and pairwise directional connectedness steps as follows:

$$X^{jnt,net}_{i,t} = X^{jnt,to}_{i\rightarrow\bullet,t} - X^{jnt,from}_{i\leftarrow\bullet,t}, \tag{16}$$

$$X^{jnt,net}_{ij,t} = gST_{ji,t} - gST_{ij,t}. \tag{17}$$

Even if the interpretations are identical to the initial connectivity method, the results are much more accurate since the shortcomings of the row count normalization method have been overcome (Caloia et al., 2019).

3.3. TVP-VAR frequency connectedness

Chatziantoniou and Gabauer (2021) introduces the TVP-VAR based frequency connectedness framework which blends the work of Baruník and Křehlík (2018) and Antonakakis et al. (2020) whereas the latter already consolidates the connectedness approach of Diebold and Yilmaz (2012, 2014) with the TVP-VAR framework of Koop and Korobilis (2014). To estimate return and volatility connectivity among GCC sectoral indices, we employ a contemporary connectedness methodology that is grounded on Generalized

Forecast Error Variance Decomposition (GFEVD), processed from a Time-varying Parameter Generalized Vector Autoregressive (TVP-VAR) aspect (Antonakakis et al., 2020). The TVP-VAR (15) implied by the Bayesian Information Criterion (BIC) is presented as:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t; \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \tag{18}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t; \quad v_t | F_{t-1} \sim N(0, \Xi_t) \tag{19}$$

where Y_t and Y_{t-1} are $N \times 1$ dimensional endogenous variable vectors; ε_t is the $N \times 1$ dimensional disturbance term with an $N \times N$ dimensional time-varying variance–covariance matrix, S_t; β_t is the $N \times N$ dimensional VAR coefficient matrix; v_t is an $N^2 \times 1$ disturbance vector with an $N^2 \times N^2$ dimensional time-varying variance–covariance matrix, Ξ_t; $vec\left(\beta_t\right)$ is the vectorization of β_t.

In order to extract the GFEVD, the TVP-VAR is transformed into Vector Moving Average (VMA) representation as:

$$Y_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} \tag{20}$$

Where A_{jt} is an $N \times N$ dimensional matrix through the customary Wold Representation Theorem.

The unscaled GFEVD $(\theta^g_{ij,t}(H))$ is expressed as:

$$\theta^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} \left(e_i' A_t S_t e_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(e_i A_t S_t A_t' e_i\right)} \tag{21}$$

To ensure that each row sums up to unity, implying that selected variables explain 100% of variable *i's* forecast error variance, we compute the scaled GFEVD $(\widetilde{\theta}^g_{ij,t}(H))$ as:

$$\widetilde{\theta}^g_{ij,t}(H) = \frac{\theta^g_{ij,t}(H)}{\sum_{j=1}^{N} \theta^g_{ij,t}(H)} \tag{22}$$

where, $\sum_{j=1}^{k} \theta^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \widetilde{\theta}^g_{ij,t}(H) = k$, and e_i is a vector with one on the i^{th} element and zero otherwise; $\widetilde{\theta}^g_{ij,t}(H)$ represents a measure of the bidirectional connectedness from index j to index i at horizon H.

The GFEVD is applied to compute various connectedness measures within the context of Diebold and Yilmaz (2014) - the total directional connectedness of index i to all indexes ($C_{\blacksquare \leftarrow i,t}(H)$) in Eq. (6), the total directional connectedness of all indexes to index $i(C_{i \leftarrow \blacksquare,t}(H))$ in Eq. (7), the net total directional connectedness $(C_{i,t}(H))$ in Eq. (8), and the net bidirectional connectedness $(C_{ij,t})$ in Eq. (9).

$$C_{\blacksquare \leftarrow i,t}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}^g_{ji,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ji,t}(H)} \times 100 \tag{23}$$

$$C_{i \leftarrow \blacksquare,t}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \widetilde{\theta}^g_{ij,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ij,t}(H)} \times 100 \tag{24}$$

$$C_{i,t}(H) = C_{\blacksquare \leftarrow i,t}(H) - C_{i \leftarrow \blacksquare,t}(H) \tag{25}$$

$$C_{ij,t} = C_{i \leftarrow j,t}(H) - C_{j \leftarrow i,t}(H) \tag{26}$$

If $C_{ij,t} > 0$ $(C_{ij,t} < 0)$, index i dominates (is dominated by) index j implying that index i influences (is influenced by) index j more than being influenced by (influencing) it.

The total connectedness index (TCI) is another relevant metric highlighting the degree of network interconnectedness and hence market risk. Considering that the TCI can be calculated as the average total directional connectedness to (from) others, it is equal to the average amount of spillovers one index transmits (receives) from all others. Chatziantoniou and Gabauer (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares the

TCI is within $[0, \frac{K-1}{K}]$. To obtain a TCI which is within [0,1], the adjusted TCI is:

$$C^g_t(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}^g_{ij,t}(H)}{\sum_{i,j=1}^{K} \widetilde{\theta}^g_{ij,t}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}^g_{ij,t}(H)}{K} \tag{27}$$

$$C^g_t(H) = \left(\frac{K}{K-1}\right) \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}^g_{ij,t}(H)}{K} \tag{28}$$

$$C_t^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}_{ij,t}^g(H)}{K-1} 0 \leq C_t^g(H) \leq 1. \tag{29}$$

As well as estimating connectedness assessment in the time domain, we also estimate connectedness assessment in the frequency domain. By using spectral decomposition method of Stiassny (1996), we can derive the frequency response function, $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where $i=\sqrt{-1}$. Hence, at a given frequency ω, we can define the spectral density of x_t as the Fourier Transform for $TVP-VMA(\infty)$ filtered series, this can be expressed as follows:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x'_{t-h}\right) e^{-i\omega h} = \Psi(e^{-i\omega h}) \sum_t \Psi'(e^{+i\omega h}) \tag{30}$$

Significantly, the frequency GFEVD is the combination of spectral density and the GFEVD. As in the time domain, we need to stabilize the frequency GFEVD which can be created as follows,

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} |\sum_{h=0}^{\infty} (\Psi(\tau)(e^{-i\omega h})\Sigma(\tau))_{ij}|^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ii}} \tag{31}$$

$$\widetilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}\omega}{\sum_{k=1}^{N} \theta_{ij}\omega} \tag{32}$$

where $\theta_{ij}(\omega)$ is the percentage of the variable ith spectrum at frequency ω that is caused by variable jth shock. It can be interpreted as a within-frequency indicator.

To evaluate short-term as well as long-term connectedness as opposed to connectedness at a single frequency, we accumulate all frequencies within a details range, $d = (a, b) : \ [a, b \in (-\Pi, \Pi), a < b]$

$$\breve{\theta}_{ij}(d) = \int_a^b \breve{\theta}_{ij}(\omega) d\omega \tag{33}$$

From here, we can determine exactly the same connectedness procedures as in Diebold and Yilmaz (2012, 2014) which can be analysed identically, nonetheless, in this case they refer to frequency connectedness steps that offer info about spillovers in a particular frequency ranges d:

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \breve{\theta}_{ji}(d) \tag{34}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \breve{\theta}_{ij}(d) \tag{35}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{36}$$

$$TCI(d) = N^{-1} \sum_{i=1}^{N} TO_i(d) = N^{-1} \sum_{i=1}^{N} FROM_i(d) \tag{37}$$

In this paper, there are three frequency bands demonstrating short-term, medium term and long-term dynamics ranging from 1 to 5 days $d_1 = (\pi/5, \pi)$, from 6 to 22 days, $d_2 = (22, \pi/5]$, and from 23 to infinite days, $d_3 = (0, \pi/22]$. Thus, $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ demonstrate the short-term total directional connectedness TO others, short-term total directional connectedness FROM others, short-term NET total directional connectedness, and short-term total connectedness index, additionally $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ demonstrate the medium-term total directional connectedness TO others, medium-term total directional connectedness FROM others, medium-term NET total directional connectedness, and medium-term total connectedness index, finally $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ illustrate the long-term total directional connectedness TO others, long-term total directional connectedness FROM others, long-term NET total directional connectedness, and long-term total connectedness index.

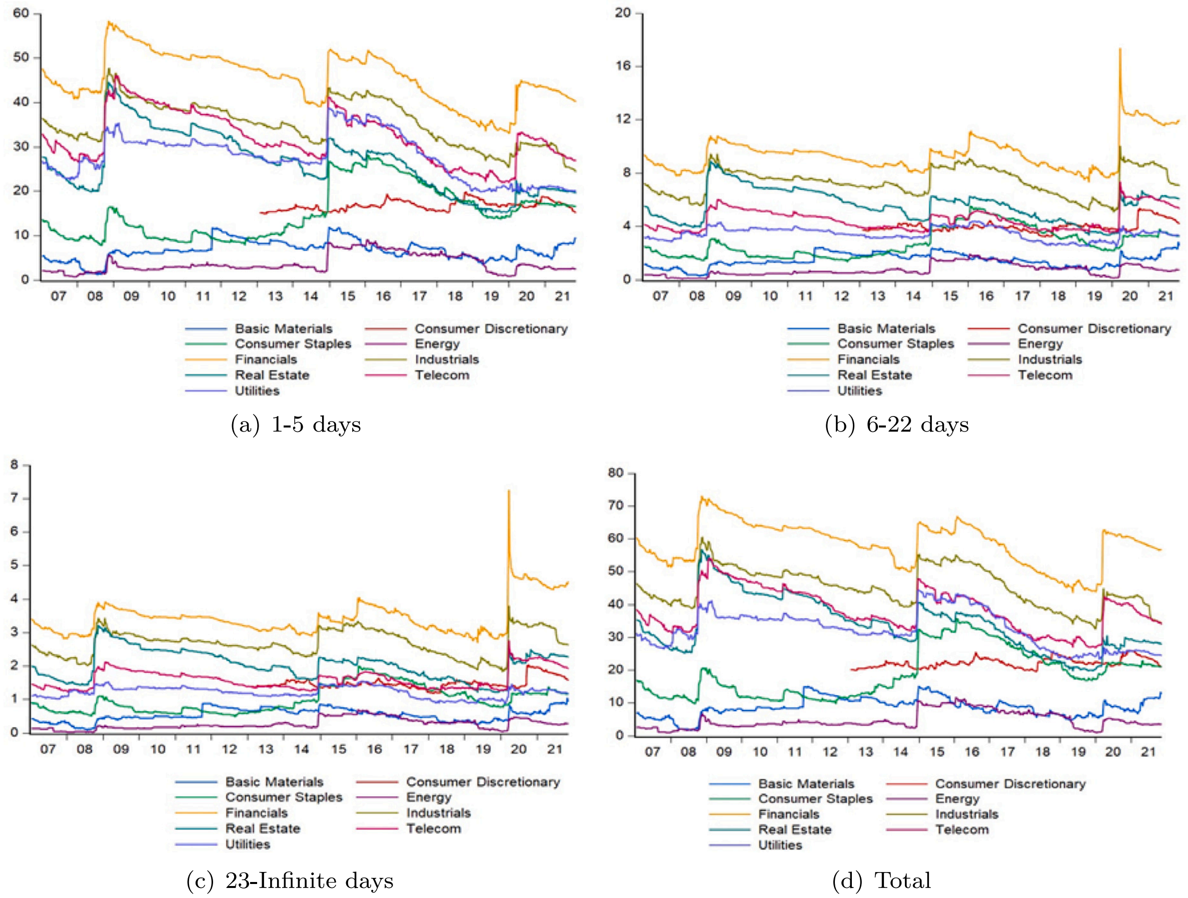
Lastly, the relationship between the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Yilmaz (2012), Diebold and Yilmaz (2014) time-domain measures:

$$TO_i(H) = \sum_d TO_i(d) \tag{38}$$

$$FROM_i(H) = \sum_d FROM_i(d) \tag{39}$$

$$NET_i(H) = \sum_d NET_i(d) \tag{40}$$

$$TCI(H) = \sum_d TCI(d) \tag{41}$$



(a) 1-5 days (b) 6-22 days (c) 23-Infinite days (d) Total

Fig. 1. Time varying analysis. Dynamic short, medium, long and total connectedness for GCC national and GCC wide sectoral indices returns between 2007 and 2021.

3.4. Panel data model

After estimating net pairwise return and volatility spillovers at different frequencies (1–5 days; 6–22 days and 23 days to infinity), we follow the traditional gravity model employed in the international trade but extended with several economic and financial structure variables as follows:

$$NET_{it}(H) = \alpha_0 + \alpha_1 MCAP_{sector,it} + \alpha_2 NetDebt/Asset_{it} + \alpha_3 InterestCoverageRatio_{it} + \alpha_4 Profit/TotalAsset_{it} + \alpha_5 EV/EBITDA_{it} + \alpha_6 NetProfitMargin_{it} + \alpha_7 Log(TotalAsset)_{it} + error_{it}$$

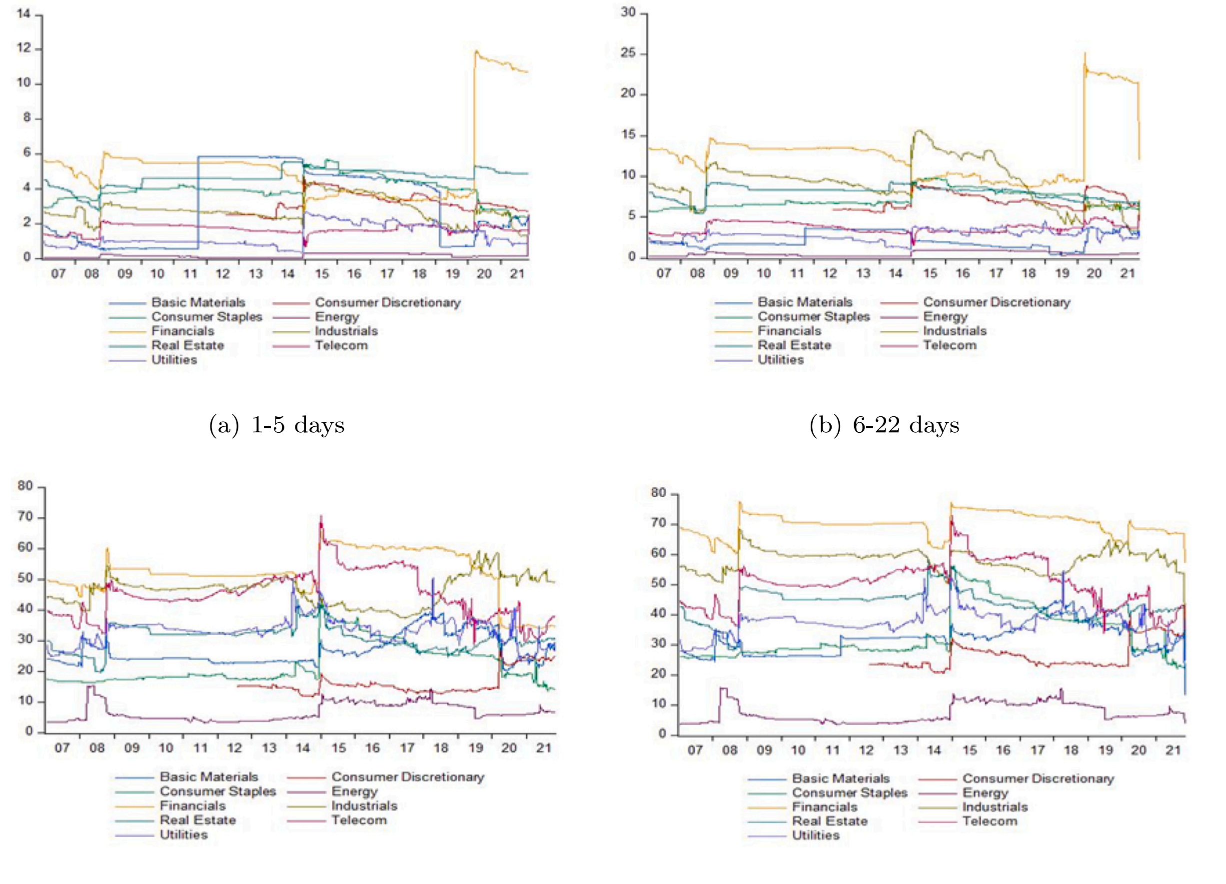
where $NET_i t(H)$ is the net return or volatility spillovers of sectoral indices i to other sectors in a country at time t for each frequency estimation.[3] In each regression, we load each economic/financial variable individually to test its explanatory capacity of the dependent variable before considering them together in the last model. This resulted in a total of eight models. We calculate the heteroskedasticity and autocorrelation corrected standard errors (HAC) in the estimations. We also test normality of the error terms, misspecification of the models (RESET) and check for the fixed and random effects through Hausman test and decide to apply fixed effect models in our estimations. The regressions are estimated for different frequencies such as short term(1–5 days), medium term (6–22 days) and long term (23 days to infinity) separately. Tables 4–9 report the findings of the panel regressions.

4. Empirical analysis

4.1. Time-varying connectedness analysis of returns and volatilities

Due to the dynamic and evolving nature of financial markets over time, connections and interdependencies between markets evolve, usually according to cyclical and structural trends (Kang et al., 2017; Kang & Yoon, 2016). Hence, connections between

[3] All explanatory variables are explained in detail in Data section.



(a) 1-5 days

(b) 6-22 days

(c) 23-Infinite days

(d) Total

Fig. 2. Time varying analysis. Dynamic short, medium, long and total connectedness for GCC national and GCC wide sectoral indices volatilities between 2007 and 2021.

sectoral equity markets fluctuate based on uncertainty. As previously mentioned, our research timeframe encompasses a series of important events, each of which may have affected the intensity and the direction of the dependence across sectoral equity markets. For this reason, we report dynamic short (1–5 days), medium (6–22 days) and long-term (longer than 23 days) and total time-varying return and volatility spillovers among the sectoral equity markets in GCC member countries and GCC regional sectoral indices in Figs. 1 and 2, respectively.

The dynamic connectedness in Figs. 1 and 2 provide evidence of increased connectedness to the end of 2008 and 2009 due to global financial crisis and Dubai debt crisis. Spillovers become stronger again as a result of the 2014 oil crisis in line with Arin et al. (2020). GCC investors' expectations and risk appetite are extremely dependent on the volatility in oil prices due to high dependence on oil revenues in the GCC region. Oil prices dropped from \$120 to \$39 between May 2014 and January 2016 which affects oil rich GCC countries exports and revenues negatively. With the start of COVID-19 pandemic in early 2020, the implementation of government restrictions on commercial activity and social distancing measures have caused extreme volatility in global financial markets. As seen from Fig. 2, COVID-19 pandemic once again intensified the spillovers (especially financials, industrials, telecom) in all sectors which is consistent with the results reported by Laborda and Olmo (2021) and Ngene (2021). The announcements on the successful development of several vaccines and economic supports by the governments lead to gradual decline in spillover levels that ultimately stabilize at the end of 2021.[4]

According to dynamic return spillovers in Fig. 1, the total connectedness reaches up to 75% in the financials industry, followed by industrials and telecom industries. However energy and basic materials industries have the lowest dynamic spillover. Hence, we find robust evidence of the highest level of contagion in the financials sector and the lowest in the energy sector during the time

[4] We have applied Bai and Perron (1998) structural break test for return and volatility sectoral spillover indices. The findings indicate that breaks coincide with Global Financial Crisis, 2014 oil crisis and COVID-19 era. Hence, our findings are immune to economic/financial phenomena happened in the past. Due to space issues, we have not shown the findings in the paper. Results are available upon request.

period under study. The reason behind the lowest contagion of energy sector is that those sectors are stronger among GCC, and oil and gas are the basic export item and these markets are more integrated with the world markets, compared to other markets, connectedness with local indices might be less.

According to dynamic volatility spillovers in Fig. 2, financials, industrials and telecom sectors have the highest connectedness whereas energy and consumer discretionary have the lowest connectedness.

In summary, our findings indicate that the crises that occurred during the research time frame intensified the total return and volatility spillovers. In particular, the return and volatility spillovers reached their highest point during 2008–2009 (global financial crisis), 2014 (oil crisis) and early 2020 (COVID-19 pandemic). In the GCC region, the highest connections are observed in the financials industry, followed by industrials and telecom industries which lowers the number of opportunities for diversification.

4.2. The connectedness network spillovers of national and GCC sectoral returns and volatilities

In this section, the findings obtained from the approximation of the return and volatility directional spillover results of national and GCC sectoral equity indices are reported. Directional short (1–5 days), medium (6–22 days), long (23 days or more) and total return spillover network effects are displayed separately. Figs. 3–6 report return analysis and Figs. 7–10 report volatility analysis. Network analysis reveals that sectoral returns and volatilities display heterogeneous level linkages among GCC member countries, which simply means that these sectoral indices of countries influence each other in different magnitudes. Hence, determinant analysis in Section 4.3 will add value to explain the drivers of sectoral return and volatility spillovers to understand the differences among linkages.

In the short-term, GCC-wide equity index is the net transmitter in all sectors. It is clearly visible that GCC regional sectoral indices play the principal role in shock transmission. Only Bahrain in the Basic Materials Sector, UAE in the Financials Sector and Qatar in the Industrials sector are also net transmitter alongside with GCC wide sectoral index. In the medium and longer term, GCC is the net transmitter in all sectors except Energy sector. In the Basic Materials sector, Saudi Arabia; in the Consumer Staples Sectors; Qatar and Saudi Arabia; in the energy sector Oman; in the financials sector, UAE, Qatar and Kuwait; in the Industrial sector, Qatar and Oman; in the Real Estate sector Kuwait and in the Telecom sector, Kuwait and Oman; in the Utilities sector Oman are the net transmitters.

The financial sector is one of the most connected sector and UAE is the net transmitter beside GCC-wide index in this sector. In the financials sector, being the net contributor is in line with UAE's strategic position as a financial and investment hub in the region by embracing international economic integration and alignment with global financial standards. This is consistent with Alkulaib et al. (2009) that argue that the UAE stock market leads all other markets in the region due to the significant growth of UAE's equity market, and its positioning as the main financial hub in the Middle East. At the general index level, Ziadat et al. (2020) and Ziadat and AlKhouri (2022) also confirm that UAE is the primary transmitter of information in the GCC region, contrary to Awartani et al. (2013) and Hammoudeh and Aleisa (2004) document that Saudi Arabia plays the leading role. The recent liberalization efforts in the UAE and its subsequent inclusion in the MSCI emerging market index in 2014 could be one of the reasons behind the changes in the role of the leaders in the GCC region, at least at the impact that is observed in the financial sector.

In the industrial sector, Qatar is one of the net transmitter alongside with GCC-wide equity index. This might be explained In the context of Qatar's National Vision 2030. Qatar's manufacturing sector is expected to employ more than 100,000 people by 2025 and will see a 30% increase in the value of production between 2019 and 2025 according to Raffoul and Hewaidi (2021).

Except Basic Materials sectors, Bahrain is the country that is less affected from other countries sectoral markets. This is also documented in Ziadat et al. (2020) and Ziadat and AlKhouri (2022) at the country indices level. This implies that Bahrain stock market is segmented from the rest of the GCC stock markets. In the Energy industry, Kuwait is the one of the transmitter.

In the medium and longer terms, the findings are not so different from the short-term findings. Among the connectedness for more than 5 days, interestingly, GCC regional index is still the main net transmitter in all sectors except Energy sector. It is expected that Energy sector is more integrated with the world, compared to other sectors in GCC region.

Overall, the results are quite heterogeneous among the regions. Earlier studies including Awartani et al. (2013) and Hammoudeh and Aleisa (2004) emphasized the influence of the Saudi Arabian markets on other GCC markets, however as the financial markets gets deeper, this impact gets weaker. We observe the UAE and Qatar sectoral indices become dominant and transmit the shocks to other markets.

4.3. Determinants of sectoral return and volatility spillovers

In this section, we test whether the return or volatility spillovers at different frequencies are affected by market capitalization ratio, net debt/asset, interest coverage ratio, profit/asset, EV/EBITDA, profit margin and total asset. In each regression, we load each variable individually to test its explanatory capacity of the dependent variable before considering them together in the last model. This resulted in a total of eight models.[5]

Tables 4, 5 and 6 present the results of the regression analysis where the dependent variable is net spillovers of sectoral returns to other sectors in the regions including the GCC sectoral index in 1–5 days (short term), 5–22 days (medium term) and 22 to

[5] The last columns of each table includes all dependent variables at the same time. The correlation matrix of the independent variables show that there is no multicollinearity between these variables.

Table 4
Net spillovers of sectoral returns to other sectors in 1–5 days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Sector Market Cap. Ratio	−0.023							−0.017
	(0.032)							(0.033)
Net Debt/Asset		1.801***						3.930***
		(0.526)						(0.751)
Interest Coverage Ratio			−0.000					0.001
			(0.000)					(0.001)
Profit/Asset				−3.820***				−5.603***
				(1.342)				(1.704)
EV/EBITDA					0.047***			0.022
					(0.013)			(0.017)
Net Profit Margin						−0.000		−0.000
						(0.000)		(0.000)
Log(Total Asset)							−0.281***	−0.593***
							(0.109)	(0.155)
Constant	−3.335***	−3.697***	−3.357***	−3.215***	−3.851***	−3.385***	1.098	5.650**
	(0.120)	(0.096)	(0.048)	(0.085)	(0.142)	(0.049)	(1.749)	(2.498)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.000	0.006	0.000	0.004	0.006	0.000	0.003	0.032
Number of sector id	42	41	42	41	42	42	41	40

infinite days (longer term), respectively. In the short term, return spillovers are negatively affected by profit/asset ratio (ROA) and total asset; but positively affected by debt/asset and EV/EBITDA ratios. The higher debt ratio variable increases the extent of return spillovers in all frequencies. ROA (Profit/Asset) provides how much profit a company is able to generate from its assets. In the short term, higher ROA indicates lower return spillover. Hence, the return spillovers of the sectors are negatively affected by high profitability. The EV/EBITDA metric is a popular valuation tool that helps investors to compare companies in order to make an investment decision. It compares the value of a company, debt included, to the company's cash earnings less non-cash expenses. In the medium and long term, spillovers increase with high EV/EBITDA. In Models 8, we have grouped the variables and test their effect jointly. In the short term, the sectors that have high profitability (ROA) and asset size are associated with a lower magnitude of shocks to other sectors in the GCC region. The sectors that are highly leveraged are associated with a higher magnitude of return shocks to other sectors in all frequencies.

Tables 7, 8 and 9 present the results of the regression analysis where the dependent variable is net spillovers of sectoral volatilities to other sectors in the regions including the GCC sectoral index in 1–5 days, 5–22 days and 22 days to infinite days, respectively. Market capitalization sectoral ratio is measured as each sector's market value of equity divided by the market value of equity of all GCC region. In the short term, sectors that have high market capitalization ratio has higher volatility spillover to other sectors. Sectors that have large asset size are associated with lower volatility spillovers to other sectors in the short and medium term. At the longer term, sectors that have high leverage and low interest coverage ratio associated wth higher volatility spillovers to the other sectors. In Models 8, we have grouped the variables and test their effect jointly. In the short term, sectors that have high market capitalization, low profitability and low asset size have higher volatility spillovers; in the medium term, high leverage, high EV/EBITDA and high asset size lead to lower spillover. However, in the longer term, high leverage gives rise to higher volatility spillovers.

5. Robustness tests

To investigate the sensitivity of our findings, we also apply Diebold and Yilmaz (2012)'s methodology to estimate dynamic return and volatility spillovers among the sectoral equity markets in GCC member countries and GCC region. Fig. 11 ands 12 in the Appendix report the robustness test for 52 and 75 week rolling window estimates with 5 and 10 week forecast horizons for return and volatility, respectively. In all subgraphs, the spillover indices of returns and volatilities have similar pattern as TVP-VAR Frequency Connectedness Approach. Spillovers intensified during stressful periods in the GCC region and the greatest correlations are observed in financial, industrial and telecommunication sectors.

6. Conclusion

This paper examines the effects of sectoral return and volatility spillovers between economic sectors of GCC countries from 2007 to 2021. Firstly, we estimate the spillovers between sectoral indices by applying TVP-VAR frequency connectedness method. Secondly, we develop a panel regression of gravity model to study the determinants of such spillovers considering various financial ratios of sectoral indices. In line with previous literature, we identify that spillovers are regime dependent increasing their intensity during turmoil periods such as 2007–2008 crisis, 2014 oil price crash and 2020 COVID-19 pandemic that is in line with Arin et al. (2020), Ngene (2021), Laborda and Olmo (2021) and Ziadat and AlKhouri (2022).

In most of the sectors, Saudi Arabia has lost its dominance role to UAE and Qatar with regards to transmitting the spillovers to other country indices. Alkulaib et al. (2009) also claim that the UAE stock market leads all other markets in the region. Moreover,

Table 5
Net spillovers of sectoral returns to other sectors in 6–22 days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mcap Sector Ratio	0.004							0.004
	(0.014)							(0.015)
Net Debt/Asset		0.712***						1.157***
		(0.229)						(0.343)
Interest Coverage Ratio			−0.000					−0.000
			(0.000)					(0.000)
Profit/Asset				−0.496				−0.797
				(0.586)				(0.779)
EV/EBITDA					0.011*			−0.006
					(0.006)			(0.008)
Net Profit Margin						0.000		−0.000
						(0.000)		(0.000)
Log Total Asset							−0.040	−0.100
							(0.047)	(0.071)
Constant	−0.708***	−0.811***	−0.697***	−0.674***	−0.823***	−0.691***	−0.054	0.811
	(0.053)	(0.042)	(0.021)	(0.037)	(0.065)	(0.022)	(0.763)	(1.142)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.000	0.005	0.001	0.000	0.002	0.000	0.000	0.009
Number of sector_id	42	41	42	41	42	42	41	40

Table 6
Net spillovers of sectoral returns to other sectors in 23–infinite days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mcap Sector Ratio	0.003							0.002
	(0.006)							(0.006)
Net Debt/Asset		0.282***						0.447***
		(0.089)						(0.133)
Interest Coverage Ratio			−0.000					−0.000
			(0.000)					(0.000)
Profit/Asset				−0.165				−0.254
				(0.227)				(0.302)
EV/EBITDA					0.005**			−0.002
					(0.002)			(0.003)
Net Profit Margin						0.000		−0.000
						(0.000)		(0.000)
Log Total Asset							−0.012	−0.033
							(0.018)	(0.027)
Constant	−0.253***	−0.290***	−0.245***	−0.237***	−0.305***	−0.243***	−0.045	0.238
	(0.021)	(0.016)	(0.008)	(0.014)	(0.025)	(0.009)	(0.296)	(0.442)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.000	0.005	0.001	0.000	0.003	0.000	0.000	0.009
Number of sector_id	42	41	42	41	42	42	41	40

studies of Ziadat et al. (2020) and Ziadat and AlKhouri (2022) pointed out the UAE as the main transmitter of the spillover in the GCC. However, some earlier studies such as Awartani et al. (2013) and Hammoudeh and Aleisa (2004) emphasized the influence of the Saudi Arabian markets on other GCC markets. Due to the significant growth of UAE's equity market as well as its positioning as the main financial hub in the Middle East and Qatar's economic and financial innovations, recently the UAE and Qatar sectoral indices become dominant in the GCC and transmit the shocks to other markets.

In general, Bahrain stock markets exhibit a weak relationship indicating that these markets are segmented and would be helpful for hedging and diversification opportunities across GCC countries in various sectors in line with Ziadat et al. (2020) and Ziadat and AlKhouri (2022). GCC sectoral indices have widespread financial (profitability and liquidity) ratios. Likewise, net spillovers are also very dispersed at different frequencies and explained successfully by relative difference in profitability and liquidity positions. The sectors that have high leverage transmit shocks to other sectors in all frequencies ranging from short-term to long-term. Hence, transmission of the market shocks from one market to another market utilizes the liquidity and financial positions as per Balli et al. (2021) that covers sectoral indices from a wide region. Sectors that have high leverage are more shock transmitters rather than shock absorbers both at the first and second moment.

Our findings related to return and volatility analysis reveal valuable information for the investors who are willing to invest in portfolios at the sectoral level with different time horizons. Sector-focused portfolios may offer more attractive risk–return trade off than aggregate stock market indices and portfolio managers should take into account the magnitude and direction of spillovers to allocate their funds and diversify their portfolios. Moreover, portfolio investors should adjust their diversified portfolios against the intensity of spillovers at different frequencies during periods of turmoil. Policy makers should coordinate globally to reduce

Table 7
Net spillovers of sectoral volatilities to other sectors in 1–5 days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mcap Sector Ratio	0.040**							0.078***
	(0.020)							(0.021)
Net Debt/Asset		−0.602*						−0.466
		(0.337)						(0.470)
Interest Coverage Ratio			−0.000					0.000
			(0.000)					(0.000)
Profit/Asset				0.700				−2.661**
				(0.861)				(1.068)
EV/EBITDA					0.005			−0.018*
					(0.008)			(0.010)
Net Profit Margin						0.000		0.000
						(0.000)		(0.000)
Log Total Asset							−0.523***	−0.907***
							(0.069)	(0.097)
Constant	−0.867***	−0.626***	−0.747***	−0.757***	−0.824***	−0.780***	7.677***	13.947***
	(0.075)	(0.061)	(0.031)	(0.054)	(0.093)	(0.031)	(1.107)	(1.565)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.002	0.002	0.000	0.000	0.000	0.000	0.027	0.053
Number of sector_id	42	41	42	41	42	42	41	40

Table 8
Net spillovers of sectoral volatilities to other sectors in 6–22 days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mcap Sector Ratio	0.055							0.109***
	(0.037)							(0.037)
Net Debt/Asset		−1.571**						−2.422***
		(0.774)						(0.850)
Interest Coverage Ratio			−0.000					−0.001
			(0.000)					(0.001)
Profit/Asset				0.019				−1.952
				(1.976)				(1.929)
EV/EBITDA					−0.011			−0.043**
					(0.018)			(0.019)
Net Profit Margin						0.000		0.000
						(0.000)		(0.000)
Log Total Asset							−0.723***	−0.988***
							(0.159)	(0.175)
Constant	−1.075***	−0.510***	−0.808***	−0.758***	−0.731***	−0.830***	10.867***	15.552***
	(0.138)	(0.141)	(0.070)	(0.125)	(0.202)	(0.070)	(2.563)	(2.828)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.001	0.002	0.000	0.000	0.000	0.000	0.010	0.032
Number of sector_id	42	41	42	41	42	42	41	40

Table 9
Net spillovers of sectoral volatilities to other sectors in 23–infinite days in the regions including the GCC sectoral index.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mcap Sector Ratio	0.386							0.059
	(0.358)							(0.372)
Net Debt/Asset		40.217***						59.073***
		(5.879)						(8.515)
Interest Coverage Ratio			−0.000*					0.004
			(0.000)					(0.009)
Profit/Asset				−18.310				31.696
				(15.159)				(19.325)
EV/EBITDA					0.052			−0.174
					(0.146)			(0.188)
Net Profit Margin						0.000		−0.000
						(0.000)		(0.000)
Log Total Asset							1.736	1.036
							(1.229)	(1.756)
Constant	−1.179	−5.888***	0.745	1.383	0.069	0.074	−27.465	−25.671
	(1.343)	(1.070)	(0.547)	(0.958)	(1.608)	(0.542)	(19.749)	(28.335)
Observations	2004	2144	2120	2144	2180	2205	2144	1864
R-squared	0.001	0.022	0.001	0.001	0.000	0.000	0.001	0.028
Number of sector_id	42	41	42	41	42	42	41	40

uncertainties in financial markets during stressful periods. Furthermore, portfolio managers can monitor the financial and liquidity positions of the sectors and guide their investment decisions based on the sector position and investment horizon of the investors.

As a future work, researchers should attempt to analyse the connectedness of the third moments in addition to the connectedness of return and volatility to incorporate skewness and kurtosis into models that have valuable impact in asset and derivative pricing, risk management, and portfolio allocation

CRediT authorship contribution statement

Burcu Kapar: Data curation, Formal analysis, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Syed Mabruk Billah:** Data curation, Formal analysis, Methodology. **Faisal Rana:** Writing – original draft, Writing – review & editing. **Faruk Balli:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

A.1. Return analysis

See Figs. 3–6.

A.2. Volatility analysis

See Figs. 7–10.

A.3. Robustness test

See Figs. 11 and 12.

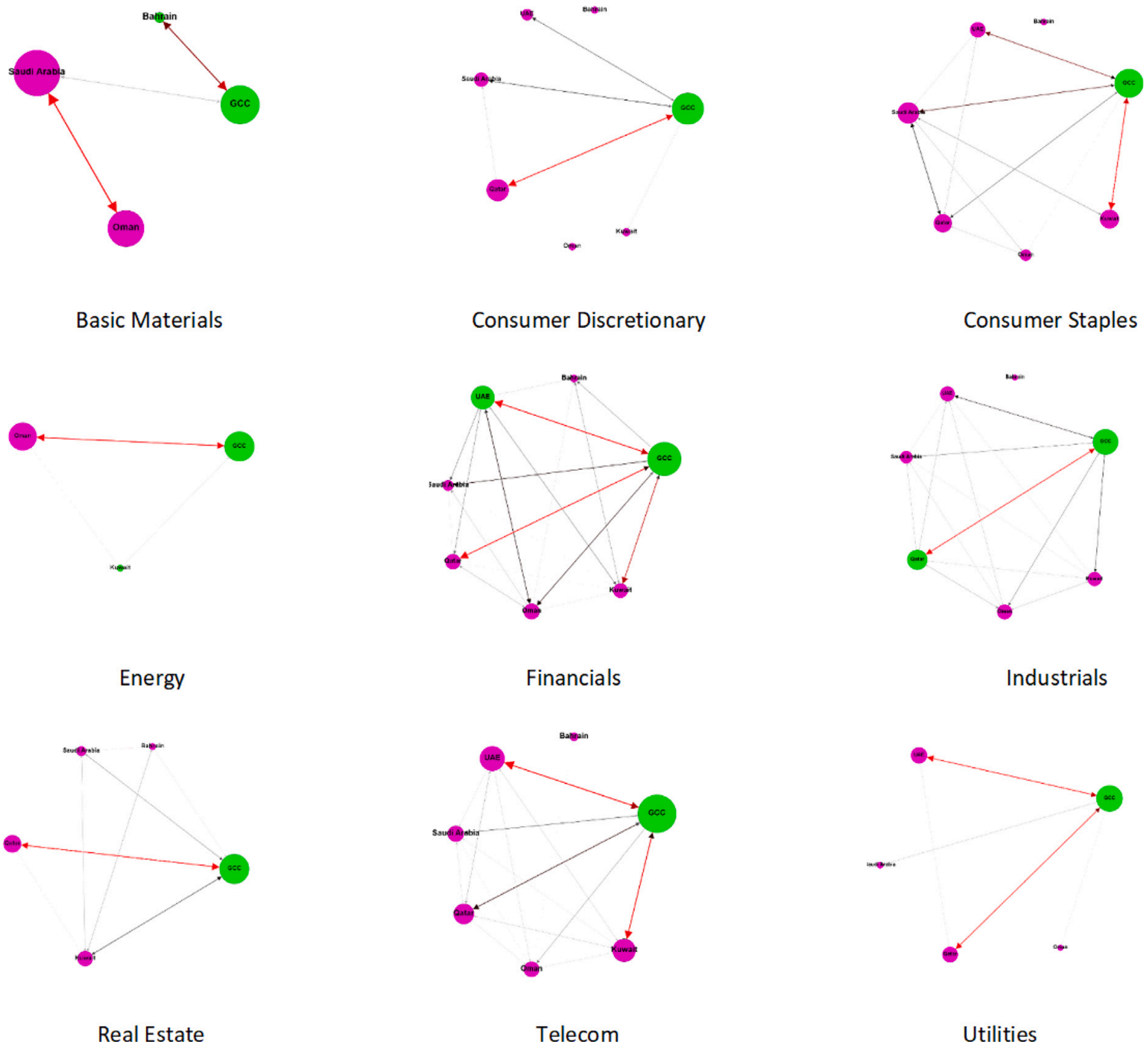


Fig. 3. Connectedness network of returns between GCC national and GCC-wide sectoral indices (1–5 days).

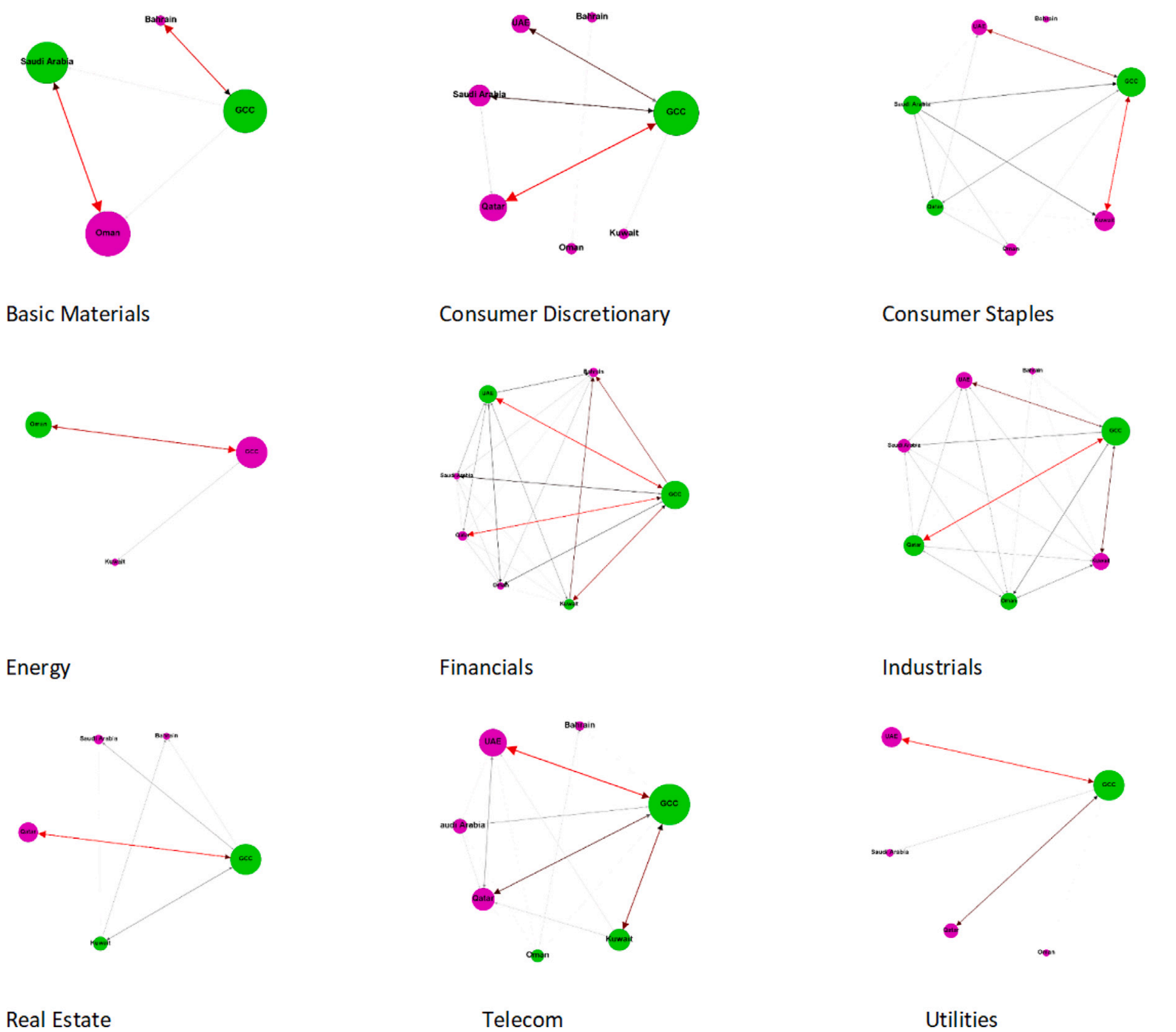


Fig. 4. Connectedness network of returns between GCC national and GCC-wide sectoral indices (6–22 days).

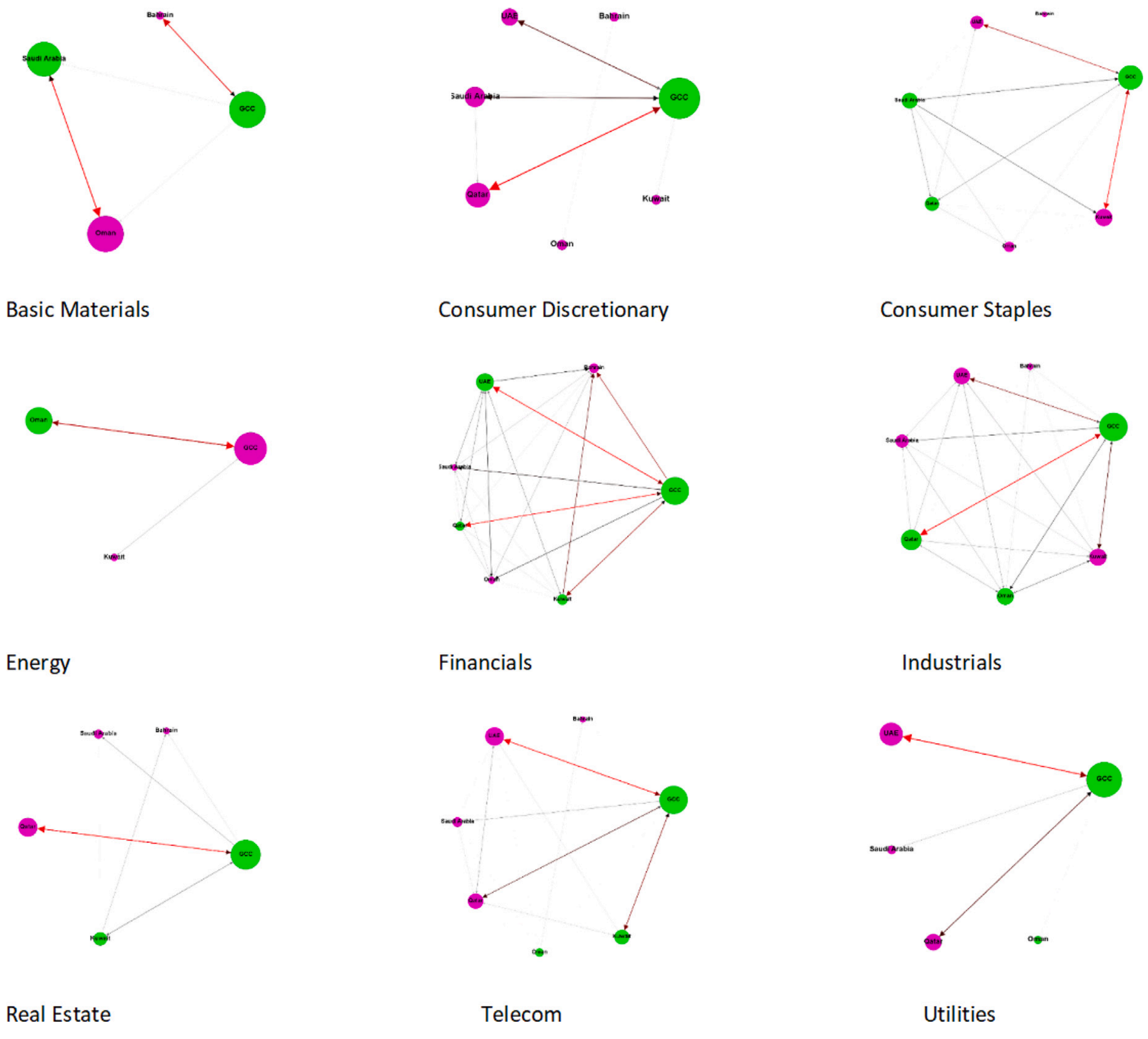


Fig. 5. Connectedness network of returns between GCC national and GCC-wide sectoral indices (23-inf days).

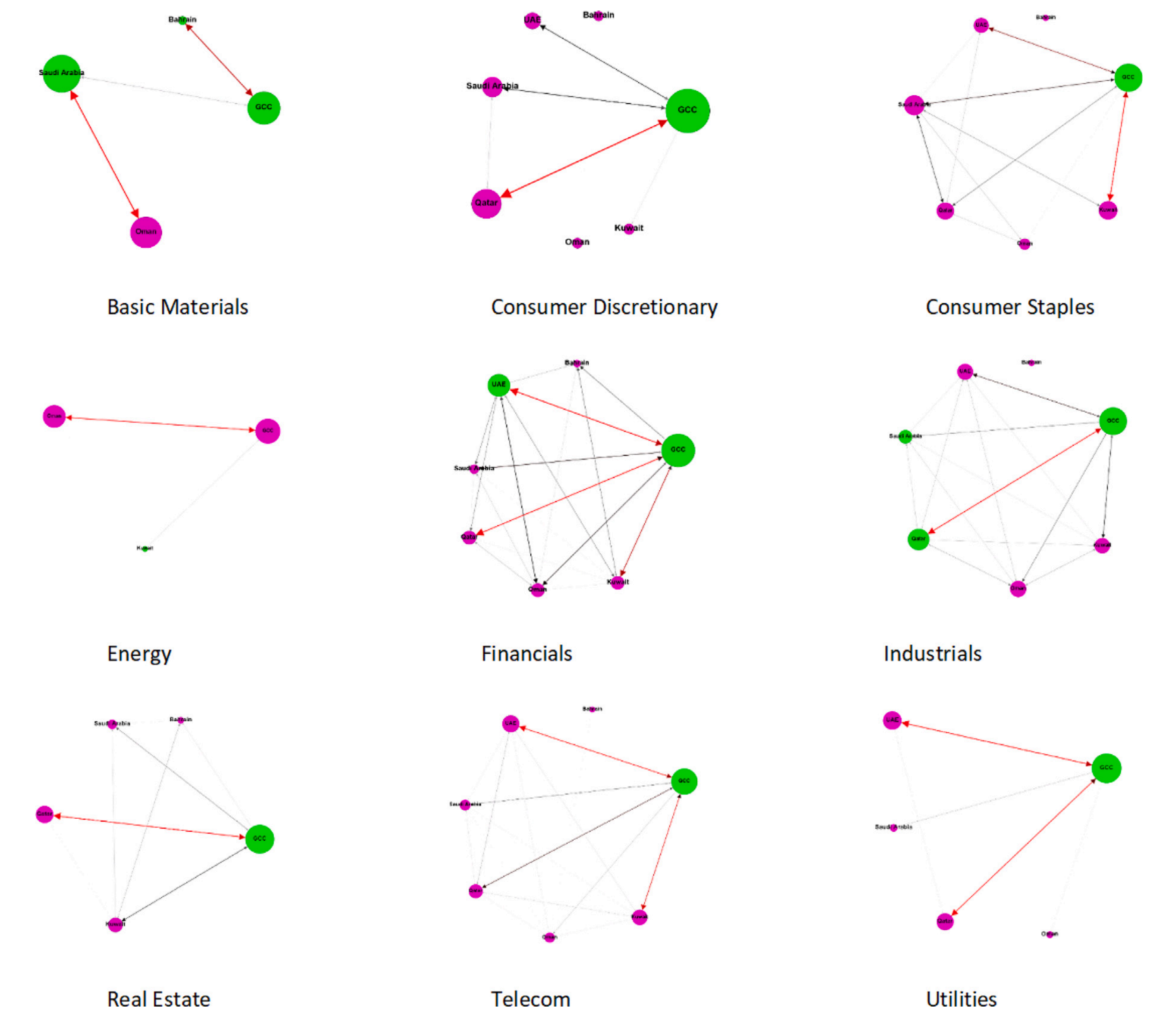


Fig. 6. Total connectedness network of returns between GCC national and GCC-wide sectoral indices.

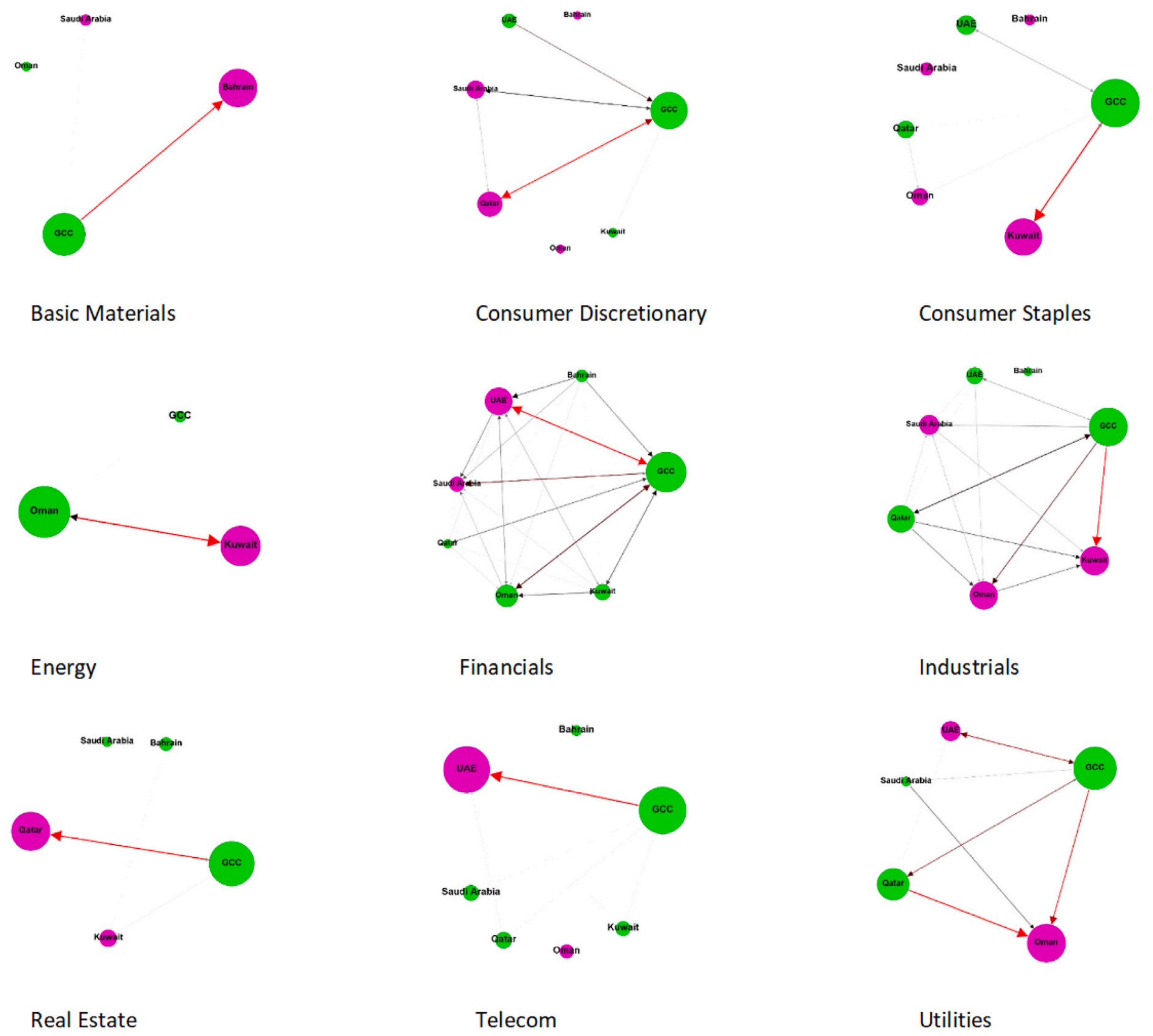


Fig. 7. Connectedness network of returns between GCC national and GCC-wide sectoral indices (1–5 days).

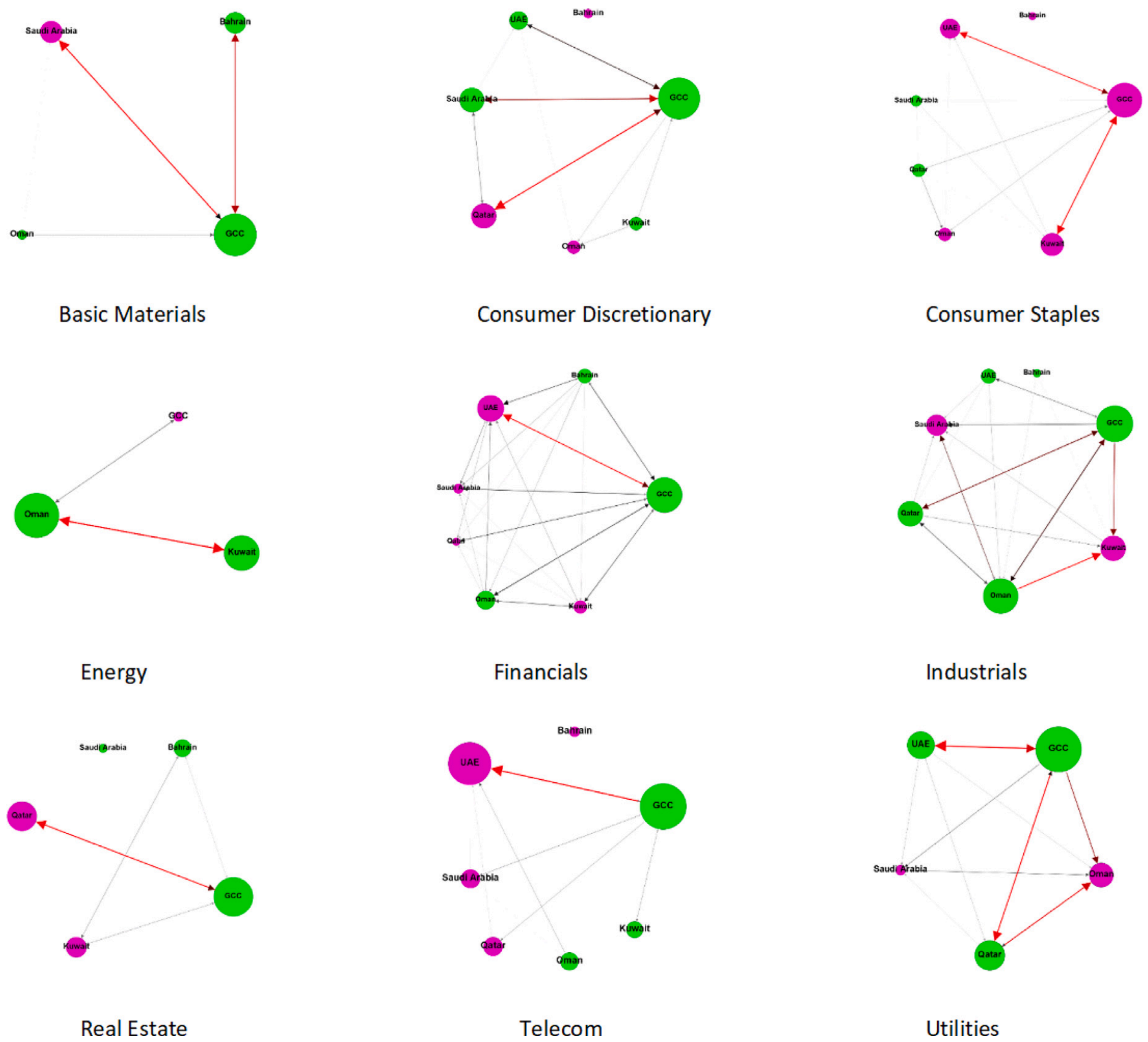


Fig. 8. Connectedness network of returns between GCC national and GCC-wide sectoral indices (6–22 days).

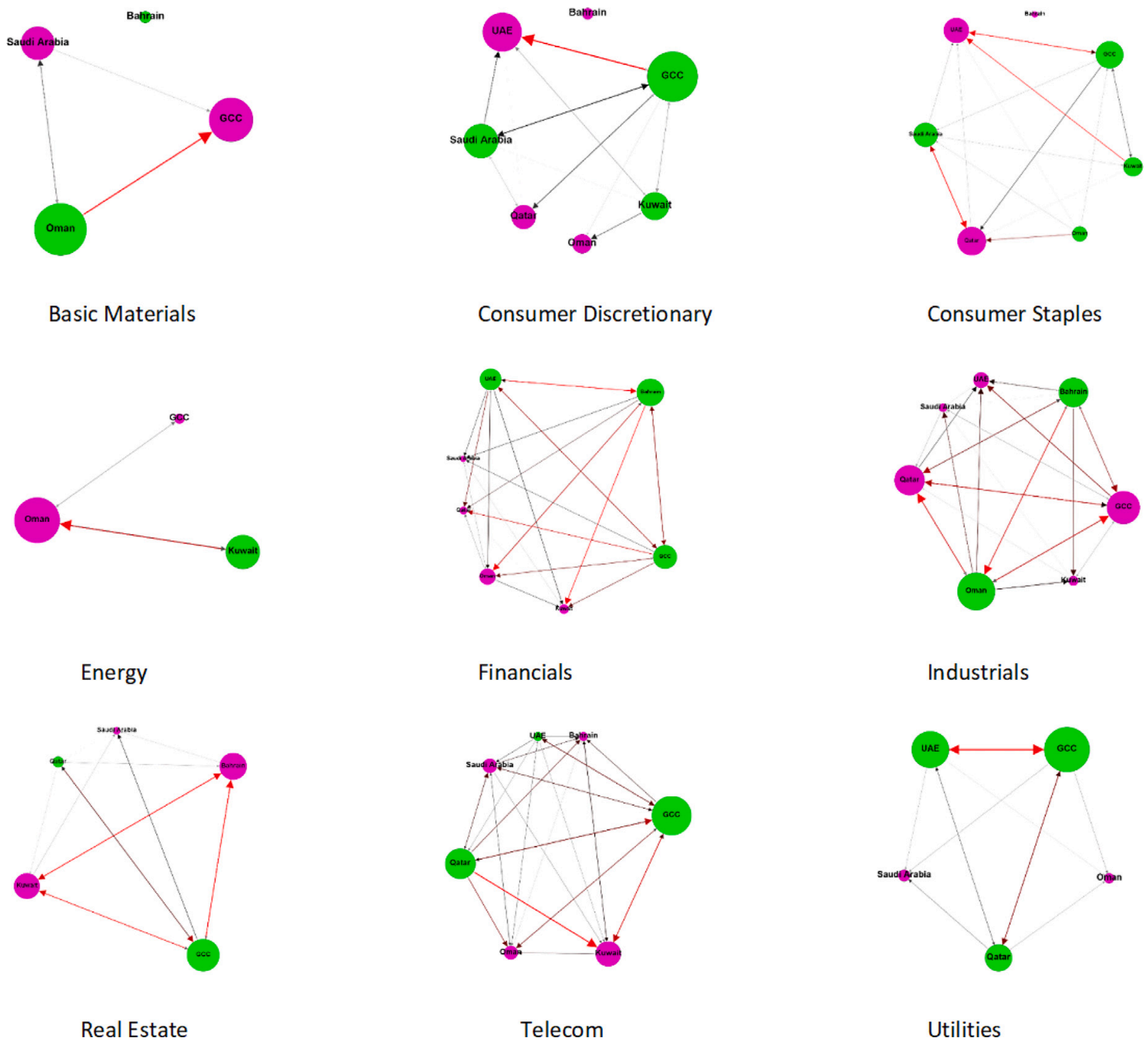


Fig. 9. Connectedness network of returns between GCC national and GCC-wide sectoral indices (23-inf days).

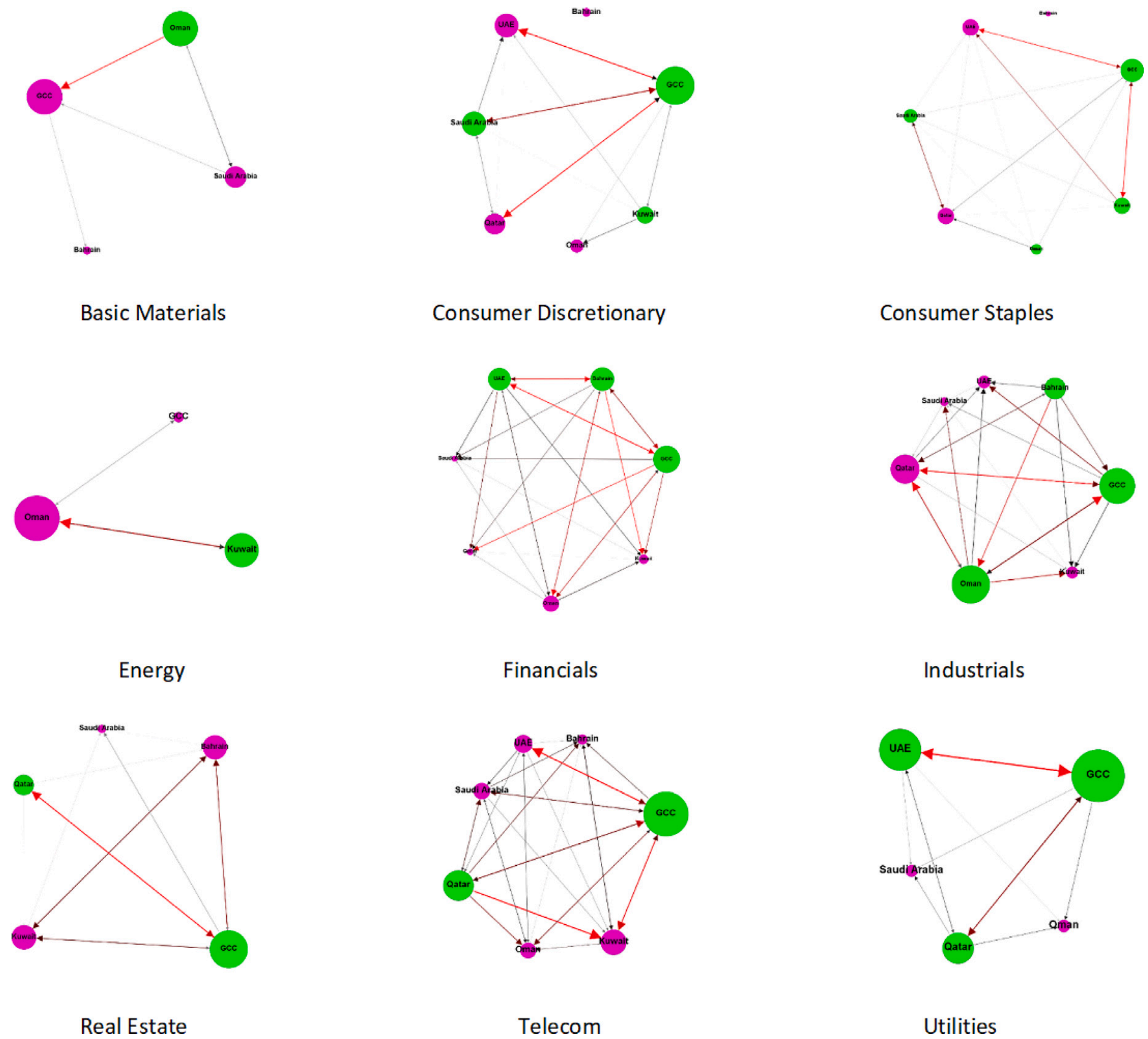
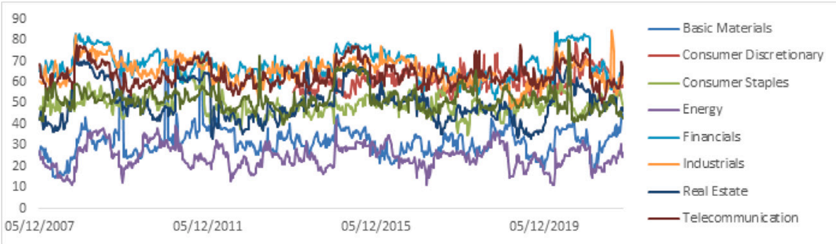
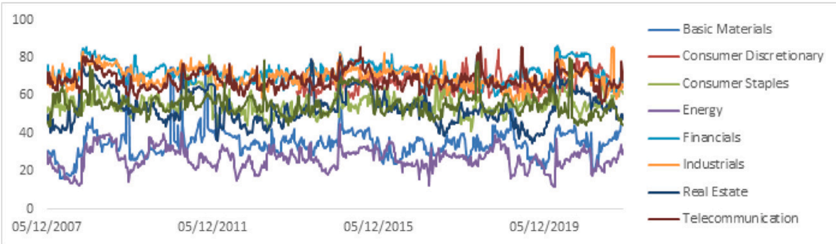


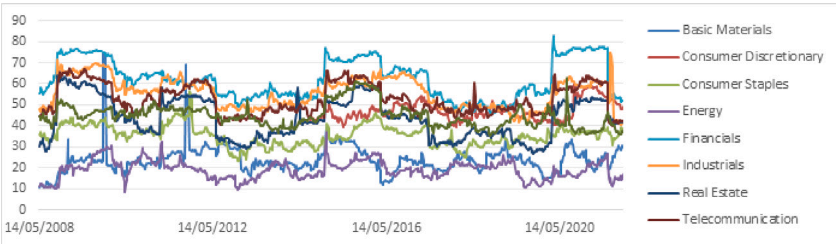
Fig. 10. Total connectedness network of returns between GCC national and GCC-wide sectoral indices.



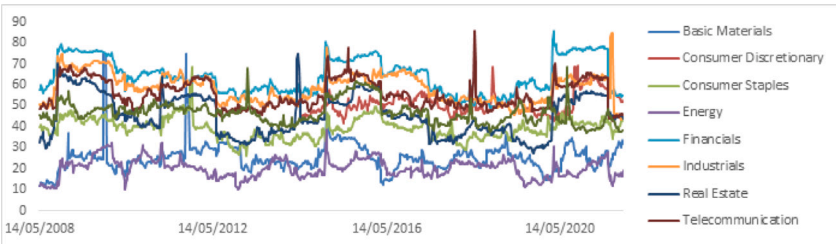
(a) 5 Week Forecast Horizon-52 week rolling window



(b) 10 Week Forecast Horizon-52 week rolling window

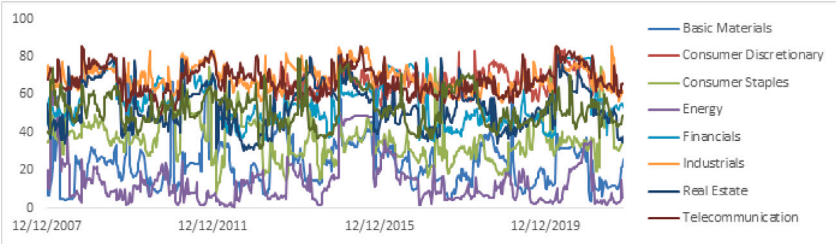


(c) 5 Week Forecast Horizon-75 week rolling window

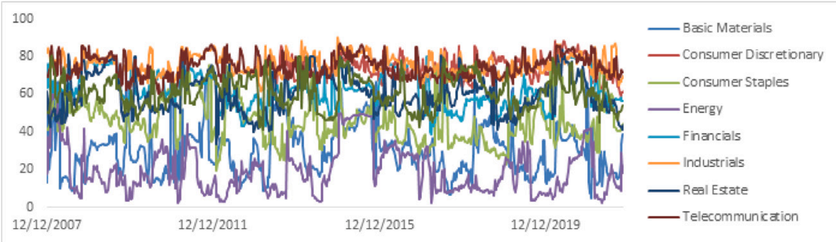


(d) 10 Week Forecast Horizon-75 week rolling window

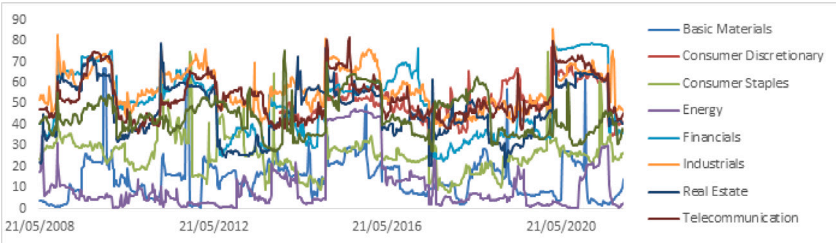
Fig. 11. The total return spillover indices are calculated with Diebold and Yilmaz (2012) methodology by re-estimating the second-order VAR approach using 52- and 75-week rolling window estimates with 5 and 10 week forecast horizons.



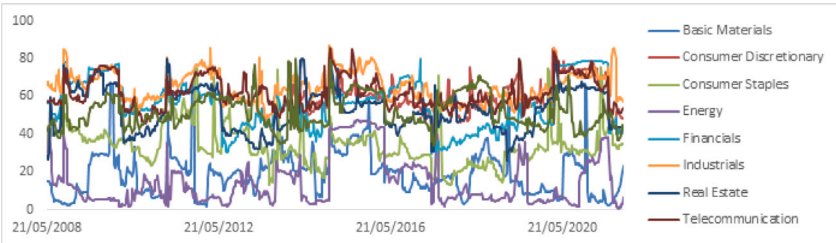
(a) 5 Week Forecast Horizon-52 week rolling window



(b) 10 Week Forecast Horizon-52 week rolling window



(c) 5 Week Forecast Horizon-75 week rolling window



(d) 10 Week Forecast Horizon-75 week rolling window

Fig. 12. The total volatility spillover indices are calculated with Diebold and Yilmaz (2012) methodology by re-estimating the second-order VAR approach using 52-and 75-week rolling window estimates with 5 and 10 week forecast horizons.

References

Alkulaib, Y. A., Najand, M., & Mashayekh, A. (2009). Dynamic linkages among equity markets in the middle east and north African countries. *Journal of Multinational Management*, *19*(1), 43–53.

Alotaibi, A. R., & Mishra, A. V. (2017). Time varying international financial integration for GCC stock markets. *The Quarterly Review of Economics and Finance*, *63*, 66–78.

Aloui, C., & Hkiri, B. (2014). Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis. *Economic Modelling*, *36*(C), 421–431.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84.

Arin, K. P., Caporale, G. M., Kyriacou, K., & Spagnolo, N. (2020). Financial integration in the GCC region: Market size versus national effects. *Open Economies Review*, *31*(2), 309–316.

Awartani, B., Maghyereh, A. I., & Al Shiab, M. (2013). Directional spillovers from the US and the Saudi market to equities in the Gulf cooperation council countries. *Journal of International Financial Markets, Instutions and Money*, *27*, 224–242.

Baele, L. (2005). Volatility spillover effects in European equity markets. *The Journal of Financial and Quantitative Analysis*, *40*(2), 373–401.

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, *66*(1), 47–78.

Balcilar, M., Demirer, R., & Hammoudeh, S. (2015). Regional and global spillovers and diversification opportunities in the GCC equity sectors. *Emerging Markets Review*, *24*, 160–187.

Balli, F., Basher, S. A., & Louis, R. J. (2013). Sectoral equity returns and portfolio diversification opportunities across the GCC region. *Journal of International Financial Markets, Institutions and Money*, *25*, 33–48.
Balli, F., Billah, M., Balli, H. O., & Bruin, A. De (2021). Spillovers to sectoral equity returns: Do liquidity and financial positions matter? *Applied Economics*, *53*(27), 3097–3130.
Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271–296.
Bekaert, G., & Harvey, C. (1997). Emerging equity market volatility. *Journal of Financial Economics*, *43*(1), 29–77.
Caloia, F. G., Cipollini, A., & Muzzioli, S. (2019). How do normalization schemes affect net spillovers? A replication of the diebold and Yilmaz (2012) study. *Energy Economics*, *84*, Article 104536.
Charfeddine, L., & Al Refai, H. (2019). Political tensions, stock market dependence and volatility spillover: Evidence from the recent intra-GCC crises. *The North American Journal of Economics and Finance*, *50*(C), Article 101032.
Chatziantoniou, I., & Gabauer, D. (2021). EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. *The Quarterly Review of Economics and Finance*, *79*, 1–14.
Chowdhury, S. S. H. (2020). Spillover of sentiments between the GCC stock markets. In *Global Business Review*. Available Online: https://protect-eu.mimecast.com/s/E6NjCNYyKH0rM09tmK9D0?domain=journals.sagepub.com.
Dickey, D. A., & Fuller, W. A. (1978). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427.
Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66.
Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*, 119–134.
Fratzscher, M. (2002). Financial market integration in Europe: On the effects of EMU on stock markets. *International Journal of Finance and Economics*, *7*(2), 165–193.
Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise connectedness within an Optimal Currency Area: Evidence from the ERMI system. *Journal of Multinational Financial Management*, *60*, Article 100680.
Hammoudeh, S., & Aleisa, E. (2004). Dynamic relationships among GCC stock markets and NYMEX oil futures. *Contemporary Economic Policy*, *22*(2), 250–269.
Kang, S. H., McIver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, *62*, 19–32.
Kang, S. H., & Yoon, S. M. (2016). Dynamic spillovers between Shanghai and London nonferrous metal futures markets. *Finance Research Letters*, *19*, 181–188.
Kapar, B., Olmo, J., & Ghalayini, R. (2020). Financial integration in the United Arab Emirates stock markets. *Finance Research Letters*, *33*, Article 101219.
Kim, S. J., Moshirian, F., & Wu, E. (2005). Dynamic stock market integration driven by the European monetary union: An empirical analysis. *Journal of Banking & Finance*, *29*(10), 2475–2502.
Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101–116.
Laborda, R., & Olmo, J. (2021). Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and COVID-19 pandemic. *Research in International Business and Finance*, *57*, Article 101402.
Lastrapes, W. D., & Wiesen, T. F. (2021). The joint spillover index. *Economic Modelling*, *94*, 681–691.
Marashdeh, H., & Shrestha, M. B. (2010). Stock market integration in the GCC countries. *International Research Journal of Finance and Economics*, *37*, 102–114.
Moerman, G. A. (2008). Diversification in euro area stock markets: Country versus industry. *Journal of International Money and Finance*, *27*(7), 1122–1134.
Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific basin. *Journal of International Money and Finance*, *19*, 207–233.
Ngene, G. M. (2021). What drives dynamic connectedness of the US equity sectors during different business cycles? *The North American Journal of Economics and Finance*, *58*, Article 101493.
Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17–29.
Raffoul, A., & Hewaidi, F. A. (2021). *How industrialisation could future-proof MENA's gulf economies*. World Economic Forum.
Stiassny, A. (1996). A spectral decomposition for structural VAR models. *Empirical Economics*, *21*, 535–555.
Yilmaz, K. (2010). Return and volatility spillovers among the east Asian equity markets. *Journal of Asian Economies*, *21*(3), 304–313.
Yousaf, I., Belkid, M., Chaibi, A., & Al Ajlouni, A. (2022). Do volatility spillover and hedging among gcc stock markets and global factors vary from normal to turbulent periods? evidence from the global financial crisis and covid-19 pandemic crisis. *Pacific-Basin Finance Journal*, *73*, Article 101764.
Yu, J., & Hassan, M. (2008). Global and regional integration of the middle east and north African (MENA) stock markets. *The Quarterly Review of Economics and Finance*, *48*(3), 482–504.
Ziadat, S., & AlKhouri, R. (2022). Revisiting volatility spillovers in the Gulf cooperation council. *Cogent Economics and Finance*, *10*(1), Article 2031683.
Ziadat, S., Herbst, P., & McMillan, D. G. (2020). Inter-and intra-regional stock market relations for the GCC bloc. *Research in International Business and Finance*, *54*, Article 101292.