International Journal of Accounting Research, 08(1),2023, 7-14
ISSN: 2617-9954
Open Access Journal
International Journal of Accounting Research
Research Article Homepage: www.j.arabianjbmr.com AOJP

Dynamic relationship between gulf stock markets in the context of COVID-19: Granger causality approach

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ABSTRACT

This paper aims to examine the volatility spillover between Gulf and Chinese stock markets by investigating the effects of Covid-19 on the relationships between these markets through examining whether there is an increase in the number or intensity of causal relationships compared with that of pre-Covid 19 period. In order to achieve the research-based objectives, we use Granger causality approach to examine the relationships in terms of volatility across stock markets. The findings indicate that the Ganger Causality between the stock markets during covid-19 is significantly higher than the pre-covid-19 period. Furthermore, new significant causal linkages arose together with the intensification of the causal relationship in 55.5% of cases in which we detect causality during both the pre-covid and covid-19 periods. These additional linkages during covid-19 period in excess of those that precede it significantly generate the international transmission development of volatility and the risk of contagion.

ARTICLE INFO

Keywords:
Covid-19, Interdependence, Gulf stock markets, Granger causality tests

JEL Classification:
C5; G1; F3

Article History:
Received: 13 Feb 2023
Accepted: 16 Mar 2023
Published: 05 May 2023

1. INTRODUCTION

Beyond a major health crisis, the COVID-19 pandemic has triggered an economic crisis that has affected many different markets around the world. The majority of the developed and emerging countries have been stricken. For instance, Dowd et al. (2020) found that the outbreak of the corona virus has an important effect on society and decimated the economy. Sharif et al., (2020) found that the combined shocks of both COVID-19 and oil volatility have an important impact on the US stock market, the US economic policy uncertainty and the US geopolitical risk. According to Baek et al. (2020), COVID-19 pandemic influenced stock markets more strongly than any other infectious disease outbreak that came before. Mazur et al., (2020) detected an extreme asymmetric volatility that correlates negatively loser stocks with stock returns. Topcu & Gulal (2020) examined the impact of COVID-19 on emerging stock markets over the period March 10 – April 30, 2020. They detected that the negative impact of pandemic on emerging stock markets has progressively fallen and started to taper off by mid-April. Salman & Ali (2021) examine the direct and spillover effect of Covid-19 on Gulf stock markets using both t-test and non-parametric Mann–Whitney tests. The results show that Corona virus had a negative short term effect on Gulf stock markets. Shamsudheen et al. (2022) examined the effect of COVID-19 cases on the stock market returns of each GCC country and the continuous dynamics of correlation between COVID-19 cases and GCC stock markets. They employed the exponential generalized auto regressive conditional heteroskedasticity model and continuous wavelet coherence in order to evaluate the stock market volatility and co-movement. The results show the presence of adverse reaction (negative returns and high volatility) during the period understudy. In view of the Corona virus disease 2019, (COVID-19) broke out in an abrupt way, it has brought an uncertainty environment in economies (Baker et al., 2016; Sharif et al., 2020), which generates an unstable economy during 2020 across the world. Economic situations during the COVID-19 period have been a considerable topic of many studies, such as, Jordà et al. (2022) who examined the long-run economic impacts. Similary, Xie et al.(2020) investigated a panel of 26 countries that comprised the G7 countries for the period 1998–2019. The results show the presence of causality from stock prices to exchange rates, in support of the portfolio balance approach.

Al-Maadid et al.(2022) examine the effect of COVID-19-related news on Gulf stock markets, using machine learning methods to examine the role of COVID-19 news in stock return predictability in these markets. They found that the stock markets in the United Arab Emirates (UAE), Qatar, Saudi Arabia, and Oman were affected by corona virus-related news. However, this news doesn't affect the stocks in Bahrain. In addition, the results show that the affected markets were influenced differently regarding the quantities and types of news. Salman & Ali (2021) examined the effects of Covid-19 on the stock markets of countries in Gulf Cooperation Council (GCC) from September 2019 to July 2020. The results show that Covid-19 had a negative short term effect on stock markets in GCC. They found also the presence of bidirectional spillover effect on GCC stock markets due to movements in Chinese stock market. This study contributes to the recently emerging literature that investigates pandemics effect on the financial markets (Gangopadhyay et al., 2010; Kowalewski & Śpiewanowski, 2020; Yousaf & Ali, 2020; Zoungrana et al., 2022). The current epidemic has had serious economic consequences around the world and it does not appear that any country is spared (Donthu and Gustafsson, 2020). Most of the above papers focus on the developed countries or on a small subset of the emerging economies. There are, instead,few studies concerning the members of the Gulf Cooperation Council (GCC) that was established in 1981 (namely, Bahrain, Qatar, Kuwait, Oman, UAE and Saudi Arabia). This paper investigates the linkages between Gulf financial markets during COVID-19. To our knowledge, many previous studies employing Granger Causality test, focused on the examination of changes in cross-market interdependencies, but in our research, Final Predictive Error is employed and, thus, the intensification or reduction in the causal relationship between Gulf and Chinese stock markets in the context of covid-19 is evaluated. The remaining paper has the following structure: Section 2 describes the utilized dataset. Section 3 illustrates the empirical methodology. Section 4 highlights the major findings of this study while Section 5 concludes the study.

2. DATA

To examine the links and interactions between Gulf and Chinese stock markets (see table 1), daily data on stock price indices is used. The study period runs from January 2, 2019 to September 12, 2022, with daily data (closing prices) from Investing.com. In order to account for the Covid-19 pandemic impact, the entire period of study was divided into two sub-periods; the pre-Covid-19 period (January2, 2019–December 28, 2020)which is the period before the Covid-19 pandemic preceding its emergence; and the Covid19 pandemic crisis period (December 29, 2019–September 12, 2020) starting from the date when the first COVID-19 contamination case was confirmed in China. The daily stock market returns will be generated as follows:

$$R_t = \log\,(P_t/P_{t-1}) \tag{1}$$

where, P_t is the closing value of the stock index on day t.

Table 1. The list of countries and indexes included in the empirical research.

Country	Stock market index
Bahrain	Bahrain All Share (BHSEASI)
China	Shanghai Stock Exchange Index (SSE)
Dubai	Dubai Financial Market (DFM)
Kuwait	Kuwait SE Market (KSE)
Oman	Oman Muscat Securities Mkt (MSM)
Qatar	Qatar Stock Exchange (QSE)
Saudi Arabia	Saudi Tadawul All Share (TASI)

3. EMPIRICAL METHODOLOGY

The methodology adopted in this paper, examining the links and interactions between stock markets, is based on Granger-causality test. In fact, we have examined the different changes in the existence and the directions of causality between these countries. Our strategy is based on the comparison of the interdependencies on two phases (before and after the covid-19).

3.1 Testing for causality

Granger causality or G-causality, which is an approach to determine if one time series is relevant in forecasting another, is named after the econometrist Clive Granger. According t o it, if a signal X1 "Granger-causes" a signal X2, then the past values of X1 should include helpful information in order to predict X2 above and beyond the information contained alone in its past values.

The *mathematical* specification of the *model is based on linear regression modelling of stochastic processes (Granger 1969).*

We can examine the presence of Granger causality by estimating the following VAR model:

$$Y_t = a_0 + a_1 Y_{t-1} + \cdots a_p Y_{t-p} + b_1 X_{t-1} + \cdots + b_p X_{t-p} + \mu_t \tag{1}$$

$$X_t = c_0 + c_1 X_{t-1} + \cdots c_p X_{t-p} + d_1 Y_{t-1} + \cdots + d_p Y_{t-p} + v_t \tag{2}$$

Then, testing H_0: $b_1 = b_2 = \cdots . = b_p$= 0, against H_A: "Not H_0", is a test that X does not Granger –cause Y.

Also, testing H_0: $d_1 = d_2 = \cdots . = d_p = 0$, againstH_A: "Not H_0", is a test that Y does not Granger –cause X.

In the event that the null hypothesis is rejected, this indicates the presence of Granger causality.

Granger-causality tests are sensitive to lag length. Consequently the selection of the appropriate lengths is an essential step to prevent the incoherent estimation of the model and consequently drawing misleading inferences (Thornton & Batten, 1985). *In this work,* Hsiao (1981) *sequential method is prosecuted in order to examine causality generalization, which combines Akaike's (1974) final predictive error (FPE) and the definition of Granger-causality* (Canova, 1995). *Essentially, the FPE criterion trades off the bias emanating from the model under-parameterization in opposition to the loss in efficiency emerging from its over-parameterization.*

The approach of the Hsiao's variant of Granger-causality test is as follows. If we want test Granger-causality for two stationary variables, $X_t$and Y_t, the mathematical specification will be:

$$Y_t = a_0 + \sum_{i=1}^{M} \Phi_i\, Y_{t-i} + \varepsilon_t \tag{3}$$

$$Y_t = a_0 + \sum_{i=1}^{M} \Phi_i\, Y_{t-i} + \sum_{j=1}^{N} \gamma_j\, X_{t-j} + \varepsilon_t \tag{4}$$

Where $X_t$and Y_t are covariance-stationary variables [i.e., they are I (0) variables].

The method is divided into six steps:

i. *Explore $Y_t$as a one-dimensional autoregressive process (Eq. 4); and detremine its FPE with the order of lags m_i varying from 1 to M. Examine the FPE*

$$\mathrm{FPE_y}(\mathrm{m_i}, 0) = \frac{\mathrm{T+m_i+1}}{\mathrm{t-m_i-1}} \cdot \frac{\mathrm{SSR}}{\mathrm{T}}$$

Where SSR represents the sum of squared residuals of OLS regression, (Eq. (4)and T is the total number of observations. Pick out $m_i$for the m value minimizing the FPE, denoting m, and representing the correspondent value as FPE_y (m, 0)

ii. *Explore Y_t as a controlled variable with m number of lags, and consider X_t a manipulated one as in (Eq.5). Determine again the FPE of (5) by changing the order of lags n_i of $X_t$from 1 to N. Consider the FPE*

$$FPE_y(m_i, 0) = \frac{T+m_i+n_i-1}{t-m_i-n_i-1} \cdot \frac{SSR}{T}$$

Select the order n_i which provides the smallest FPE, denoted n, and represent the appropriate FPE as FPE_y (m,n).

iii. *Compare FPE_y(m, 0) with FPE_y(m,n) [i.e., compare the smallest FPE in step (i) with the smallest FPE in step (ii)]. If FPE_y (m,0) − FPE_y (m,n) > 0, consequently we can state that $X_t$causes Y_t. If FPE_y (m,0) − FPE_y (m,n) < 0, then Y_t is an independent process.*

iv. *Repeat steps i) to iii) for the $X_t$variable, considering$Y_t$as the manipulated variable.*

When X_t and Y_t are not stationary variables, but first-difference stationary [i.e., they are I (1) variables] and co-integrated, we may analyze the causal relationships from ΔX_t to ΔY_t and from ΔY_t to ΔX_t, employing the following error correction models:

$$\Delta Y_t = a_0 + \beta Z_{t-1} + \sum_{i=1}^{M} \Phi_i\, \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

$$\Delta Y_t = a_0 + \beta Z_{t-1} + \sum_{i=1}^{M} \Phi_i\, \Delta Y_{t-i} + \varepsilon_t \tag{6}$$

Where $Z_t$is the OLS residual of the cointegrating regression ($Y_t = \mu + \lambda X_t$), known as the error-correction term. In the case that$X_t$and $Y_t$are I (1) variables but are not co-integrated, then β in *(6)* and *(7)* is supposed to be equal to zero.

In both cases [i.e., X_t and $Y_t$are I(1) variables, either cointegrated or not], we can use Hsiao's sequential procedure replacing Y_t with ΔY_t and X_t with ΔX_t in steps (i) to (iv), as well as replacing equations*(4)*and *(5)* with Eqs. *(6)* and *(7)*.

3.2 Testing for causality intensification

Toexamine possible causal relationships between stock markets, we use Granger causality tests. In fact, thisresearch proposes a comprehensive methodology to get some insights on different patterns of contagion transmission across emerging markets, by applying Granger causality. As the statistic employed to examine Granger-causality is $\mathrm{FPE_y}$ (m,0) − $\mathrm{FPE_y}$ (m,n), we can calculate it before and after the endogenously identified breakpoint (Covid-19). Employing this approach allows us to identify contagion by evaluating the intensification or reduction in the causal relationship for pairs in which we have found Granger-causality in both period, and then examining the presence of new significant relationships among countries after this shock. Consequently, an increase of Granger causality reflects an expansion of the statistical predictability of one time series over another one, as a confirmation of intensification in the transmission mechanism between them. Therefore, we start by examining the causality, both in the pre-covid 19period and during it. Then, we compare FPE_y (m,0) − FPE_y(m,n). If this statistic is higher in the covid-19 period than the quiet period, we are talking about intensification in the causal relationship. In opposition, if this statistic is lower in the crisis period than in the tranquil one. So, we can note a reduction in the causal relationship.

4. RESULTS AND DISCUSSION

Alotaibi and Mishra (2015) examined the impacts of return spillovers from regional (Saudi Arabia) and American stock markets to GCC stock markets (Bahrain, Oman, Kuwait, Qatar, United Arab Emirates). They found that significant return spillover effects exist from Saudi Arabia and US to GCC markets. We may note that the regional volatility spillovers from Saudi Arabia to GCC markets are significantly affected by trade, institutional quality and turnover.

Table 2. Summary stastics for daily returns

	RTBAX	RTCHINA	RTDFM	RTKSE	RTMSM	RTPQE	RTTASI
Mean	0.018	0.011	0.03429	0.005282	0.0023	0.009	0.018
Median	0.026	0.0219	0.00001	0.00001	0.0002	0.0134	0.058
Maximum	1.486	2.41	7.12	4.771	1.199	1.466	2.966
Minimum	-2.606	-3.491	-7.639	-6.505	-2.490	-4.433	-3.771
Std. Dev.	0.268	0.492	1.271	1.360	0.246	0.3976	0.475
Skewness	-1.592	-0.707	0.540	-0.229	-1.264	-1.711	-1.7149
Kurtosis	18.539	8.804	11.395	4.908	17.388	22.461	16.743
Jarque-Bera	9519***	1350 ***	2710 ***	145 ***	8073 ***	1477***	7591***
Q(24)	87.57**	262.5***	89.276**	48.671***	72.578***	41.194***	44.65***
Qs(24)	220.66**	33.765*	508.8***	109.8***	71.56***	89.02***	275 .4***

The descriptive statistics of the variables are provided in Table 2. The distributions of most stock market returns are negatively skewed. As it can be seen, the high values of skewness and kurtosis reflect clear evidence of deviations from normality. The Jarque–Bera test shows that selected series are not normally distributed. The statistics (LB) for the returns are very significant at 5% for all markets, reflecting the presence of serial correlation.

4.1 VAR modeling and Granger causality test

In what follows, we will use VAR test, Granger-causality tests, the computation of impulse response functions and the forecast error variance decompositions. Therefore, in order to examine the interdependencies between the different volatility series, we will start by using the VAR model, combined with a standard GARCH model for examining the causal relationships in terms of volatility across stock markets (see Table 3). In order to investigate and evaluate the interdependence between the volatility series, we carry out VAR estimation. We start by examining the optimal lag structure through Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The tests indicate three lags.

Table 3. Estimated results for the VAR (3) (whole sample)

Independant variables	Estimated parameters	Bahrain	China	Dubai	Kuwait	Oman	Qatar	Saudi-Arabia
Bahrain	Φ_{t-1}	0.877***	0.271	-0.168	-0.397	0.026	0.654***	0.232
	Φ_{t-2}	-0.2***	-0.189	0.130	0.977	0.117**	0.165	1.107***
	Φ_{t-3}	0.144***	0.157	-1.029	-0.511	-0.14**	-0.51***	-1.16***
China	Φ_{t-1}	0.005	0.313***	-0.026	0.066	0.002	0.008	-0.001
	Φ_{t-2}	0.007*	-0.006	-0.029	0.243**	0.003	0.022	0.031
	Φ_{t-3}	-0.002	-0.003	-0.002	-0.112*	-0.002	-0.021	-0.009
Dubai	Φ_{t-1}	0.001	-0.003	0.949***	0.029	-0.01**	-0.009	-0.008
	Φ_{t-2}	-0.002	0.010	0.054	-0.082*	0.013***	0.017**	0.036**
	Φ_{t-3}	-0.000	-0.011	-0.052	0.070***	-0.01**	-0.007	-0.025**
Kuwait	Φ_{t-1}	-0.01**	0.012	-0.078*	0.941***	-0.001	-0.004	-0.003
	Φ_{t-2}	0.003	0.021	0.205***	0.026	-7E-05	0.006	-0.003
	Φ_{t-3}	0.002	-0.021	-0.13**	-0.031	0.001	-0.001	0.010
Oman	Φ_{t-1}	-0.011	0.009	-0.259	-0.004	0.664***	-0.121	0.364**
	Φ_{t-2}	0.034	0.323	-0.919	0.258	-0.053	0.459***	-0.166
	Φ_{t-3}	0.212**	-0.131	2.186***	-0.018	0.027	-0.42***	-0.361**
Qatar	Φ_{t-1}	0.012	0.020	0.462*	0.321*	0.34***	1.003***	0.554***
	Φ_{t-2}	-0.1***	-0.035	-0.618*	-0.447	-0.34**	-0.15***	-0.224*
	Φ_{t-3}	0.057***	-0.113	0.408	0.124	0.044**	0.003	-0.18***
Saudi Arabia	Φ_{t-1}	0.022***	-0.070	0.004	0.072	0.019**	0.039	0.800***
	Φ_{t-2}	0.017*	0.051	0.351*	-0.132	-0.02**	-0.019	-0.010
	Φ_{t-3}	-0.02**	0.010	-0.284*	0.089	0.001	-0.035	-0.060

C	-0.1***	0.149***	0.066	0.020	0.010	0.005	0.018*
Adj R-squard	0.947	0.120	0.925	0.907	0.836	0.898	0.863

As we can notice in Table 3, the adjusted R-squared is high and larger than 80% for the most of stock markets, indicating that the model fits the data quite well. In addition, the results of the Granger -causality test, presented on Table 4, reflect the presence volatility interdependence. This may be noted through the results of changes in the number and intensity of Granger-causal relationships.

4.1.1 Changes in the number and intensity of Granger-causal relationships

The causal relationships resulting from the estimated FPE statistics for the pre-covid 19 and covid-19 periods jointly are presented in Table 4. Using this approach allows us to have a clear idea on the Granger causality test among 42 (7*6) possible relationships between Gulf and Chinese stock markets. In each estimation, we employ Hsiao's (1981) sequential method to determine the optimum FPE (m, 0) and FPE (m, n) statistics for every relationship. If the difference is positive in the case XX -> YY, this signifies the presence of a statistically significant Granger-causality relationship running from country XX towards country YY. Then in order to examine the intensity of the causal relationships between different markets, for the 23 cases where causality was detected, we have compared $\mathrm{FPE_y}$ *(m,0)* − $\mathrm{FPE_y}$ *(m,n)* in the two periods. If this statistic is higher in the covid-19 period than in the pre-covid-19 period, we may note intensification in the causal relationship in the covid-19 period. Otherwise, it will be considered as a reduction in the causal relationship oppositely.

The causality changes are reported in the last column of Table 4. The results reveal that for the 42 granger causality relationships examined; there is causality intensification in 2 cases, and 21 new causal appearing. The sample was divided in two sub-periods: the pre-Covid-19 period (January 2, 2019– December 28, 2020) and the Covid 19 pandemic period (December 29, 2019– September 12, 2020). As the results noticed for the two subsamples of countries, the number of new causal relationships increases as the covid-19 pandemic develops in the world. These latter ones are more frequent between Gulf markets than with the Chinese one. In other words, the Gulf markets are the most influential and the most affected at the same time. This may be observed by examining the number of Granger causal relationships which runs mostly from Gulf stock markets. Regarding the causal relationships running between gulf and Chinese stock markets, an increase in causality after the Covid-19 is detected; for the 42 relationships examined, we have found the appearance of 21 new causal relationships, nearly 50% of the cases studies. Interestingly, the Bahrain market is the most influential in stock markets. These findings are in line with previous researchers. For instance, Abbes and Trichilli (2015)found that Islamic indices of Bahrain and Egypt cause the dynamic of other Islamic indices (Kuwait, Oman, Jordan and Morocco).

Abdennadher and Hellara (2018) study the interdependencies of emerging stock markets and examine the impact of Global Financial Crisis (GFC) on them. As a result, they found that GCC stock markets are highly inter-related added to the fact that each one of them generally has an influence on the rest.

Table 4. Causality running between stock markets

Causal relationship	Pre-covid 19 period	Covid-19 period	Causality changes
Dubai->Bahrain	No	No	--
Bahrain ->Dubai	No	Yes	New
Kuwait-> Bahrain	No	No	--
Bahrain -> kuwait	No	Yes	New
Oman->Bahrain	No	Yes	New
Bahrain->Oman	No	Yes	New
Qatar-> Bahrain	No	Yes	New
Bahrain-> Qatar	No	Yes	New
China->Bahrain	No	No	--
Bahrain-> China	No	No	--
Bahrain-> Saudi Arabia	No	Yes	New
Saudi Arabia-> Bahrain	No	Yes	New
Dubai-> China	No	No	--
China-> Dubai	No	No	--
Kuwait-> China	No	No	--
China-> Kuwait	Yes	Yes	Intensification
Oman-> China	No	No	--
China-> Oman	No	No	--
Qatar-> china	No	No	--
China-> Qatar	No	Yes	New
Saudi Arabia-> China	Yes	No	--
China-> Saudi Arabia	No	No	--
Kuwait-> Dubai	No	No	--

Dubai -> Kuwait	No	Yes	New
Oman-> Dubai	No	Yes	New
Dubai -> Oman	No	Yes	New
Qatar-> Dubai	No	Yes	New
Dubai-> Qatar	No	No	--
Saudi Arabia-> Dubai	No	Yes	New
Dubai-> Saudi Arabia	Yes	No	--
Oman-> Kuwait	No	No	--
Kuwait-> Oman	No	No	--
Qatar-> Kuwait	Yes	Yes	Intensification
Kuwait-> Qatar	No	No	--
Saudi Arabia-> Kuwait	No	Yes	New
Kuwait-> Saudi Arabia	No	No	--
Qatar-> Oman	No	Yes	New
Oman-> Qatar	No	Yes	New
Saudi Arabia-> Oman	No	Yes	New
Oman-> Saudi Arabia	No	Yes	New
Saudi Arabia-> Qatar	No	No	--
Qatar-> Saudi Arabia	No	Yes	New

As it can be seen , no country is spared from covid-19 effects (Donthu and Gustafsson, 2020). Al-Maadid et al. (2022)investigate the impact of COVID-19-related news on the stock markets in Gulf. Consequently, they found that the stock markets in the United Arab Emirates (UAE), Qatar, Saudi Arabia, and Oman were impacted by corona virus-related news. However, this news had no impact on the stocks in Bahrain.

4.1.2 *Impulse response functions analyses*

The Granger causality test indicates the presence of several causal relationships between the various stock markets' volatility. These results reflect the presence of a dynamic interaction between the different studied markets to the extent that each one reacts to other markets shocks. In order to have a clear picture about the degree of each market reaction to its own shocks, other markets shocks, and how long the potential impacts of these shocks will disappear, the investigation of individual market response is very informative. Such investigation can be done by having recourse the to the generalized impulse response functions (GIRF). Based on the concept of IRF, Koop, Pesaran, & Potter (1996), developed the generalized impulse response function (GIRF) showing impacts of independent shocks on volatility through time. Contrary to the traditional impulse response function, GIRF is not sensitive to the way the variables are ordered.

Figure 1 represents the results of generalized impulse response function under VAR. It shows the impulse-response functions for the 5, 10, 20 and 60 day horizon. We report a graphical representation in which time (days since the shock hit the market) is on the horizontal axis and the volatility response (relative difference between a baseline and the response after the shock) is on the vertical axis. Through the figure 1, we can note that the highest level of any country's conditional volatility is attributable to its own shocks, and most often the own impacts decrease over time. We note that impulse responses of Dubai, Bahrain and Saudi conditional volatility appear to be statistically significant to each other shocks. Another remark can also be drawn; the Dubai market is the less impacted market from shocks emanating from the Chinese one.

4.1.3 *Analysis of the decomposition of the forecast error variance*

We also present the Variance Decompositions (VDCs), which show the percent of the movements in one variable explained by its own shocks, versus shocks to the other variables, accumulated over time. The variance decompositions reflect the magnitude of the total effect. We report the total effect accumulated over the 5-day, 10 -day, 20- day, 30- day and 60- day forecast horizons. The results of variance decomposition presented in Table 4, show that there is a big interaction between different Gulf markets variances. At 10-day horizon, the cumulative percentage of the forecast-error variance accounted for by Dubai market amounts to 62.6% for Oman, 61.9% for Qatar and 56.8% to Saudi Arabia. Likewise, the cumulative forecast-error variance attributable to Qatar market shocks is 78.5 % to own shocks, 40.25% for Oman and 46.43% for Saudi Arabia at 10-day horizon. The Kuwait market is largely explicated by its own-volatilities innovations to a percentage of 97.14% at a 5-day horizon, to decrease to 82.67% on a 30-day horizon. While, for the effect of the foreign markets, the Kuwait market forecast-error variances is the highest affected from the Chinese market (84% on a 30-day horizon), this result is consistent with previous results in the part of granger causality test where we noted a new causal relationships from the Chinese to the Kuwait stock market in the covid-19 period.

We may note also that Kuwaiti market innovations explain 93.2% of the Bahrain forecast-error variance (at 5-day horizon). On another front, the Chinese volatility shocks are mostly explained by its own-volatilities innovations, it accounts for 98.33% and 97.44% at 5-day and 60-days horizon respectively. We may note that the results of the variance decomposition confirm those found previously which is consistent with the financial literature approving the presence of big interaction between Gulf stock markets (Abdennadher & Helara, 2021; Abdennadher & Hellara, 2018a; Salman & Ali, 2021; Shamsudheen et al., 2022).

4.2 Volatility transmission

The results found previously lend support to the hypothesis of volatility transmission between Gulf stock markets. Similarly, Covid-19 has an impact on the transmission of volatility. In the covid-19 period, we can notice not only the appearance of new links of causality patterns which had been absent before its start, but also an intensification of causality in 2 cases. In other words, the 21 new causality patterns, together with the intensification of the causal relationship constitute nearly 55.5% of the cases.

This investigation concerning volatility transmission and contagion shows the presence of unidirectional as well as bidirectional spillovers between GULF stock markets. These interdependencies generate volatility transmission between these countries, which reflect the level of contagion between these markets. The findings are consistent with the financial literature investigating the volatility movements that may cause uncertainty of from one country to another. That is to say, the increase of interdependence which may be represented by additional linkages during crisis periods in excess of those that arise during non-crisis periods may be considered an important operative measure of contagion (Abdennadher & Hellara, 2018b; Forbes & Rigobon, 2002; Gómez-Puig & Sosvilla-Rivero, 2014, 2016; Masson, 1999).

5. CONCLUSION

In this paper, we have examined the relationship between Gulf and Chinese stock markets using daily data up from January 2, 2019 to September 12, 2022. We use Granger Causality approach in order to examine the impacts of the Covid-19 on these markets through the investigating existence and the evolution of possible Granger causal relationships. The results show the presence of volatility transmission especially in the Covid-19 period (contagion). This can be noted through the appearance of new causality patterns which represent together with the intensification of the causal relationship, almost 55.5% of the cases. This is consistent with the previous researches confirming that covid-19 accentuates the interdependencies between markets. Such interdependence is a great indicative of volatility transmission between stock markets and can be examined as an important operative measure of contagion. In addition, the investigation of the impulse response functions (IRFs) and the forecast errors variance decompositions (FEVDs) allows also to examine the volatility interdependencies pattern (magnitude, speed…), where the results confirm the presence of big interaction between Gulf stock markets.

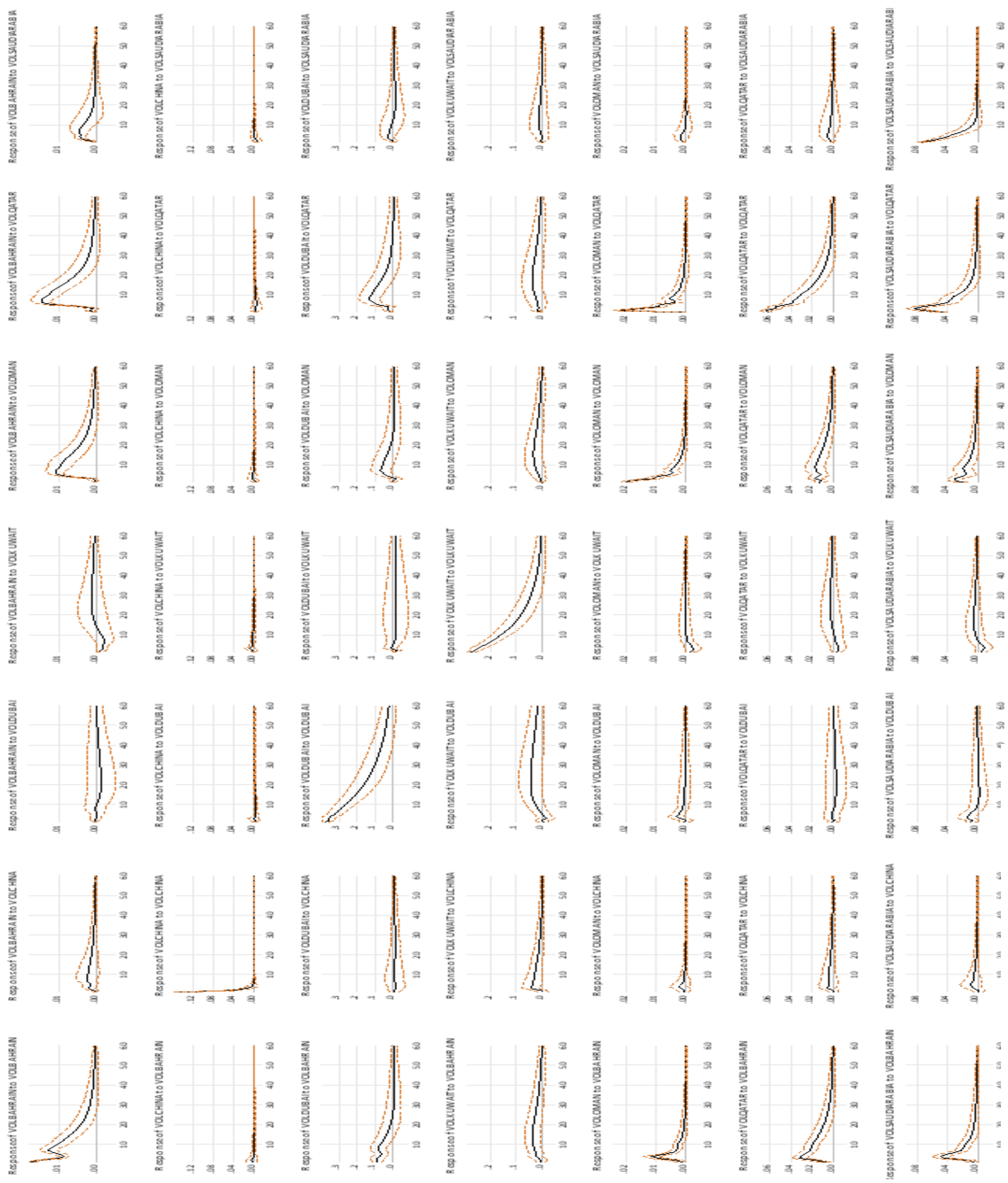

Figure 1
Generalized impulse response function

Table 5. Variance decompositions of stock market volatility series (%).

Dependant variables	Periods	Independant variables: Bahrain	China	Dubai	Kuwait	Oman	Qatar	Saudi Arabia
Bahrain	5-period	67,150	0,784	0,031	0,932	13,259	13,070	4,773
	10-period	42,382	1,084	0,017	0,826	19,451	32,206	4,034
	20-period	36,523	1,280	0,218	0,618	21,573	36,506	3,281
	30-period	35,797	1,361	0,492	0,850	21,784	36,562	3,154
	60-period	35,513	1,404	0,641	1,211	21,757	36,351	3,124
China	5-period	0,344	98,336	0,081	0,670	0,194	0,230	0,144
	10-period	0,360	97,775	0,140	0,845	0,290	0,416	0,174
	20-period	0,365	97,528	0,166	1,006	0,317	0,431	0,186
	30-period	0,365	97,468	0,168	1,061	0,319	0,432	0,187
	60-period	0,367	97,440	0,170	1,083	0,320	0,433	0,187
Dubai	5-period	5,046	0,103	92,542	0,120	0,423	1,434	0,333
	10-period	5,207	0,073	85,246	0,120	1,886	7,152	0,316
	20-period	4,514	0,096	83,869	0,205	2,086	8,974	0,255
	30-period	4,116	0,153	84,642	0,311	1,910	8,566	0,302
	60-period	3,954	0,240	84,841	0,600	1,883	8,127	0,356
Kuwait	5-period	0,449	1,680	0,134	97,149	0,159	0,412	0,017
	10-period	1,265	2,118	0,446	94,485	0,709	0,850	0,127
	20-period	2,821	2,259	2,701	87,226	2,036	2,641	0,316
	30-period	3,421	2,206	4,983	82,674	2,634	3,746	0,336
	60-period	3,563	2,104	8,029	78,888	2,794	4,300	0,321
Oman	5-period	12,854	0,559	0,985	0,771	44,130	40,255	0,445
	10-period	13,661	0,626	1,320	0,711	43,302	39,888	0,492
	20-period	13,891	0,653	1,424	0,741	42,869	39,945	0,476
	30-period	13,901	0,657	1,469	0,786	42,791	39,921	0,475
	60-period	13,896	0,657	1,521	0,808	42,748	39,897	0,474
Qatar	5-period	15,134	0,434	0,086	0,329	4,932	78,560	0,525
	10-period	18,010	0,619	0,072	0,253	7,870	72,527	0,650
	20-period	19,364	0,827	0,181	0,300	10,463	68,191	0,674
	30-period	19,543	0,904	0,301	0,519	11,017	67,032	0,684
	60-period	19,553	0,943	0,360	0,808	11,156	66,487	0,693
Saudi Arabia	5-period	13,125	0,369	1,322	0,451	6,054	46,636	32,044
	10-period	14,479	0,568	1,229	0,399	7,484	47,807	28,033
	20-period	14,836	0,684	1,228	0,732	8,282	47,780	26,457
	30-period	14,864	0,711	1,251	0,980	8,376	47,585	26,233
	60-period	14,871	0,724	1,250	1,138	8,410	47,475	26,131

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