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ORIGINAL PAPER

Financial connectedness of GCC emerging stock markets

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Abstract
This paper investigates the financial interrelatedness via mean and volatility spillovers across stock markets for the Gulf Cooperation Council countries (Bahrain, Kuwait, Qatar, Oman, Saudi Arabia, and the United Arab Emirates) during the period 2008–2019 utilizing both the spillover index and the multivariate DECO-GARCH model. The results suggest that the average return equicorrelation among GCC stock markets is positive, even though it is found to be very time-varying with specific periods, which impair the benefits of GCC portfolio diversification. Besides, our spillover analysis findings provide several straightforward insights into both the level and the dynamics of stock market integration in the GCC countries over the past 10 years. Our results report significant heterogeneity among GCC stock markets in the degree of spillovers over time, strengthening our understanding of the economic channels through which GCC equity markets are correlated.

Keywords GCC · Volatility spillover · DECO · Stock markets

JEL Classification C15 · C51 · G15

1 Introduction

Over the past two decades, stock market co-movement behavior has become a crucial issue in finance since it has significant implications for understanding business cycles and evaluating diversification opportunities across emerging equity markets (Kang & Yoon 2019; Chaffai & Medhioub, 2018; Hung, 2021). This issue has received much attention from academic researchers and practitioners, and emerging markets have witnessed substantial economic and financial development owing to their outstanding contribution to the macroeconomic relationship in the international economy (Aloui & Hkiri, 2014). The evolution of the emerging equity

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markets has remarkably risen its market size, leverage, and association with an international financial mechanism. Price and volatility spillovers across financial markets are larger when market interconnectedness is high. Meanwhile, market prices tend to be more connected when volatility increases, and essential periods of high variation are associated with market downturns (Baruník et al., 2016). Market volatility, particularly for crisis growth, then spills rapidly across markets (Hung, 2020a). More precisely, a strong connectedness among national markets around the world might effectively result in higher exposure to contagious impacts if one market in the system goes through a crisis or witnesses a severe crash (Chevallier et al., 2018).

The GCC countries play a prominent role in the international economy, jointly accounting for 40% and 23% of proven oil and gas reserves, respectively, while stock market behavior is somewhat under-researched (Ziadat et al., 2020). Furthermore, the GCC economies, known as emerging or frontier markets, are experiencing a financial liberalization process, which would lead to a considerable connection with the global economy. As a result, understanding the nature of the association among these markets is indispensable for investors who might seek for achieving cross-country diversification benefits. This study looks into the financial association via return and volatility spillover effects between stock market returns for the Gulf Cooperation Council (GCC) countries (Bahrain, Kuwait, Qatar, Oman, Saudi Arabia, and the United Arab Emirates) over the period 2008–2019. The primary purpose of this paper is to examine the direction and extent of the interdependence of GCC stock markets. To this end, we employ a multivariate generalized autoregressive conditional heteroscedasticity model with a dynamic equicorrelation specification (DECO-GARCH) (Engle & Kelly, 2012) and Diebold and Yilmaz (2012)'s spillover index. Obviously, the intercorrelation between GCC stock markets plays a vital role in designing portfolio diversification since the performance of a portfolio relies on the connection between these assets. Hence, the DECO model is a helpful and straightforward approach to capture the global stock markets' co-movement, which helps investors reshape portfolio diversification and investment decision (Kang & Yoon 2019; Hung, 2019). We also use the spillover measure of Diebold and Yilmaz (2012) to evaluate the cross-market interdependence and direction of spillovers among sample markets. The essential advantage of this method is that the spillover estimates the time-varying magnitude of price and volatility transmission over time and measures the direction of spillovers (Kang et al., 2019; Ziadat et al., 2020). For the combination of these methods, several recent papers have perfectly captured the spillover effects among financial markets (Kang & Yoon, 2019; Ahmad et al., 2018; McIver & Kang, 2020; Kang et al. 2019).

In light of the above discussion, this study contributes to the related literature in some ways. First, we analyze the time-varying connectedness among GCC stock markets, employing a multivariate GARCH model with the DECO framework. Indeed, DECO uses more information to estimate time-varying condition correlations between each pair of examined variables than the DCC model, which declines the estimation noise of the correlations (Kang & Yoon, 2019; Kang et al. 2019). As a result, these multivariate GARCH models are crucial for strengthening our understanding of the interrelatedness between the volatilities of our studied indicators. In the second stage, we quantify the directional return and volatility spillovers by using the spillover index of Diebold and Yilmaz (2012) that a particular equity market receives from other markets. The strength of the connection is further magnified by the use of networks that help trace the magnitude and speed of information transmission between GCC stock indices. The measurement of directional price and volatility is significant for understanding the spillover channels within the inter-regional market of the GCC countries. Our main results reveal a positive equicorrelation across GCC stock market returns, even though it is found to be very time-varying with specific periods, which impairs the benefits of GCC portfolio diversification. Besides, our spillover analysis findings provide several straightforward insights into both the level and dynamics of stock market integration in the GCC countries over the past 10 years. The study reports that UAE, followed by Saudi and Qatar, represent an active transmission of volatility shocks to others among GCC stock market returns. This situation is also confirmed by the magnitudes of net returns and volatility spillovers transferring from one market to all other markets, which implies that UAE, Saudi, and Qatar might act as catalysts for risk triggers after the global financial crisis. This information would be useful to both local and global investors and policymakers.

The remainder of this study is organized as follows: Sect. 2 provides the related literature. Section 3 depicts the data and methodology. Section 4 reports empirical results. Finally, Sect. 5 concludes.

2 Literature review

An overview of existing literature on stock market integration uncovers the interconnectedness between global stock and GCC stock markets. Increasing literature has addressed the stock returns and volatility spillover effects between financial markets. The information in relation to the spillover effect is of crucial importance for risk management, which can be helpful in a number of applications consisting of the evaluation of portfolio hedge ratio effectiveness, value-at-risk, and optimal portfolio weights (Alotaibi & Mishra, 2015, 2017; Aloui & Hkiri, 2014; Aloui et al., 2015; Al-Shboul & Alsharari, 2019; Balli et al., 2019; Charfeddine & Al Refai, 2019; Charfeddine & Khediri, 2016; Daly et al., 2019; Finta et al., 2019; Hung, 2020b; Isik & Hassan, 2002). For example, Kapar et al. (2020) investigate the financial connectedness in the United Arab Emirates Stock Markets and suggest the persistence of a long-run equilibrium nexus between three stock markets, which means that UAE stock markets are integrated. Shahateet (2019) determines the dynamic interconnectedness among 15 Arab stock markets. He concludes that Arab stock markets have a weak relationship with the exception of those of the GCC. Finta et al. (2019) estimate the volatility spillovers among oil and the US and Saudi Arabian stock markets and show the existence of asymmetry in contemporaneous spillover effects. Chaffai and Medhioub (2018) explore the presence of herb behavior in the Islamic Gulf Cooperation Council stock markets, and provide evidence of herd behavior in the GCC stock markets. Aloui et al. (2015) show a strong dependence between sharia stock and Sukuk indexes and the benefits of portfolio diversification change across frequencies and time.

Within the GARCH framework, Yousef and Masih (2017) suggest that dynamic conditional correlation among GCC stock returns is low, which is useful for investors interested in investing in the GCC markets. Alotaibi and Mishra (2015) unveil significant return spillover effects from Saudi Arabia and the US to GCC markets. Charfeddine and Khediri (2016) reveal that GCC markets have divergent degrees of time-varying efficiency. They also provide evidence of structural breaks in all GCC markets. In the same vein, Jamaani and Roca (2015) show that GCC stock markets are not individually weak-form efficient because the movements of past prices of one GCC stock market can be applied to forecast the current price movement of another GCC stock market. Chowdhury et al. (2015) find that Bahrain, Oman, and Qatar experience a strong positive correlation, while Abu Dhabi exhibits negative autocorrelation of returns. Alotaibi and Mishra (2017) show wide ranges in the degree of integration for GCC stock markets using the global asset pricing model of dynamic market integration and DCC model. They suggest that trade openness, financial market development, turnover, and oil revenue have a dramatic influence on the integration index of GCC stock markets. Mensi et al. (2016) investigate the time-varying tail dependence structure for the Gulf equity indices, and find strong asymmetric dependence at middle and long investment horizons. More recently, Charfeddine and Al Refai (2019) show volatility spillover effects between Qatar and the other GCC countries. Al-Shboul and Alsharari (2019) uncover that the Dubai financial market and the Abu Dhabi stock exchange experience evidence of evolving efficiency, suggesting that stock prices are predictable and possible arbitrage opportunities are present. Similarly, Mensi et al. (2018) reveal that five GCC stock markets experience multifractal features and evidence of time-varying persistence.

Besides this, few studies have also investigated relationships across stock markets using various econometric techniques. Alhashel (2021) examines whether stock returns in the frontier markets of the GCC are driven by the same drivers by explaining a significant proportion of the cross-section of returns in terms of size and book-to-market. The authors conclude that the empirical asset pricing model is useful to describe returns in the GCC markets. Buigut and Kapar (2020) analyze Qatar's effect on seven stock markets in GCC countries. Their results provide evidence that Qatar's economy reacts negatively to the crisis over the shorter event windows, while Saudi Arabia's banking industry, Dubai's real estate industry, and Abu Dhabi's energy industry register positive abnormal returns.

Under the GCC market setting, a limited number of papers have responded to the need for stock market making in emerging economies. Chowdhury (2020) studies how stock market sentiment in the GCC stock market might spill over to affect other markets' sentiments using the DCC model. The results show that Kuwait and Qatar stock markets are segregated from other markets in the region, while Saudi Arabia and the United Arab Emirates markets are well integrated. Al-Yahyaee et al. (2020) investigate the dependence structure and systematic risk between Sukuk, Sharia, and GCC stock markets, and provide evidence of dynamic symmetric tail dependence between Islamic stock markets and GCC stock markets. Alqahtani and Chevallier (2020) estimate the conditional correlations between GCC stock markets. They find that GCC stock market returns are negatively correlated with each of the volatility measures, and Saudi Arabia and Qatar are the most responsive to all shocks among the GCC countries. Ziadat et al. (2020) investigate the patterns of information transmission for seven GCC stock markets using the DCC mode and the Diebold Yilmaz spillover index. The paper reports that GCC markets correlate strongly with the EU and the US. More importantly, the UAE is the primary transmitter and receiver of spillover between GCC and world markets, and Bahrain and Kuwait markets correlate weakly with the GCC stock returns. In the same vein, Arin et al. (2020) take into account financial spillovers among the four largest equity markets in the GCC region. They find significant spillover effects from the largest market of Saudi Arabia to Qatar and the UAE in terms of mean and volatility, which identifies that market capitalization is a more crucial factor of financial connectedness than belonging to a federal union. Besides, Aloui and Hkiri (2014) confirm an increasing strength of dependence among the GCC stock markets after the global financial crisis, which might influence the multi-country portfolio's value at risk levels.

In spite of growing international attention on the GCC stock markets, relevant empirical research on spillovers remains strictly limited, supporting the case for further study. In addition, the interdependence across markets is frequently captured utilizing the variance–covariance matrix, which cannot evaluate the direction and intensity of spillover through time. Therefore, an adequate understanding of the transmission direction is crucial for constructing optimal portfolio and risk management strategies in terms of hedging practices and providing information on the significant cross-country sources of variations in policymakers' business cycle activity.

Overall, our in-depth analysis of equicorrelation and spillover effects among GCC stock markets appears to extend the studies of Alotaibi and Mishra (2015) and Balli et al. (2019). Alotaibi and Mishra (2015) examined the effect of price spillovers from regional (Saudi Arabia) and global US markets to GCC stock markets, while Balli et al. (2019) take into account the pairwise, net, and the total price and volatility spillover across 15 Islamic equity markets. Unlike previous works, ours is the first attempt to explore the equicorrelation and connectedness among GCC stock markets. Empirical estimations are developed by employing the methodologies of equicorrelation advanced by Engle and Kelly (2012) and the connectedness analysis introduced by Diebold and Yilmaz (2012). These approaches perfectly complement each other, allowing us to determine systematic information transmission across GCC stock markets. More accurately, the time-varying equicorrelation (DECO) model is to identify co-movement between markets. This framework is an extreme case of a dynamic conditional correlation model where correlations are equal across all pairs, but the common equicorrelation changes over time (Kang & Yoon, 2019). By analyzing the net connectedness and pairwise relationship, the second model detects the source and recipients of innovation, tackling the flow of shock transmission. Besides, the regional markets' focus allows us to provide global investors and cross-border portfolio managers with valuable information. The specific clusters of price and volatility spillovers suggest possible contagion risk, restricting GCC portfolio holders.

3 Methodology

3.1 Directional spillover model

The present paper uses the Diebold and Yilmaz (2012) (DY) specification to examine the magnitude and volatility spillovers across variables under study throughout sample period. The DY approach is built on the VAR model of order p and N variables, $x_i = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_i$, where $\varepsilon \sim \left(0, \sum\right)$ is a vector of independent and identically distributed distances. The intercept for an AR process, that is,$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ where $N \times N$ coefficient matrix A_i is obtained by the recursive substitution, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with $A_0 = I_n$, which is an identity matrix of order n, and $A_i = 0$ for $i < 0$. The MA presentation can be employed to forecast the future with the H-step-ahead.

The H-step-ahead generalized forecast-error variance decomposition can be written as:

$$\phi_{ij}^{g}(H) = \frac{\sigma_{ij} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_i\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{1}$$

here σ_{ii} stands for standard deviation of the stochastic term for the ith equation, while e_i is the selection vector with 1 as the ith elements, and 0 otherwise. The sum of the contribution of variance of the forecast is not equal to unit under the generalized framework $\sum_{j=1}^{N} \phi_{ij}^{g}(H) \neq 1$.

The normalized entry for each variance decomposition matrix is normalized by the row sum as

$$\tilde{\theta}_{ij}^{g} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2}$$

where $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

Total volatility spillover index proposed by Diebold and Yilmaz (2012) is defined as

$$S^{g}(H) = \frac{\sum_{i,j=1,j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3}$$

The directional volatility spillovers received by market i from all other markets j can be written as:

$$S_{i.}^{g}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4}$$

The directional spillovers transmitted by market i to all other markets j is:

$$S_{i.}^{g}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\times 100 \tag{5}$$

Finally, the net volatility spillover for each market by calculating the difference between (5) and (4) is computed:

$$S_{i}^{g}(H)=S_{.i}^{g}(H)-S_{i.}^{g}(H) \tag{6}$$

3.2 DECO-MGARCH model

To perfectly capture the interdependence results, this study employs a dynamic equicorrelation model of multivariate generalized autoregressive conditional heteroscedasticity (DECO-MGARCH) proposed by Engle and Kelly (2012). Engle and Kelly (2012) proposed the DECO model, which handles a large number of variables and makes simple computational and presentation challenges with respect to a high-dimensional system to overcome the issue of curse-of-dimensionality. Similar to MGARCH-DCC model, the DECO model also follows the two-step estimation procedure. First, we roughly calculate univariate GARCH model for each variable to gain the conditional variance. Second, we employ DCC model from standardized residuals to estimate the dynamic conditional correlation.

The conditional covariance matrix H_t is now defined as,

$$\mathrm{H}_t=D_tR_tD_t \tag{7}$$

where $D_t=diag\sqrt{\{\mathrm{H}_t\}}$ is the diagonal matrix with conditional variances along the diagonal, and R_t is the time-varying correlation matrix.

In matrix form,

$$Q_t=\bar{Q}(1-\alpha-\beta)+\alpha e_{t-1}e_{t-1}^{'}+\beta Q_{t-1} \tag{8}$$

where $\bar{Q}=Cov\left[e_t,e_t^{'}\right]=E\left[e_t,e_t^{'}\right]$ is unconditional covariance matrix of the standardized errors $\bar{Q}$ can be estimated as,

$$\bar{Q}=\frac{1}{T}\sum_{t=1}^{T}e_te_t^{'} \tag{9}$$

R_t is then obtained by

$$R_t = \left(Q_t^*\right)^{1/2} Q_t \left(Q_t^*\right)^{1/2} \tag{10}$$

where $Q_t^* = diag\left\{Q_t\right\}$.

Nevertheless, Aielli (2013) suggests that the estimation of the covariance matrix Q_t is inconsistent because $E[R_t] \neq E[Q_t]$. He illustrates the following consistent model with the correlation-driving process (cDCC):

$$Q_t = (1 - \alpha - \beta)S^* + \alpha\left(Q_{t-1}^{*1/2}\varepsilon_{t-1}\varepsilon_{t-1}^{'}Q_{t-1}^{*1/2}\right) + \beta Q_{t-1}, \tag{11}$$

where S^* is the unconditional covariance matrix of $Q_t^{*1/2}\varepsilon_t$.

Engle and Kelly (2012) suggest modeling ρ_t using the cDCC process to gain the conditional correlation matrix Q_t and then taking the mean of its off-diagonal elements. DECO specification reduces the estimation time. The scalar equicorrelation can be written as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(K_n^{'}R^{cDCC}K_n - n\right) = \frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{12}$$

where $q_{ij,t} = \rho_t^{DECO} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \rho_t^{DECO}\right) + \beta_{ECO}\left(q_{ij,t} - \rho_t^{DECO}\right)$, K is a vector of ones and $q_{i,j,t}$ is the (i, jth) components of the matrix Q_t from the DCC model. Then, we apply ρ_t^{DECO} to capture the conditional correlation matrix.

$$R_t^{DECO} = (1 - \rho_t)I_n + \rho_t K_n \tag{13}$$

where I_n is the n-dimensional identity matrix.

3.3 Data

In this paper, we use daily stock index prices of six GCC stock markets: United Arab Emirates (UAE), Qatar (QATAR), Saudi Arabia (SAUDI), Oman (OMAN), Kuwait (KUWAIT), Bahrain (BAHRAIN). Intraday price observations are obtained from the Bloomberg database, and the sample period covers from 2 January 2008 to 31 December 2019 for a total of 3018 daily prices. We compute the continuously compounded daily returns by taking the difference in the natural logarithm of two consecutive prices.

Table 1 provides details of summary statistics for the return and volatility series. It is clear that all examined variables are not normally distributed, with respect to the Jarque–Bera statistic for normality, which means that empirical distribution is characterized by skewness and slight excess kurtosis. The augmented Dickey–Fuller (ADF) test reveals, for its parts, that all series are stationary at conventional levels. ARCH-LM tests for squared variables under study are also employed to check the ARCH effect. The results of this test confirm that the application of the multivariate GARCH types model to estimate the return and volatility of daily data series is justified, and thus appropriate for further statistical analysis.

Table 1 Descriptive statistics of the GCC stock indices

	UAE	SAUDI	QATAR	OMAN	BAHRAIN	KUWAIT
Panel A: Return						
Mean	0.0166	– 0.0114	0.0163	– 0.0118	– 0.0295	– 0.1941
SD	1.0784	1.6672	1.3412	1.0109	0.0615	6.6189
Max	7.6294	16.3995	9.4219	8.0388	0.0010	21.1467
Min	– 8.6792	– 13.4905	– 11.2794	– 8.6989	– 1.0380	– 33.1246
Skew	– 0.2286	– 0.9568	– 0.4725	– 1.2260	– 7.3651	– 38.5959
Kurt	11.5029	15.9970	13.9305	22.7392	81.7334	1882.672
J-B	9114.960***	21,695.56***	15,131.57***	49,736.72***	806,536.8***	445,423.2***
ADF	– 45.3761***	– 28.9276***	– 47.0783***	– 11.5016***	– 6.7226***	– 56.6615***
ARCH-LM	344.0425***	110.8974***	218.2990***	881.5762***	27.2559***	321.7452***
Panel B: Volatility						
Mean	0.0224	0.0023	0.0253	– 0.0067	– 0.0295	– 0.0731
SD	1.0777	1.6558	1.3381	1.0051	0.0613	3.4854
Max	7.9280	17.8208	9.8801	8.3707	0.0000	3.3549
Min	– 8.3132	– 12.620	– 10.666	– 8.3313	– 1.0326	– 9.6054
Skew	– 0.0591	– 0.5967	– 0.2182	– 0.9196	– 7.3407	– 6.9307
Kurt	11.5307	16.3334	13.6277	22.0563	81.2127	196.4348
J-B	9150.082***	22,527.43***	14,222.54***	46,075.53***	796,083.4***	472,778.5***
ADF	– 45.4508***	– 29.2165***	– 47.1726***	– 11.6428***	– 6.7191***	– 57.9548***
ARCH-LM	349.0662***	102.1939***	231.4726***	903.7836***	27.6410***	16.0969***

The asterisks ***,**,* illustrate significance at the 1%, 5% and 10% levels, respectively

Next, we look into the unconditional correlation across the GCC stock markets using the correlation matrix. As shown in Fig. 1, the connectedness between the GCC stock markets is relatively high, based on the linearity assumption. More importantly, all return series share both negative and positive dependence, which means that GCC stock markets have the divergent directional co-movement. This outcome implies the existence of ample diversification opportunities for investors who look for constructing a portfolio. Further, the distribution of the examined variables follows the non-normal shape. Figure 1 provides us with further insight into the data contribution and correlation structure of the selected variables.

4 Empirical findings

4.1 Estimates of DECO-GARCH model

Table 2 reports the estimated results of the DECO-ARMA-GARCH model across six GCC stock markets. The lags selection of $p = 1$ and $q = 1$ based on the lowest values of Akaike and Schwarz information criteria was implemented to opt for

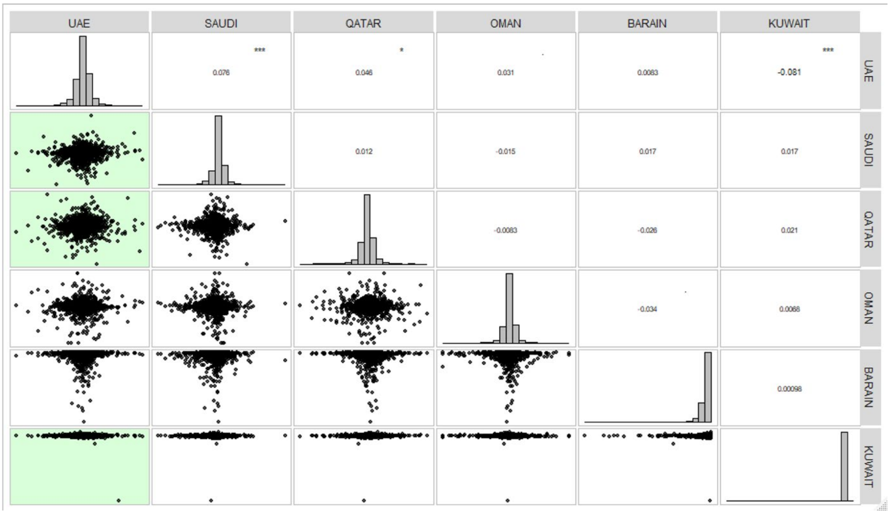


Fig. 1 The data distribution and correlation structure

an appropriate the ARMA(1,1)-GARCH(1,1) for all combination returns. Panel A documents that ARCH and GARCH coefficients for all the examined variables are statistically significant at 1% level. Specifically, the sum of these coefficients for all series is close to one and significant, indicating that the conditional variance is mean-reverting. These results show that the one-period lagged future returns explain the current future returns and long-term memory behavior for all markets under investigation.

Panel B of Table 2 shows the results of the DECO model. The time-varying equicorrelation coefficient is found to be positive (0.077) and statistically significant at the traditional level, implying a sign of potential diversification benefits between stock portfolio and a high degree of integration across these stock markets. The parameter A_{DECO} is positive and significant, underlying the role of innovation between GCC stock markets. At the same time, we can observe that volatility throughout stock markets continues to increase since the B_{DECO} parameter is also statistically significant. Put another way, equicorrelations are highly dependent on past correlations. Besides, the sum of A_{DECO} B_{DECO} estimates is nearly equal to unity, showing that the volatility equicorrelation is integrated. The significance of the two parameters justifies the appropriateness of the DECO-GARCH model, we can verify that the DECO parameters lie in the range of standard estimates originating from the GARCH (1,1) model. This implies that the equicorrelation among stock may be stable. These findings are consistent with Yousef and Masih (2017); Alotaibi and Mishra (2015).

The diagnostic tests are documented in Panel C. The Ljung-Box test statistics for the standardized squared residuals do not reject the null hypothesis of no serial correlation for all markets, which means that the residuals reveal no autocorrelation. We can conclude that there is no misspecification in our model. Furthermore, the Hosking and McLeod and Li test results suggest that the null

Table 2 Estimation results of the ARMA-GARCH with DECO specification

	UAE	SAUDI	QATAR	OMAN	BAHRAIN	KUWAIT
Panel A: Estimates of the univariate ARMA (1,1)- GARCH (1,1) model						
Const (M)	0.0363 (0.0503)	0.0252 (0.0550)	0.0299 (0.0459)	0.0067 (0.0663)	– 0.0170 (0.0165)	– 0.3901 (0.2564)
AR(1)	0.3931** (0.1623)	– 0.2386* (0.1301)	0.4180*** (0.0786)	0.1518 (0.1215)	0.9744*** (0.0079)	– 0.0515 (0.3014)
MA(1)	– 0.2440* (0.1745)	0.3690*** (0.1190)	– 0.2598** (0.0864)	0.1405 (0.1322)	– 0.8595*** (0.0141)	– 0.2436 (0.2733)
Const(V)	0.7310*** (0.1682)	1.7094*** (0.1650)	1.0615*** (0.1632)	0.6552*** (0.0732)	0.0012*** (9.00E– 05)	2.8380*** (0.5642)
ARCH	0.1251*** (0.0328)	0.0526*** (0.0081)	0.0426*** (0.1632)	0.1410*** (0.0224)	0.1488*** (0.0178)	0.0566** (0.0249)
GARCH	0.5751*** (0.0922)	0.5026*** (0.0443)	0.4926*** (0.0748)	0.5910*** (0.0421)	0.5988*** (0.0280)	0.5066*** (0.1348)
Panel B: Estimates of the DECO model						
Average ρ_{ij}	0.0771*** (0.0001)					
A_{DECO}	0.0451*** (0.0263)					
B_{DECO}	0.3448** (0.5097)					
Panel C: Diagnostic tests						
$Q^2(5)$	3.5818 [0.310]	8.421 [0.541]	2.9912 [0.393]	6.5113 [0.842]	2.5746 [0.634]	1.9288 [0.142]
Hosking^2	453.4461 [0.3015]					
McLeod-Li^2(20)	421.3241 [0.2604					

$Q^2(5)$ represents the Ljung-Box test statistics employed to the squared standardized residuals

The asterisks ***,**,* illustrate significance at the 1%, 5% and 10% levels, respectively. The p-values are in brackets, and the standard errors in parentheses

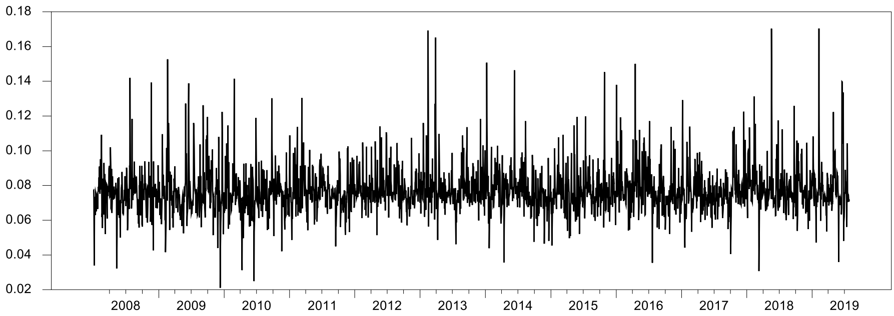


Fig. 2 Dynamic equicorrelation for returns across GCC stock markets

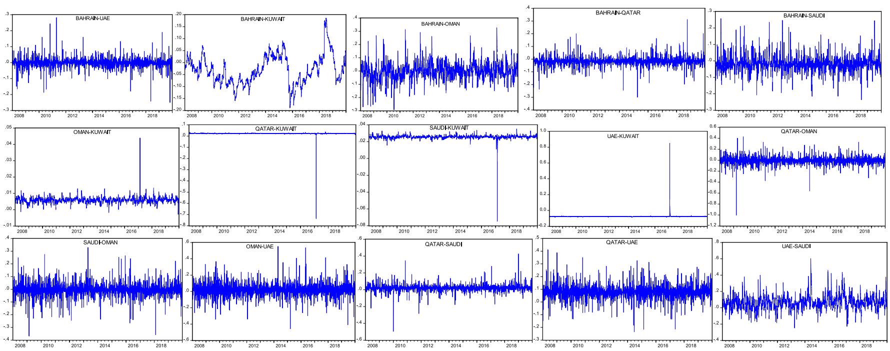


Fig. 3 Dynamic conditional correlation among GCC stock markets

hypothesis of no serial correlation in the conditional variances estimated by the DECO-GARCH model is accepted, showing that our selected DECO-GARCH model is correctly specified.

We plot the time-varying conditional equicorrelation among GCC stock markets, which is obtained from the ARMA-GARCH model with the DECO specification. The visual evidence is shown in Fig. 2 and supports the results in Table 2. The line graph depicts a positive and time-varying correlation over the sample period with a correlation level varying from a minimum of 2% to a maximum of 18%. The equicorrelation between GCC stock markets slightly declined from 2013 to 2014 as a result of the 2014 oil crisis, supporting a decoupling hypothesis, which is identified as a significant increase in correlation across stock markets in various countries during the crisis period (Hung, 2019; Kang et al., 2019).

For robustness check, we estimate dynamic conditional correlation (DCC) models across GCC stock markets. The pairwise DCC findings are reported in Fig. 3, which tallies with the DECO estimations indicated in Fig. 2. The conditional correlations between the two variables under consideration were time-varying and increased during the European debt crises. As a result, the pairwise DCC outcomes affirm our results obtained for the six GCC stock markets based on the

DECO estimation of Fig. 2. To confirm the results documented by the DECO model, we also estimate the return and volatility spillovers.

4.2 Total return and volatility spillovers

Spillover analysis is depicted in this section. Table 3 illustrates the total spillover index matrices of means and volatilities based on a full sample analysis. All results are built on the VAR framework with optimum lag as suggested by the AIC, and generalized variance decompositions of 10-day-ahead forecast errors. The *ijth* entry in the tables shows the estimated contribution of sector j to the forecast error variance of sector i. Each series is related to one of the counterpart nations. Therefore, the diagonal components ($i = j$) explain own-variable transmissions of means and volatility across nations, while the off-diagonal components ($i \neq j$) show cross-variable transmissions through mean and volatility and across GCC nations. Furthermore,

Table 3 Directional spillovers

	UAE	SAUDI	QATAR	OMAN	BAHRAIN	KUWAIT	From others
Panel A: Return spillover							
UAE	96.72	1.23	0.29	0.84	0.05	0.87	3.3
SAUDI	0.63	98.4	0.04	0.55	0.30	0.03	1.6
QATAR	5.19	0.48	93.32	0.80	0.13	0.08	6.7
OMAN	1.05	0.64	0.19	97.87	0.20	0.04	2.1
BAHRAIN	0.03	0.70	0.06	0.01	99.18	0.02	0.8
KUWAIT	0.82	0.05	0.15	0.04	0.03	98.92	1.1
Contribution to others	7.7	3.1	0.7	2.2	0.7	1.1	15.6
Contribution including own	104.4	101.5	94.1	100.1	99.9	100.0	**Spillover index = 2.6%**
Net spillovers	4.4	1.5	-5.9	0.1	-0.1	0	
Panel B: Volatility spillover							
UAE	97.17	1.41	0.16	0.70	0.05	0.52	2.8
SAUDI	0.78	98.24	0.07	0.46	0.21	0.24	1.8
QATAR	5.81	0.86	92.35	0.52	0.11	0.34	7.6
OMAN	1.41	0.58	0.16	97.47	0.18	0.21	2.5
BAHRAIN	0.02	0.64	0.09	0.04	98.9	0.31	1.1
KUWAIT	0.56	0.16	0.36	0.23	0.25	98.44	1.6
Contribution to others	8.6	3.6	0.8	2.0	0.8	1.6	17.4
Contribution including own	105.7	101.9	93.2	99.4	99.7	100.1	**Spillover index = 2.9%**
Net spillovers	5.7	1.9	-6.8	-0.6	-0.3	0.1	

The underlying variance decomposition is based on a daily VAR system with 4 lags and generalized variance decompositions of 10-day-ahead volatility forecast errors the row sums, "from others" and column sums, "contribution to others", measure the total spillover to (transmitter) and from (receiver) each market index. Finally, the total spillover index, given on the bottom of each panel, is calculated by the aggregation of the row and column, with the exclusion of the own variable spillover shock, performed in percentage points.

Panel A of Table 3 illustrates the total spillover index across six GCC stock market returns, decomposed by transmitters and return spillovers recipients. There is a slightly above average total spillover index of around 2.6% on average for return forecast error variance. This implies the bi-directional return spillover across GCC countries. It is noticeable that UAE is the largest contributor to the other countries, followed by SAUDI and OMAN. UAE has gross and net contributions of 7.7% and 4.4%, respectively. SAUDI contributes 3.1% to the other markets, while it receives 1.6% from other markets. As a result, it contributes 1.5% more to other market returns in net terms than it receives from other market returns. However, the other markets (QATAR, BAHRAIN) are net recipients since their contributions to all the other markets are less than what they receive from the other markets. This finding is consistent with Ziadat et al. (2020).

Panel B of Table 3 shows that the total volatility spillovers attain a value of 2.9%. UAE has the highest impact on the variance of the rest of the markets (105.7%), followed by the indices of QATAR and KUWAIT. In addition, UAE contributes 5.8% on the forecasting variance of QATAR, 1.41% on OMAN and 0.78% on SAUDI. More precisely, UAE is the largest transmitter of volatility spillovers, with the net spillover estimated at 5.7%. This finding is consistent with the results of return spillovers. QATAR is the largest recipient of volatility spillovers, with the value of (-6.8%), followed by OMAN (-0.6%). The results can be attributed to several determinants that confirm the GCC regional financial integration. Past shocks from the regional markets (AUE and SAUDI) have significant price and volatility spillover effects in each local GCC stock market, perhaps resulting from liberalization policies and international capital flows (Ziadat et al., 2020). By contrast, Qatar and Kuwait are captured with minimum impact of volatility transmissions, leading to isolation from the GCC markets. This implies that it is necessary to enhance the cross-border regulation framework to reinforce local asset stability. This result supports the findings of Alotaibi and Mishra (2015), who confirm that Saudi Arabia has causal associations for UAE and Kuwait markets. The findings uncover that the domination of regional innovations is due to the time-varying interdependences, let alone economic openness across the GCC nations, which might be the oil-rich GCC frontier nations act as the primary source of co-moving stresses to each other (Al-Yahyaee et al. 2020). Specifically, global investors can simultaneously access the GCC stock markets, reflecting synchronized sentiments in connection with political, economic, and financial uncertainties about the GCC region. Hence, this situation might have a considerable influence on their market performance and the stance of their regional stock market interdependence (Aloui & Hkiri, 2014; Alqahtani & Chevallier, 2020). Overall, the significant relationship among the different GCC stock markets is due to the strong economic ties, diversification approaches, openness and liberalization, geographic proximity, harmonization of the regulations and policy coordination, monetary interdependence, inter-trade, cross-listing in stock markets, the cohesion of governmental involvement, all in favor of achieving the declared goal of the GCC of becoming a unified regional well-rounded economic bloc.

4.3 Rolling—sample analysis: spillover dynamics

Figures 4 and 5 describe the resulting spillover indices, including return and volatility based on the 200-day rolling window samples, following the Diebold and Yilmaz (2012) framework. For both spillover indices, they reveal similar cyclical movements and bursts over time. The return spillover index fell to a minimum of less than 4% between 2012 and 2014 and remains low until 2016. In the more recent past, the return spillover index slightly increased to 12%. The volatility spillover index has a similar pattern with the return spillover index. Nevertheless, there was a significant fluctuation between 2014 and 2018. The spillover index nearly doubled from 5 to 10%, which indicated financial contagion. Overall, spillovers across GCC stock markets have become stronger as a result of the 2014 oil crisis. This finding suggests an increase in portfolio diversification and supports the study of Arin et al. (2020). The speculators and portfolio managers should take into account the contagion period and macroeconomic determinants in constructing risk management portfolios.

We estimate the time-varying net return and volatility spillovers based on 200-day rolling windows to identify which stock markets are net recipients and net transmitters. Positive (negative) values reveal a transmitter (recipient) to (from) other stock markets. Figure 6 depicts the net return spillovers across GCC stock markets over time. The results show that the UAE was almost always a net giver of spillover to other countries in return spillovers, reaching a peak of 50% between 2009 and 2010. Besides, the second-largest contributor was Saudi, with an average net contribution of 50% in 2016–2017, followed by Oman. By contrast, the other three markets were

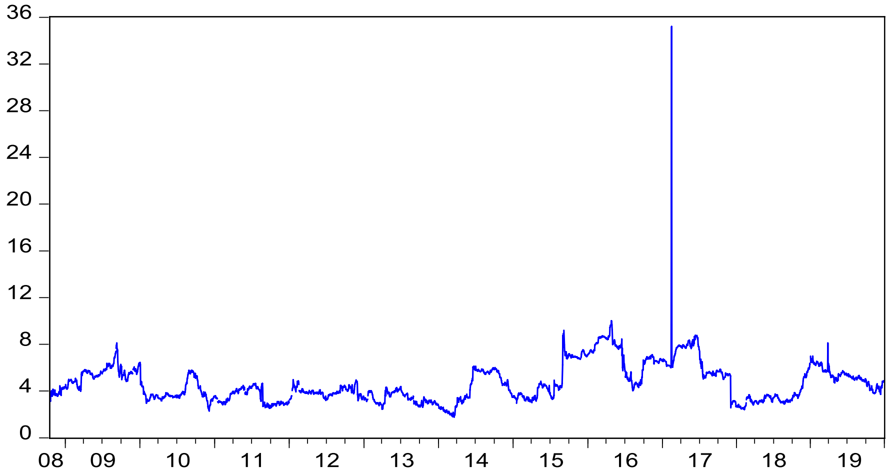


Fig. 4 Total return spillover indices for GCC stock markets. The underlying variance decomposition is based on a daily VAR system with 4 lags and generalized variance decompositions of 10-day-ahead volatility forecast errors

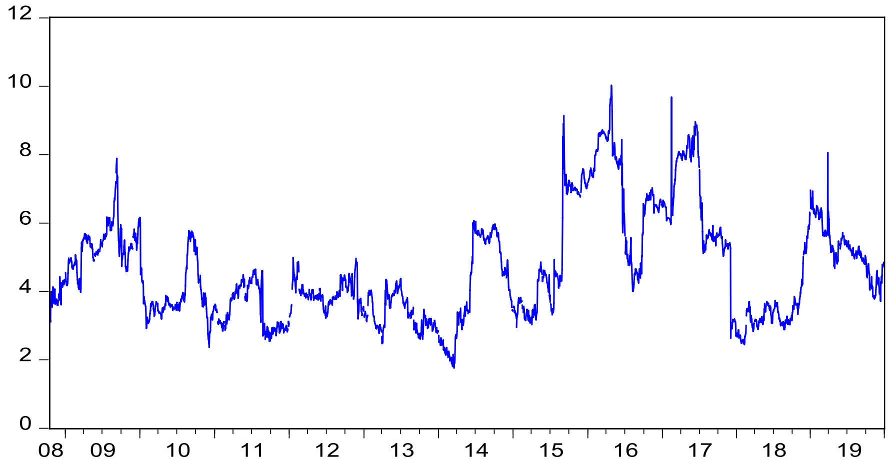


Fig. 5 Total volatility spillover indices for GCC stock markets. The underlying variance decomposition is based on a daily VAR system with 4 lags and generalized variance decompositions of 10-day-ahead volatility forecast errors

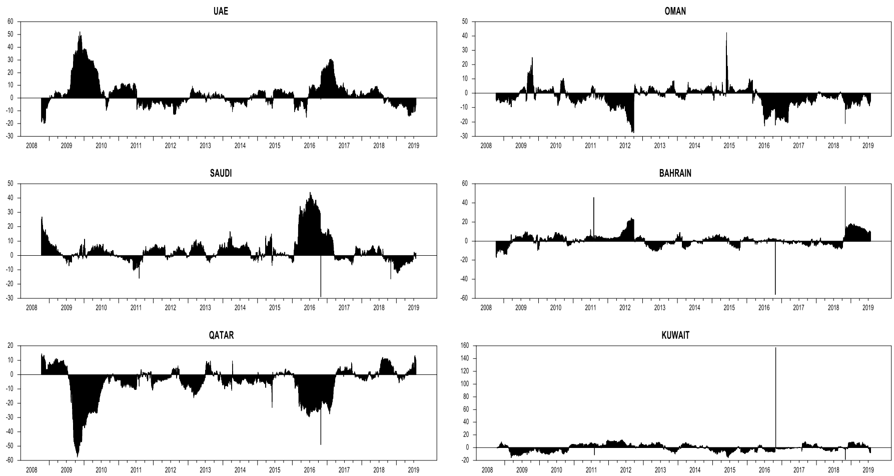


Fig. 6 Net return spillovers for GCC stock markets. The underlying variance decomposition is based on a daily VAR system with 4 lags, generalized variance decompositions of 10-day-ahead volatility forecast errors and 200-day rolling windows

net recipients for most of the rolling-sample periods. Consistent with the findings in Table 3, Fig. 7 shows the dynamic evolution of the net volatility spillover index for GCC stock markets. A close inspection of this figure demonstrates that Qatar, Oman, and Bahrain markets are net receivers of shocks from other markets. The UAE, Saudi, and Kuwait markets are the net contributor to shocks and significantly affect the other markets. However, the UAE and Saudi markets are net recipients of

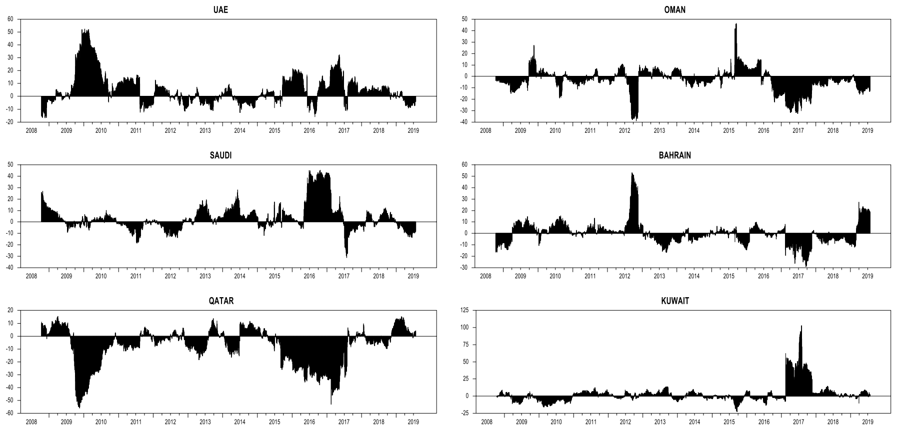


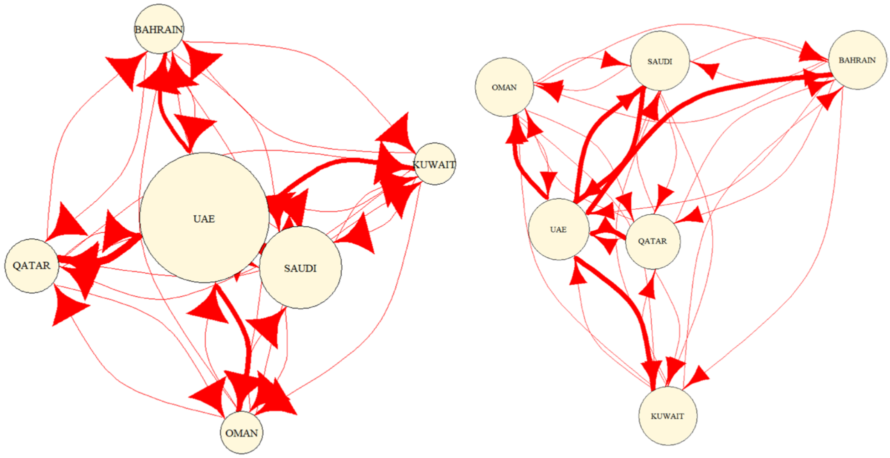
Fig. 7 Net volatility spillovers for GCC stock markets. The underlying variance decomposition is based on a daily VAR system with 4 lags, generalized variance decompositions of 10-day-ahead volatility forecast errors and 200-day rolling windows

volatility spillovers during certain periods. Overall, it is hard to determine the source of the recipient of net return and volatility spillovers since the net spillover bursts in either a negative or positive direction. This supports the paper of Ziadat et al. (2020).

To obtain a complete picture of the return and volatility spillovers among the examined markets, we take into consideration the network of net-pairwise directional connectedness over the sample period. Figure 8 demonstrates the structure of return and volatility spillovers across GCC stock markets, particularly the ones where the magnitudes of directional spillovers are large. The thick and pronounced red lines illustrate a greater extent of spillover in comparison with thicker ones. More precisely, the size of the country circle presents the total spillover contribution to all other markets, and the width of the arrows represents the forecast error contribution to a specific country. The graphical evidence is in line with the findings of Table 3. Specifically, UAE, Saudi, and Qatar markets are strong transmitters of shocks to other markets. This supports Charfeddine and Al Refai (2019)'s article.

In general, the net return spillovers fluctuated with high spikes during certain periods, while the net volatility spillovers moved somewhat smoothly through time. The bar graphs in each stock market exhibited asymmetric positive (transmitter) and negative (net recipient) values over time. As a result, investors should pay much attention to what happened in GCC stock markets because volatility spillovers exist between UAE, Saudi and other countries. These findings are consistent with the studies of Chowdhury (2020), Arin et al. (2020), Charfeddine and Khediri (2016).

This stylized fact supports previous studies. For example, Aloui and Hkiri (2014) and Mensi et al. (2018) show the persistence of the short term and long-term dependencies among GCC stock markets. Alqahtani and Chevallier (2020) feature extra sensitivity of Saudi Arabia and Qatar in terms of volatility indices, which would be extremely useful for policymakers and banking analysts. Intra-regionally,



a) Return spillover b) Volatility spillover

Fig. 8 Network Analysis of Return and Volatility Spillovers. The underlying variance decomposition is based on a daily VAR system with 4 lags, generalized variance decompositions of 10-day-ahead volatility forecast errors and 200-day rolling windows

Ziadat et al. (2020) confirm UAE is the primary transmitter of information in the GCC.

5 Conclusion

This study examines the time-varying nature of returns and volatility spillover effects across stock markets for the Gulf Cooperation Council countries (Bahrain, Kuwait, Qatar, Saudi Arabia, Oman, and the United Arab Emirates) during the period 2008–2019 using both the multivariate DECO-GARCH model and the spillover index of Diebold and Yilmaz (2012).

Our dynamic conditional correlation model's empirical results rely on the assumption that any pairs of stock markets are equicorrelated on a given day, but this correlation varies over time. The results suggest that the average return equicorrelation among GCC stock markets is positive, even though it is found to be very time-varying with certain periods, which impairs the benefits of GCC portfolio diversification. Besides, our spillover analysis findings provide several straightforward insights into both the level and the dynamics of stock market integration in the GCC countries over the past 10 years. The study reports that UAE, followed by Saudi and Qatar, represents an active transmission of volatility shocks to others among GCC stock market returns. This situation is also confirmed by the magnitudes of net returns and volatility spillovers moving from one variable to all others, which implies that UAE, Saudi, and Qatar might act as catalysts for risk triggers after the global financial crisis. On the other hand, Kuwait, Bahrain, and Oman stock markets exhibit a weak relationship, indicating that these markets would be helpful for hedging and diversification opportunities in GCC countries. Overall, the directional nexus from UAE, Saudi, and Qatar to the other markets is higher than that in the opposite direction. One of the striking results of this paper is that the plots of total return and volatility spillovers are able to capture the main turning points over the period shown. The plot of the DECO-GARCH model further confirms this. Finally, our findings document significant heterogeneity among GCC stock markets in the degree of spillovers over time, strengthening our understanding of the economic channels through which GCC equity markets are correlated.

The above-mentioned empirical results have significant implications for portfolio investors and market policymakers addressing the GCC stock markets, predicting portfolio market risk exposures, and identifying the persistence of diversification benefits in the markets under consideration. From the policymaker's perspective, the outcomes help to construct decoupling strategies to protect to safeguard the markets against adverse risks. The net transmitter plays a vital role as a hub of the information channels, while the net recipient serves as a node of the spillover effect (McIver & Kang, 2020). From the asset allocation perspective, UAE and Saudi seem to be the most attractive markets for hedging and risk minimization because of lower magnitudes with other stock market indices among GCC countries. Portfolio investors should adjust their diversified portfolios against the intensity of spillovers during periods of turmoil.

Future research works can extend this study's results by investigating the time–frequency nexus across stock markets in the GCC regions and checking if the developed stock markets impact GCC financial markets in a particular market state/regime. From an investment perspective, it would be helpful for investors to adjust their portfolio structure under low, medium, and high frequencies and across time horizons to obtain the optimal decision-making process.

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Declarations

Competing interests The authors declare that they have no competing interests.

References

Ahmad, W., Mishra, A. V., & Daly, K. J. (2018). Financial connectedness of BRICS and global sovereign bond markets. *Emerging Markets Review, 37*, 1–16.

Aielli, G. P. (2013). Dynamic conditional correlation: On properties and estimation. *Journal of Business & Economic Statistics, 31*(3), 282–299.

Alhashel, B. S. (2021). Cross-section of returns in frontier markets: Evidence from the GCC markets. *Emerging Markets Finance and Trade, 57*(3), 798–823.
Alotaibi, A. R., & Mishra, A. V. (2015). Global and regional volatility spillovers to GCC stock markets. *Economic Modelling, 45*, 38–49.
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., Hammoudeh, S., & Hamida, H. B. (2015). Co-movement between sharia stocks and sukuk in the GCC markets: A time-frequency analysis. *Journal of International Financial Markets, Institutions and Money, 34*, 69–79.
Aloui, C., & Hkiri, B. (2014). Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis. *Economic Modelling, 36*, 421–431.
Alqahtani, A., & Chevallier, J. (2020). Dynamic spillovers between Gulf Cooperation Council's Stocks, VIX, Oil and Gold Volatility Indices. *Journal of Risk and Financial Management, 13*(4), 69.
Al-Shboul, M., & Alsharari, N. (2019). The dynamic behavior of evolving efficiency: Evidence from the UAE stock markets. *The Quarterly Review of Economics and Finance, 73*, 119–135.
Al-Yahyaee, K. H., Mensi, W., Sensoy, A., & Kang, S. H. (2019). Energy, precious metals, and GCC stock markets: Is there any risk spillover? *Pacific-Basin Finance Journal, 56*, 45–70.
Al-Yahyaee, K. H., Shahzad, S. J. H., Mensi, W., & Yoon, S. M. (2020). Is there a systemic risk between Sharia, Sukuk, and GCC stock markets? A ΔCoVaR risk metric-based copula approach. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.1942
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.
Balli, F., de Bruin, A., & Chowdhury, M. I. H. (2019). Spillovers and the determinants in Islamic equity markets. *The North American Journal of Economics and Finance, 50*, 101040.
Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. *Journal of Financial Markets, 27*, 55–78.
Buigut, S., & Kapar, B. (2020). Effect of Qatar diplomatic and economic isolation on GCC stock markets: An event study approach. *Finance Research Letters, 37*, 101352.
Chaffai, M., & Medhioub, I. (2018). Herding behavior in Islamic GCC stock market: a daily analysis. *International Journal of Islamic and Middle Eastern Finance and Management*, *11*(2), 182–193. https://doi.org/10.1108/IMEFM-08-2017-0220.
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*, 101032.
Charfeddine, L., & Khediri, K. B. (2016). Time varying market efficiency of the GCC stock markets. *Physica a: Statistical Mechanics and Its Applications, 444*, 487–504.
Chevallier, J., Nguyen, D. K., Siverskog, J., & Uddin, G. S. (2018). Market integration and financial linkages among stock markets in Pacific Basin countries. *Journal of Empirical Finance, 46*, 77–92.
Chowdhury, S. S. H. (2020). Spillover of sentiments between the GCC stock markets. *Global Business Review*, 0972150920935595. https://doi.org/10.1177/0972150920935595 (online first)
Chowdhury, S. S. H., Rahman, M. A., & Sadique, M. S. (2015). Behaviour of stock return autocorrelation in the GCC stock markets. *Global Business Review, 16*(5), 737–746.
Daly, K., Batten, J. A., Mishra, A. V., & Choudhury, T. (2019). Contagion risk in global banking sector. *Journal of International Financial Markets, Institutions and Money, 63*, 101136.
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.
Engle, R., & Kelly, B. (2012). Dynamic equicorrelation. *Journal of Business & Economic Statistics, 30*(2), 212–228.
Finta, M. A., Frijns, B., & Tourani-Rad, A. (2019). Volatility spillovers among oil and stock markets in the US and Saudi Arabia. *Applied Economics, 51*(4), 329–345.
Hung, N. T. (2019). An analysis of CEE equity market integration and their volatility spillover effects. *European Journal of Management and Business Economics, 29*(1), 23–40. https://doi.org/10.1108/EJMBE-01-2019-0007
Hung, N. T. (2020a). Market integration among foreign exchange rate movements in central and eastern European countries. *Society and Economy, 42*(1), 1–20.

Hung, N. T. (2020b). Does volatility transmission between stock market returns of Central and Eastern European countries vary from normal to turbulent periods? *Acta Oeconomica, 70*(3), 449–468.
Hung, N. T. (2021). Volatility behaviour of the foreign exchange rate and transmission among Central and Eastern European Countries: Evidence from the EGARCH Model. *Global Business Review, 22*(1), 36–56.
Isik, I., & Hassan, M. K. (2002). Technical, scale and allocative efficiencies of Turkish banking industry. *Journal of Banking & Finance, 26*(4), 719–766.
Jamaani, F., & Roca, E. (2015). Are the regional Gulf stock markets weak-form efficient as single stock markets and as a regional stock market? *Research in International Business and Finance, 33*, 221–246.
Kang, S. H., Uddin, G. S., Troster, V., & Yoon, S. M. (2019). Directional spillover effects between ASEAN and world stock markets. *Journal of Multinational Financial Management, 52*, 100592.
Kang, S. H., & Yoon, S. M. (2019). Financial crises and dynamic spillovers among Chinese stock and commodity futures markets. *Physica A: Statistical Mechanics and Its Applications, 531*, 121776.
Kapar, B., Olmo, J., & Ghalayini, R. (2020). Financial integration in the United Arab Emirates Stock Markets. *Finance Research Letters, 33*, 101219.
McIver, R. P., & Kang, S. H. (2020). Financial crises and the dynamics of the spillovers between the US and BRICS stock markets. *Research in International Business and Finance, 54*, 101276.
Mensi, W., Hammoudeh, S., & Tiwari, A. K. (2016). New evidence on hedges and safe havens for Gulf stock markets using the wavelet-based quantile. *Emerging Markets Review, 28*, 155–183.
Mensi, W., Hamdi, A., & Yoon, S. M. (2018). Modelling multifractality and efficiency of GCC stock markets using the MF-DFA approach: A comparative analysis of global, regional and Islamic markets. *Physica a: Statistical Mechanics and Its Applications, 503*, 1107–1116.
Shahateet, M. (2019). Testing the linkages of Arab stock markets: A multivariate GARCH approach. *Investment Management & Financial Innovations, 16*(4), 192.
Yousef, M., & Masih, M. (2017). Time-varying correlation between Islamic stock indices: evidence from the GCC countries based on MGARCH-DCC approach.
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*, 101292.