

The directional spillover effects and time-frequency nexus between stock markets, cryptocurrency, and investor sentiment during the COVID-19 pandemic

Directional
spillover
effects during
COVID-19

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Abstract

Purpose – This paper aims to analyze the connectedness between Gulf Cooperation Council (GCC) stock market index and cryptocurrencies. It investigates the relevant impact of RavenPack COVID sentiment on the dynamic of stock market indices and conventional cryptocurrencies as well as their Islamic counterparts during the onset of the COVID-19 crisis.

Design/methodology/approach – The authors rely on the methodology of Diebold and Yilmaz (2012, 2014) to construct network-associated measures. Then, the wavelet coherence model was applied to explore co-movements between GCC stock markets, cryptocurrencies and RavenPack COVID sentiment. As a robustness check, the authors used the time-frequency connectedness developed by Barunik and Krehlik (2018) to verify the direction and scale connectedness among these markets.

Findings – The results illustrate the effect of COVID-19 on all cryptocurrency markets. The time variations of stock returns display stylized fact tails and volatility clustering for all return series. This stressful period increased investor pessimism and fears and generated negative emotions. The findings also highlight a high spillover of shocks between RavenPack COVID sentiment, Islamic and conventional stock return indices and cryptocurrencies. In addition, we find that RavenPack COVID sentiment is the main net transmitter of shocks for all conventional market indices and that most Islamic indices and cryptocurrencies are net receivers.

Practical implications – This study provides two main types of implications: On the one hand, it helps fund managers adjust the risk exposure of their portfolio by including stocks that significantly respond to COVID-19 sentiment and those that do not. On the other hand, the volatility mechanism and investor sentiment can be interesting for investors as it allows them to consider the dynamics of each market and thus optimize the asset portfolio allocation.

Originality/value – This finding suggests that the RavenPack COVID sentiment is a net transmitter of shocks. It is considered a prominent channel of shock spillovers during the health crisis, which confirms the behavioral contagion. This study also identifies the contribution of particular interest to fund managers and investors. In fact, it helps them design their portfolio strategy accordingly.

Keywords Cryptocurrencies, RavenPack COVID sentiment, COVID-19 pandemic, Diebold–Yilmaz spillover index, Wavelet coherence

Paper type Research paper

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1. Introduction

The COVID-19 pandemic is not only a health crisis. It also poses a growing threat to the fragile Chinese and global financial markets, which have faced tremendous uncertainties during this period. It differs from other crises in its broad impact and distributional consequences. Indeed, it is hitting already stagnant and fragile economies in the Middle East and North Africa (MENA) with lockdowns, disrupted supply chains, dramatic declines in tourism revenues and labor remittances and temporarily low oil prices (Alaoui Mdaghri *et al.*, 2021; Bani-Khalaf and Taspinar, 2022; Mehdi *et al.*, 2022).

Indeed, over the past two decades, shocks and crises transmitted to financial markets have led to structural changes in the volatility of cryptocurrencies. This has prompted investors to examine the interconnectivity, risk transfer and hedging strategies between the financial markets and cryptocurrencies. In fact, cryptocurrencies have received substantial attention from the public, in general, and investors and researchers, in particular. Specifically, the launch of cryptocurrencies in the MENA region is expected to have a significant impact on the economic and financial system of the region. Thus, the low cost and security of virtual transactions highlight the importance of this electronic payment method and its significant role in the financial system of the MENA region (Sayed and Abbas, 2018). Therefore, understanding the impact of the cryptocurrency market as one of the determinants of Gulf Cooperation Council (GCC) stock market returns is crucial.

For instance, several recent research studies focused on the impact of COVID-19 on financial markets in general and financial assets, such as cryptocurrencies and gold, in particular (Corbet *et al.*, 2020; Zhang *et al.*, 2020). In fact, Zhang *et al.* (2020) conclude that the instability and economic damage caused by the pandemic made the financial market highly unpredictable and volatile. In addition, Al-Awadhi *et al.* (2020) state that the daily growth of total cases and deaths negatively correlates with the stock market performance. In fact, investors' expectations of risk and return have changed, leading them to reallocate their portfolios. Although some studies have examined the relationship between cryptocurrencies and financial markets, many have been limited many to a single country (Al-Awadhi *et al.*, 2020; Narayan *et al.*, 2020) or have used it an international sample without considering the issue of connectivity (Bouri *et al.*, 2021). The gap in existing research motivated us to investigate the shock transmission between RavenPack COVID sentiment, GCC financial stock market and cryptocurrencies during the COVID-19 pandemic.

To the best of our knowledge, this study is the first to conduct a formal and robust empirical investigation of the impact of COVID-19 on the volatility interconnection between the RavenPack COVID sentiment, the GCC financial market, and, particularly, the Islamic and conventional cryptocurrencies. To achieve this goal, we examine spillover effects between these variables using the VAR-based spillover index approach from the generalized VAR framework introduced by Diebold and Yilmaz (2012). This method identifies the directional connectedness perspective. It also measures the levels of this connectedness, i.e. total connectedness, total directional connectedness, and pairwise directional connectedness from one variable to another. Additionally, we apply wavelet coherence to examine the co-movements between these variables in a joint time-frequency domain. This technique was proposed to improve the accuracy of financial time series forecasting, which can provide a matrix to accommodate the correlation at each time and frequency point. This advantage allows us to observe the change in consistency between GCC stock market returns, cryptocurrency returns and RavenPack COVID sentiment.

The paper is therefore organized as follows: Section 2 reviews recent research relevant to our study. Section 3 describes the applied methodology in detail. Section 4 introduces the data and our preliminary analyses. In section 5, we reveal and discuss the main empirical results achieved in this research. Finally, the last section concludes the paper.

2. Literature review

The COVID-19 pandemic has been one of the most economically costly pandemics in recent history. In fact, [Ashraf \(2021\)](#) shows that the decline in stock returns as a response to the increasing number of confirmed cases is greater in countries whose investors have higher domestic uncertainty aversion. For their part, [Liu et al. \(2021\)](#) indicate that COVID-19 increases the risk of stock market crashes in China. More precisely, financial markets continue to experience a downward trend worldwide due to investors' lack of interest in riskier assets and have lost nearly \$3 trillion since the start of the pandemic ([Forbes, 2020](#)). In fact, the COVID-19 crisis differs from other crises because of its broad impacts and distributional consequences. It is clear that the MENA region will not be the same after this pandemic. Indeed, the economic impacts are felt the most: financial markets collapse, tourists evaporate due to flight bans and closures, and oil prices drop. With the UAE canceling its Expo 2020 and Saudi Arabia banning the annual hajj pilgrimage, both states have lost hundreds of millions of dollars. In fact, the UAE was expected to attract 25mn visitors to its Expo 2020 in October 2020, and Saudi Arabia used to receive 20mn religious pilgrims each year ([Ng, 2020](#)). Meanwhile, Egypt is losing about \$1bn per month in lost tourist revenue ([Bianco and Wildangel, 2020](#)). Indeed, the pandemic has depressed the oil price as demand dries up. Like global markets, GCC markets have also been trending downward by an average of 20% since the reporting of the first case of COVID-19 in the UAE. Investors continue to lose daily due to the declining market trend. In March 2020, investors in Dubai, Abu Dhabi, Saudi Arabia, Kuwait and Qatar lost nearly \$6bn, \$8.3bn, \$41bn, \$2.8bn and \$11.9bn, respectively, in a single day ([Khaleej Times, 2020](#)). One of the most affected sectors in the UAE is real estate, with Chinese businessmen being the main investors in real estate projects in Dubai ([Ng, 2020](#)). As China recovers from the effects of the pandemic, many Chinese investors remain reluctant to make new transactions. Even before the epidemic, the UAE faced an economic catastrophe due to the Dubai bubble ([Solomon, 2020](#)). In addition, Qatar's stock markets are also suffering from the impact of COVID-19, including the oil and gas, financial services, real estate and telecommunication stock markets, which have collapsed despite a 10bn Rial stimulus package for the stock market ([KPMG, 2020](#)).

The pandemic disrupted businesses and caused unprecedented fluctuations in commodity prices, resulting in a 21 and 6.15% decline in the stock markets of Bahrain and Kuwait, respectively ([KPMG, 2020](#)). The [The World Bank Economic Update \(2020\)](#) indicates that Oman's economy will also remain under stress as the oil and gas, banking, tourism and logistics sectors are in a deficit. Likewise, [Mensi et al. \(2020\)](#) examine the impacts of COVID-19 on the multifractality of gold and oil prices under upward and downward trends. They show strong evidence of asymmetric multifractality that increases with a rising fractality scale. Moreover, multifractality is particularly higher in the downtrend (uptrend) for Brent oil (gold). This excess asymmetry increased during the COVID-19 outbreak. [Akhtaruzzaman et al. \(2021\)](#) also examine the way financial contagion occurs across financial and non-financial firms between China and G7 countries during COVID-19. Their empirical results show that financial and non-financial listed firms in these countries experience a significant increase in conditional correlations between their stock returns. However, there is little industry-level research on the effect of COVID-19 on cryptocurrency prices in the existing literature. There are also several industry limitations at the economic level of COVID-19 ([Yang et al., 2016](#); [Bouri et al., 2019](#); [Gomes and Gubareva, 2021](#)).

These studies on the interdependence of foreign exchange and cryptocurrency markets are attracting considerable research interest from a contagion perspective. Specifically, the COVID-19 crisis has negatively influenced the potential role of cryptocurrencies as diversified investments ([Tiwari et al., 2019](#); [Gil-Alana et al., 2020](#)). Therefore, studying the dynamics of fiat currencies and cryptocurrencies through the COVID-19 bear market and its initial recovery can be beneficial. It offers a unique opportunity to examine the economic

impact of this pandemic on the financial system and its stability as a whole. In fact, joint dynamics of conventional currencies, such as EUR, GBP and RMB, and major cryptocurrencies have been explored recently (e.g. [Kristjanpoller and Bouri, 2019](#)). Therefore, analyzing the behavior of cryptocurrencies relative to major fiat currencies is recommended. In fact, it helps to assess the potential ability of cryptocurrencies to serve as a hedging medium for fiat currencies in times of global crisis, such as the COVID-19 pandemic turmoil.

Recently, [Fakhfekh and Jeribi \(2020\)](#) have focused on modeling the volatility dynamics of cryptocurrencies. However, few studies have investigated volatility transmission between Bitcoin and other cryptocurrencies ([Katsiampa et al., 2019](#); [Beneki et al., 2019](#)). Indeed, [Agosto and Cafferata \(2020\)](#) study the relationship between the explosive behaviors of cryptocurrencies using a unit root test approach. They prove a strong interdependence in the cryptocurrency market (as [Corbet et al., 2018](#) and [Yi et al., 2018](#)). In this context, [Aslanidis et al. \(2019\)](#) examine the conditional correlations between four cryptocurrencies (Bitcoin, Monero, Dash and Ripple), the S&P 500, bonds and gold. They show that the studied cryptocurrencies are highly correlated. However, the association between cryptocurrencies and conventional financial assets is negligible.

Using a copula-ADCC-EGARCH model, [Tiwari et al. \(2019\)](#) investigate the time-varying correlations between six cryptocurrencies and the S&P 500 index markets. They state that the overall time-varying correlations are very low, which indicates that cryptocurrencies serve as a hedging asset against the risk of the S&P 500 stock market. They also show that volatilities respond more to a negative than a positive shock in both markets. In addition, they identify Litecoin as the most effective hedging asset against S&P 500 risk. As a result, they conclude that cryptocurrency might be one of the most important elements in portfolio diversification. Furthermore, [Charfeddine et al. \(2020\)](#) study the dynamic relationship between Bitcoin and Ethereum and major commodities and financial stocks. They confirm that these two cryptocurrencies can be ideal for financial diversification. More interestingly, [Banerjee et al. \(2022\)](#) find that COVID-19 news sentiment influences cryptocurrency returns. In fact, unlike previous results, the link is unidirectional between news sentiment and cryptocurrency returns. Indeed, [Ozdamar et al. \(2022\)](#) attest that retail (institutional) investor attention has a negative (positive) effect on cryptocurrency returns. Moreover, retail (institutional) investor attention aggravates (constrains) idiosyncratic risk while both types of attention boost cryptocurrency market liquidity.

Unlike traditional cryptocurrencies, Islamic cryptocurrencies are supported by quantifiable financial fundamentals that maintain their value. They are new technical applications that leverage existing blockchains to meet the religious requirements of some investors. The most common cryptocurrencies that comply with Islamic laws are X8X, HelloGold and OneGram ([Lahmiri and Bekiros, 2019](#)). These are based on gold, which is one of six "Rabawi" commodities approved by Muslim investors. For those seeking to satisfy religious needs, investing in these emerging innovations is an intriguing proposition. Nevertheless, there is little investigation into the dynamics of Islamic and conventional cryptocurrencies during the health crisis ([Mnif et al., 2020](#)). To fill this gap in the existing literature, this study aims to examine the relevant impact of RavenPack COVID sentiment on the dynamics of stock market indices and conventional cryptocurrencies as well as their Islamic counterparts during the onset of the COVID-19 crisis.

3. Methodological approach

This study aims to examine the impact of RavenPack COVID sentiment on the dynamics of conventional and Islamic stock indices, as well as cryptocurrencies, during the onset of the COVID-19 crisis. It analyzes the correlation between these variables over the health crisis

period. For our modeling objective, we use a two-step methodology: First, in order to analyze the spillover effect between investor sentiment proxies and stock market return, we start with the methodology proposed by [Diebold and Yilmaz \(2012\)](#). More precisely, we apply Diebold and Yilmaz's connectedness index to quantify the static and dynamic connectedness of investor sentiment and financial markets during the COVID-19 crisis. Second, we use the wavelet coherence model to explore the co-movements between these variables for different time frequencies.

3.1 The directional spillover model

In this research, we explore the co-movement between the RavenPack COVID sentiment and conventional and Islamic stock indices, as well as cryptocurrencies, using the spillover index approach developed by [Diebold and Yilmaz \(2012\)](#). In fact, total, directional and net spillovers can all be identified using this approach. Indeed, the DY model is based on the vector autoregressive VAR model ([Pesaran and Shin, 1998](#)), which is described as follows:

$$y_t = \sum_{i=1}^p \pi_i y_{t-i} + \varepsilon_t, \quad (1)$$

where $\varepsilon_t \sim i.i.d \sim (0, \Sigma)$, π_i contains $N \times N$ matrix of regression parameters, ε_t is the vector of identically and independently distributed errors with Σ being their variance-covariance matrix.

The VAR (p) model can therefore be written as follows:

$$y_t = \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \quad (2)$$

$$\theta_i = \pi_1 \theta_{i-1} + \pi_2 \theta_{i-2} + \dots + \pi_p \theta_{i-p} \quad (3)$$

where θ_i is the $N \times N$ matrix of moving average coefficients and θ_0 provides an $N \times N$ identity matrix and $\theta_i = 0 \forall i < 0$.

According to [Pesaran and Shin \(1998\)](#), the H -step-ahead forecast-error variance decomposition is expressed as follows:

$$d_{ij}^g(H) = \frac{\partial_{ij}^{-1} \sum_{h=0}^{H-1} (e'_j \pi_h \sum \varepsilon_j)^2}{\sum_{h=0}^{H-1} (e'_j \pi_h \sum \varepsilon_i)^2} \quad (4)$$

The square root of the diagonal elements of the variance-covariance matrix is represented by ∂_{ij} . In the VAR model, the shocks to each variable are not orthogonal, i.e. they are different from one of the sums of own and cross-variance of the variables in each row of the variance decomposition matrix. As a result, the elements of the decomposition matrix are normalized:

$$\check{d}_{ij}^g(H) = \frac{d_{ij}^g(H)}{\sum_{j=1}^N d_{ij}^g(H)} \quad (5)$$

with, $\sum_{j=1}^N \check{d}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \check{d}_{ij}^g(H) = N$.

In fact, the normalized elements of the decomposition matrix in [equation \(6\)](#) can be used to generate a total spillover (TS). Furthermore, we can calculate the directional and net spillover (NS) as follows:

$$TS^g(H) = \frac{\sum_{i \neq j} \check{d}_{ij}^g(H)}{\sum_{i,j=1}^N \check{d}_{ij}^g(H)} \times 100 = \frac{\sum_{i \neq j} \check{d}_{ij}^g(H)}{N} \times 100 \quad (6)$$

$$\text{With : } DS_{i \leftarrow j}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{d}_{ji}^g(H)}{N} \times 100 \quad (7)$$

$$DS_{i \leftarrow j}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{d}_{ji}^g(H)}{N} \times 100 \quad (8)$$

$$NS_i^g(H) = DS_{i \leftarrow j}^g(H) - DS_{i \leftarrow j}^g(H) \quad (9)$$

Then, the average contribution of the shock spillovers across the variables to the total forecast error variance is measured by the TS index. In fact, the DS in [equation \(7\)](#) estimates the spillover effects from all other markets j to market i for $i \neq j$. However, the DS in [equation \(8\)](#) measures the spillover effects from market i to all other markets j .

Moreover, we should note that [equations \(7\) and \(8\)](#) are used to calculate NS to identify the variables as senders or receivers of net shocks. Therefore, when NS is negative, market i is a net receiver of spillover effects. However, a positive value of NS indicates that spillover effects originate from market i to all other markets (net transmitter).

3.2 The wavelet coherence model

The continuous wavelet decomposition model is used to identify the multi-horizon nature of the co-movement between RavenPack COVID sentiment, conventional and Islamic index returns and cryptocurrencies. It allows us to illustrate the evolution of local correlations over time and frequency. Thus, a red area at the top (bottom) of the graph denotes a strong correlation at high (low) frequency, while a red area on the left (right) implies a strong correlation at the beginning (end) of the sample period. For two-time series $x(t)$ and $y(t)$, the wavelet-squared coherence, similar to Fourier's analysis, is defined as the absolute squared value of the smoothed cross-wavelet spectrum, which is normalized by the power spectrum of the smoothed wavelets:

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{x,y}(\tau, s))|^2}{|S(s^{-1}W_x(\tau, s))||S(s^{-1}W_y(\tau, s))|} \quad (10)$$

where: S denotes a smoothing operator in time and scale. Since the theoretical distributions of wavelet coherence are unknown, the 5% statistical significance level is determined using Monte Carlo Simulation. We can use the wavelet-squared coherence to measure the traditional correlation of two-time series in time and scale. As a result, the wavelet squared coherence coefficient $R^2(\tau, s)$ is between 0 and 1, with a high (low) dependence value representing a strong (weak) co-movement. By observing the wavelet squared coherence graph, we can detect regions in time-frequency space where the two-time series move together and particularly capture both time- and frequency-varying co-movement features ([Grinsted et al., 2004](#); [Rua and Nunes, 2009](#); [Dewandaru et al., 2014](#)).

4. Data and preliminary analysis

4.1 Data

In this study, we use daily and monthly price data from the GCC stock market indices, the RavenPack COVID sentiment, and the six major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) and their Islamic counterparts X8X Token (X8X), Halalchain (HLC), and HelloGold (HGT). Closing prices were obtained from Datastream and CoinMarketCap [1]. We choose these cryptocurrencies based on their market capitalization and availability. The conventional cryptocurrencies, Bitcoin, Ethereum, and Ripple (XRP), have the largest market capitalization. On the other hand, Halalchain, HelloGold, and X8X have been certified as

Islamic compliant. The study period is from January 1, 2018, to December 21, 2022. We consider two sub-periods: the pre-crisis period (January 1, 2018, to November 30, 2019) and the COVID-19 period (December 2, 2019, to December 21, 2022). The daily return is calculated as follows:

$$RET_t = \ln P_t - \ln P_{t-1} \quad (11)$$

where: P_t and P_{t-1} denote the closing price of the GCC stock index or cryptocurrencies at time t and $t-1$, respectively. Following [Forbes and Rigobon \(2002\)](#) and [Akhtaruzzaman and Shamsuddin \(2016\)](#), closing prices are recorded in local currencies. Furthermore, [Mink \(2015\)](#) argues that it would be more appropriate to use returns denominated in local currency than those in a common currency (e.g. returns denominated in US dollars). This is because only returns denominated in local currency accurately reflect price fluctuations in national stock markets. However, returns converted into a common currency reflect exchange rate fluctuations.

Therefore, RavenPack COVID sentiment is a new indicator to measure the GCC investor sentiment from December 2, 2019, to December 21, 2022. We obtain data for RavenPack COVID sentiment from the RavenPack database [\[2\]](#).

4.2 Preliminary analysis

[Table 1](#) presents the descriptive statistics of conventional and Islamic returns for the six financial markets (Panel A and Panel B, respectively) and the six cryptocurrencies (Panel C). In fact, for all periods studied, a closer look at this table shows a positive average for most conventional and Islamic stock returns, except Bahrain and Oman. All conventional and Islamic monthly return series show excess kurtosis. Moreover, for both skewness and kurtosis measures, the results of the Jarque–Bera normality test reject the null hypothesis of normal distribution. However, during the COVID-19 shock period, RavenPack’s COVID sentiment showed negative average returns. We also notice that the conventional cryptocurrency (Bitcoin) has the lowest risk. However, Islamic cryptocurrencies (Halachain, HelloGold and X8X_Token) register the highest risk with standard deviations of 0.247641, 0.277908, and 0.245447, respectively. According to the skewness and kurtosis indicators, as well as the Jarque–Bera test, all series significantly deviate from the normal distribution.

[Figures 1 and 2](#) illustrate the evolution of the GCC stock market and cryptocurrency returns from January 1, 2018, to December 21, 2022. After extreme volatility starting in December 2019, the GCC stock market index declined significantly. Indeed, since the global spread of COVID-19, panic has prevailed in the financial markets. As a result, several markets around the world continued to fall. Moreover, according to [Figure 2](#), cryptocurrency returns show high fluctuations. In fact, the impact of COVID-19 is observed in all cryptocurrency markets. The time variations in stock returns display stylized fat tails and volatility clustering for all return series. This stressful period increased investor pessimism and fears and generated negative emotions. As a result, it drove investors to sell their shares and exit the stock market. Interestingly, this behavior further amplified the deterioration of the GCC financial market.

5. Empirical results and discussion

5.1 The spillover structure between the RavenPack COVID sentiment and financial market index returns

In this section, we refer to the spillover index approach developed by [Diebold and Yilmaz \(2012\)](#) to explore the co-movement between the RavenPack COVID sentiment and

Full sample: From January 1, 2018 to December 21, 2022						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
<i>Panel A: Conventional index returns</i>						
Mean	0.000394	0.000361	7.59E-06	0.000162	0.000370	0.000592
Max	0.034233	0.061446	0.027620	0.048530	0.068315	0.080762
Min	-0.060006	-0.293565	-0.057350	-0.102077	-0.086846	-0.084063
St. D	0.005030	0.011395	0.004988	0.008520	0.009450	0.010264
Sk	-1.587710	-11.05766	-0.827988	-0.983397	-1.384840	-0.363630
Kur	22.46852	262.1617	15.72638	17.40558	16.40645	19.39977
JB	29409.98	5113504	12448.80	15977.49	14164.61	20368.30
<i>Panel B: Islamic index returns</i>						
Mean	-0.000150	0.000355	-0.000129	5.07E-05	0.000197	0.000299
Max	0.088677	0.056758	0.030007	0.050791	0.078117	0.076350
Min	-0.082752	-0.111291	-0.049481	-0.099417	-0.081500	-0.100405
St. D	0.010707	0.008769	0.005990	0.007829	0.008873	0.009846
Sk	-0.215506	-2.989991	-0.579469	-1.025973	-1.293249	-1.281378
Kur	15.66093	43.09163	12.32175	21.45611	20.07758	27.37355
JB	12063.12	123506.3	6632.572	25920.37	22424.74	45147.92
<hr/>						
	BITCOIN	ETHEREUM	XPR	HALALCHAIN	HELLOGOLD	X8X_TOKEN
<i>Panel C: Cryptocurrencies returns</i>						
Mean	0.001895	0.002206	0.001247	-0.002094	-0.000811	0.014790
Max	0.176044	0.219405	0.423353	1.966510	4.009822	2.773463
Min	-0.433714	-0.563071	-0.549549	-1.618760	-4.543656	-1.971844
St. D	0.038626	0.0524499	0.062193	0.186324	0.302688	0.235321
Sk	-1.215413	-1.367350	0.045004	0.102793	-0.906739	3.030687
Kur	19.14438	17.26383	17.96167	30.01108	115.3699	50.32298
JB	12461.20	9861.226	10465.44	34110.71	590466.0	106412.6
<hr/>						
COVID-19 health crisis period (from December 2, 2019 to December 21, 2022)						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
<i>Panel A: Conventional index returns</i>						
Mean	0.000335	0.000284	0.000195	0.000156	0.000362	0.000588
Max	0.034233	0.061446	0.027620	0.034106	0.068315	0.080762
Min	-0.060006	-0.116340	-0.057350	-0.102077	-0.086846	-0.084063
St. D	0.005670	0.010529	0.005407	0.008492	0.010034	0.011523
Sk	-1.830149	-3.264765	-1.121334	-1.727672	-1.794459	-0.452809
Kur	22.00037	39.45543	17.57530	24.42590	18.98901	19.09522
JB	17425.74	63838.11	10121.37	21921.52	12497.78	12095.07
<i>Panel B: Islamic index returns</i>						
Mean	8.76E-05	0.000323	-3.08E-06	3.84E-05	0.000258	0.000650
Max	0.088677	0.056758	0.030007	0.036374	0.078117	0.076350
Min	-0.082752	-0.111291	-0.049481	-0.099417	-0.081500	-0.100405
St. D	0.010497	0.010201	0.006427	0.007762	0.009562	0.011435
Sk	0.002146	-3.078752	-0.716844	-1.842290	-1.616923	-1.379493
Kur	21.54297	37.79873	13.16410	29.39142	21.97256	23.85981
JB	15888.35	57708.03	4868.715	32811.77	17116.29	20458.44
<i>Panel C: RavenPack COVID sentiment</i>						
Mean	-2.315216	-2.205838	-3.495595	-2.025324	-6.980351	-8.204676
Max	11.50000	15.36000	19.40000	23.39000	20.78000	17.89000
Min	-23.23000	-27.94000	-30.04000	-33.85000	-51.29000	-45.21000

Table 1.
Descriptive statistics

(continued)

COVID-19 health crisis period (from December 2, 2019 to December 21, 2022)						
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
St. D	4.791915	5.928783	6.010876	6.105490	10.77691	10.53742
Sk	-0.663279	-0.774372	-0.699203	-0.875094	-0.782618	-0.705348
Kur	4.746236	4.869607	5.268650	6.228517	4.425496	3.426449
JB	148.2805	181.7328	218.9880	415.8330	138.1951	66.96756

	BITCOIN	ETHEREUM	XPR	HALACHAIN	HELLOGOLD	X8X_TOKEN
<i>Panel D: Cryptocurrencies returns</i>						
Mean	0.002969	0.004639	0.001554	0.000321	0.002115	0.025222
Max	0.176044	0.219405	0.423353	1.966510	3.681385	2.773463
Min	-0.433714	-0.563071	-0.549549	-1.618760	-3.689977	-1.971844
St. D	0.039801	0.054248	0.065894	0.247641	0.277908	0.245447
Sk	-2.202687	-2.141302	-0.575578	0.011170	0.003367	2.822560
Kur	29.43642	25.91587	20.90638	19.12190	114.1190	40.32355
JB	33430.48	25294.36	14984.73	12096.94	574670.4	66317.92

Note(s): Max: maximum, Min: minimum, St. D: standard deviation, Sk:skewness, Kur:kurtosis, JB:Jarque-Bera

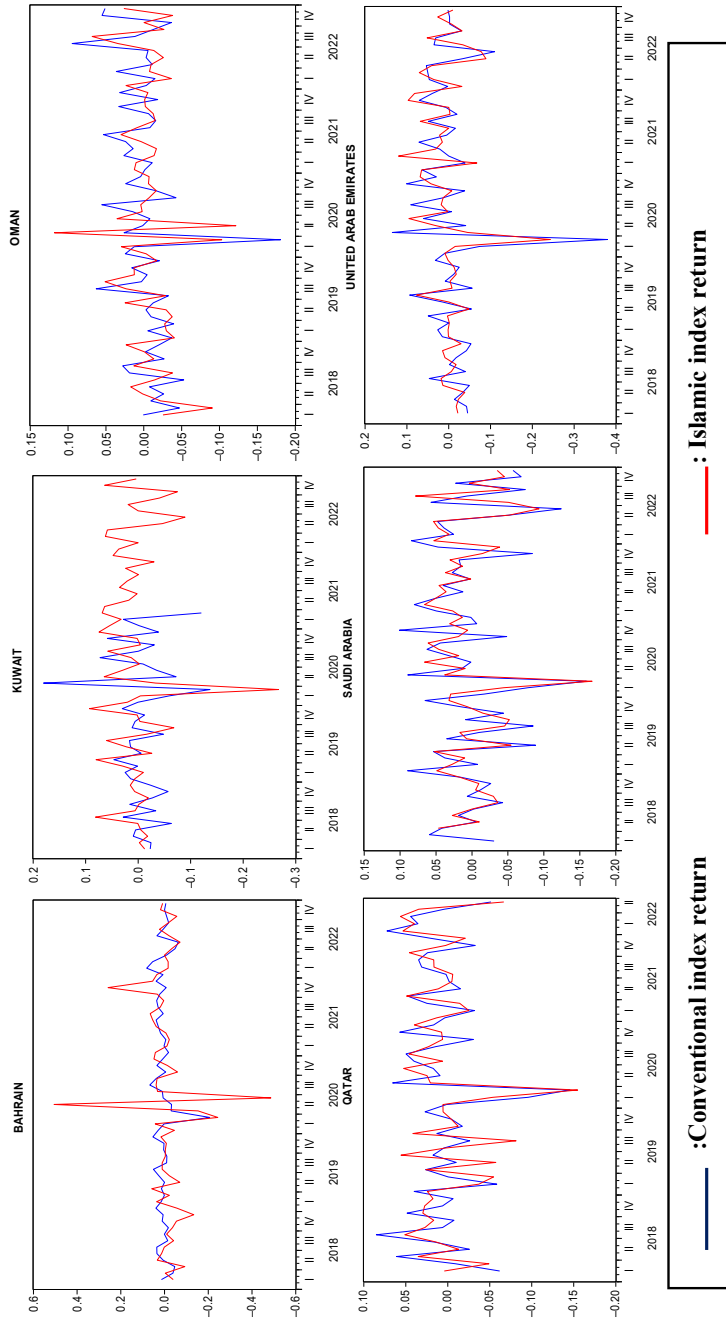
Source(s): Authors' calculations

Table 1.

conventional and Islamic stock indices, as well as cryptocurrencies. In fact, [Table 2](#) displays the total volatility spillovers calculated for the health crisis period. For each country, the ij th entry represents the estimated contribution to the forecast error variance of index i from innovations in index j . For example, we learn from Bahrain that innovations to the RavenPack COVID sentiment are responsible for 1.1%, 0.5%, 0.2% and 1.8% of the variance in the forecast error of conventional and Islamic index returns, Bitcoin and X8X-token, respectively. However, innovations in conventional and Islamic index returns, Bitcoin and X8X-token are responsible for 0.4%, 0.1%, 0.2% and 0.2% of the variance in the forecast error of RavenPack COVID sentiment, respectively.

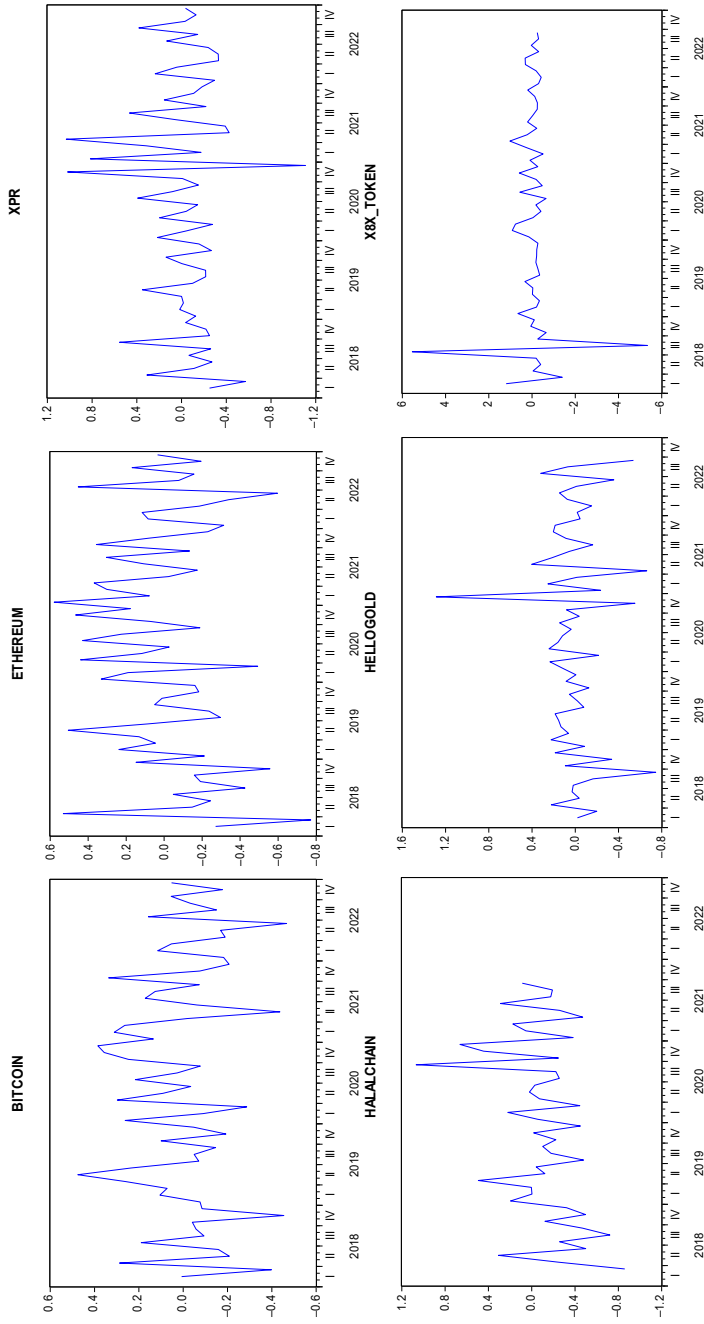
Directional spillovers (DSs) to others capture the spillover effects directed from index i to all other indices. Similarly, DSs from others report the spillover effects received by index i from all other indices. Analyzing [Table 2](#) and focusing on Bahrain, we note that the total volatility spillovers from RavenPack COVID sentiment to others (i.e. contributions from RavenPack COVID sentiment to others) are larger than the total volatility spillovers from others to RavenPack COVID sentiment (i.e. RavenPack COVID sentiment contributions from others). This result indicates that volatility spillover is higher from RavenPack COVID sentiment to returns. This result is similar to Oman and the UAE. In fact, they exhibit higher DS from RavenPack COVID sentiments to others than the total volatility spillover from index returns to RavenPack COVID sentiment. More precisely, by analyzing the direction of spillover (NS's row) in [Table 2](#), we find that RavenPack COVID sentiments are the primary transmitters of net shock for all conventional market indices.

On the other hand, the majority of Islamic indices and cryptocurrencies are net receivers. This finding demonstrates the critical role of the RavenPack COVID sentiment shock on conventional indices. Moreover, the TS index is quite high. Indeed, it rises from 5.7% to 16.5% in all Islamic and conventional index markets. Thus, these results report a high shock spillover between the RavenPack COVID sentiment, the Islamic and conventional stock return indices and cryptocurrencies.



Source(s): Authors' elaborations

Figure 1.
Time series plot of
returns of the stock
markets



Source(s): Authors' elaborations

Figure 2.
Time series plot of
returns of the
cryptocurrency
markets

Table 2.
Directional spillover indexes (%) between RavenPack COVID sentiment and conventional and Islamic stock markets, index and cryptocurrencies returns

To	Bahrain From				Kuwait From				From others	To	Sentkw	ret_kwc	ret_kwi	ret_btc	ret_x8x_token	From others
	Sentba	ret_bac	ret_bai	ret_btc	ret_bac	ret_bai	ret_btc	ret_x8x_token								
sentba	99	0.4	0.1	0.2	0.2	0.2	1	sentkw	95.8	0.5	1.8	1.4	1.4	0.5	4.2	
ret_bac	1.1	95.8	1.7	1.1	0.3	0.3	4.2	ret_kwc	0.5	90	7.9	1.4	1.4	0.3	10	
ret_bai	0.5	11	87.4	0.9	0.3	12.6	ret_kwi	0.4	52.6	45	1.7	0.3	1.7	0.3	55	
ret_btc	0.2	4.7	0.9	93.6	0.6	6.4	ret_btc	1.1	2.2	0.5	95.6	0.6	0.6	0.6	4.4	
ret_x8x_token	1.8	0.7	0.7	1	95.8	4.2	ret_x8x_token	1.1	0.2	0.2	1	97.4	0.6	0.6	2.6	
Contribution to Others	3.6	16.8	3.4	3.3	1.4	28.4	Contribution to Others	3.1	55.5	10.4	5.5	1.8	1.8	1.8	76.2	
Net contribution (To - From)	2.6	12.6	-9.2	-3.1	-2.8	Total Connectedness 5.7%	Net recipient	-1.1	45.5	-44.6	1.1	-0.8	-0.8	-0.8	Total Connectedness 15.2%	
Conclusion	Net transmitter	Net transmitter	Net recipient	Net recipient	Net recipient	Conclusion	Conclusion	Net recipient	Net transmitter	Net recipient	Net transmitter	Net recipient	Net transmitter	Net recipient	Conclusion	
To	Oman From				Qatar From				From others	To	Sentqa	ret_qac	ret_qai	ret_btc	ret_x8x_token	From others
	Sentom	ret_omc	ret_omi	ret_btc	ret_omc	ret_omi	ret_btc	ret_x8x_token								
sentom	98.8	0.1	0.1	0.7	0.3	1.2	Sentqa	96.8	1.1	1.7	0.2	0.2	0.2	0.2	3.2	
ret_omc	0.8	97.2	0.9	1	0.2	2.8	ret_qac	0.2	97.3	0.9	1	0.5	1	0.5	2.7	
ret_omi	2.4	20.6	76.2	0.6	0.2	23.8	ret_qai	0.3	35.9	63.2	0.4	0.3	0.4	0.3	36.8	
ret_btc	0.3	2.3	1.6	95.1	0.7	4.9	ret_btc	0.5	1.8	1.9	95.1	0.8	0.8	0.8	4.9	
ret_x8x_token	0.7	0.3	0.6	0.9	97.5	2.5	ret_x8x_token	0.4	0.7	0.2	1.1	97.5	0.8	0.8	2.5	

(continued)

		Oman From				Qatar From							
To	Sentom	ret_omc	ret_omi	ret_btc	ret_x8x_token	From others	To	Sentqa	ret_qac	ret_qai	ret_btc	ret_x8x_token	From others
Contribution to Others	4.2	23.4	3.2	3.1	1.4	35.3	Contribution to Others	1.4	39.5	4.7	2.7	1.8	50.1
Net contribution (To - From)	3	20.6	-20.6	-1.8	-1.1	Total Connectedness 7.1%	Net	-1.8	36.8	-32.1	-2.2	-0.7	Total Connectedness 10%
Conclusion	Net transmitter	Net transmitter	Net recipient	Net recipient	Net recipient	Net recipient	Conclusion (To - From)	Net recipient	Net transmitter	Net recipient	Net recipient	Net recipient	Net recipient
Saudi Arabia From													
To	Sentsa	ret_sac	ret_sai	ret_btc	ret_x8x_token	From others	To	Sentuae	ret_uaec	ret_uaei	ret_btc	ret_x8x_token	From others
Sentsa	94.9	3.8	0.1	1	0.3	5.1	sentuae	97.7	0.7	0.9	0.5	0.3	2.3
ret_sac	0.3	84.7	13.7	1.1	0.2	15.3	ret_uaec	1.4	95	1.3	2.1	0.2	5
ret_sai	0.6	53.3	45.2	0.6	0.3	54.8	ret_uaei	1.2	31.6	66.3	0.8	0.1	33.7
ret_btc	0.9	1.8	2.1	94.6	0.7	5.4	ret_btc	0.3	2.1	0.9	96	0.7	4
ret_x8x_token	0.5	0.1	0.2	1	98.2	1.8	ret_x8x_token	0.3	0.2	0.1	1.1	98.4	1.7
Contribution to Others	2.2	58.9	16.1	3.8	1.4	82.4	Contribution to Others	3.1	34.6	3.2	4.4	1.4	46.8
Net contribution (To - From)	-2.9	43.6	-38.7	-1.6	-0.4	Total Connectedness 16.5%	Net	0.8	29.6	-30.5	0.4	-0.3	Total Connectedness 9.4%
Conclusion	Net transmitter	Net transmitter	Net recipient	Net recipient	Net recipient	Net recipient	Conclusion (To - From)	Net transmitter	Net transmitter	Net recipient	Net transmitter	Net transmitter	Net recipient

Source(s): Authors' calculations

Directional spillover effects during COVID-19

Table 2.

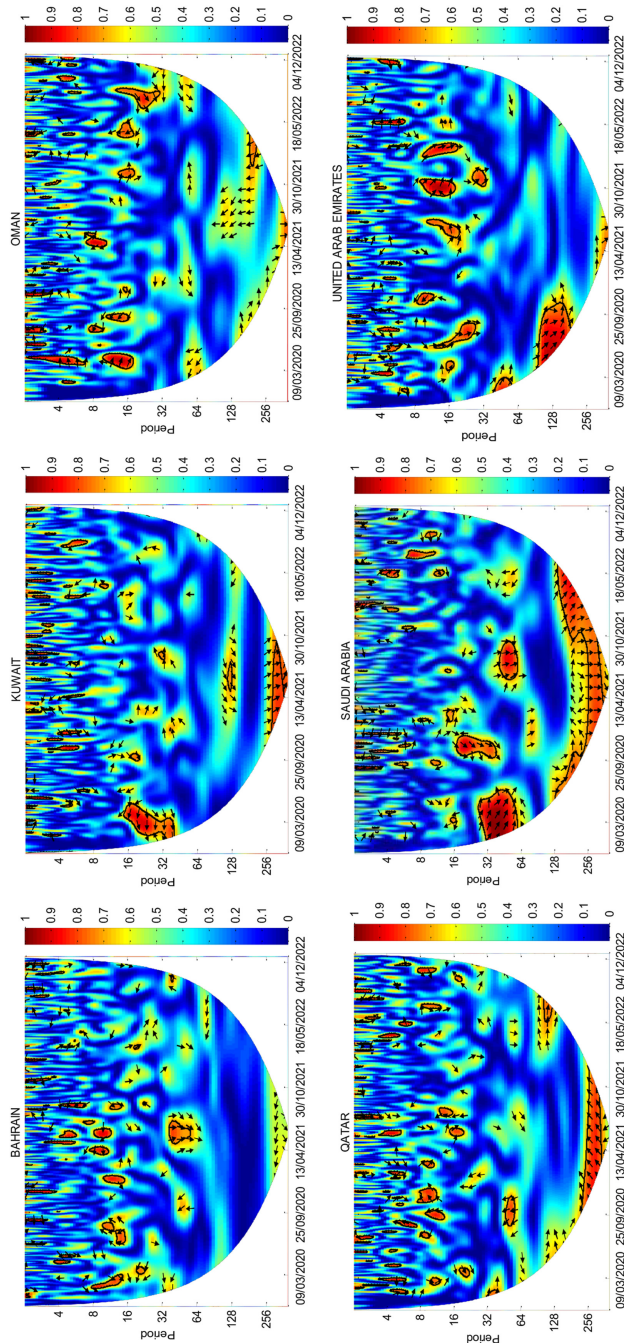
Therefore, we conclude that shocks from the RavenPack sentiment index are transmitted to the Islamic and conventional market indices. They are also transferred to cryptocurrencies corroborating the predictive power of the RavenPack COVID sentiment as it transmits the shock to the financial markets and shows a lead effect. This result supports [Soltani and Boujelbene Abbes \(2022\)](#), who find a significant peak of connectivity between investor sentiment and Chinese stock market return during the turmoil periods of 2015–2016 and late 2019–2020. Interestingly, the information on shock receivers and transmitters is useful in predicting potential portfolio risk and helping investors make appropriate adjustments to their portfolios. Indeed, it greatly improves their investment decisions.

5.2 RavenPack COVID sentiment and the market index returns: lead or lag effect

Using wavelet coherence, we can distinguish the short- and long-term co-movement dynamics between RavenPack COVID sentiment, conventional and Islamic index returns, and cryptocurrencies. [Figures 3–5](#) represent the estimated wavelet coherence between the RavenPack investor index and conventional index returns, between RavenPack COVID sentiment and Islamic index returns, and between the RavenPack investor index and cryptocurrency returns, respectively. Furthermore, we can determine the significance level of wavelet coherence based on Monte Carlo simulations. The vertical axis presents the scale, whereas the horizontal axis indicates the time intervals. The blue (red) colored area shows weak (strong) co-movement at high and low frequencies. Arrows pointing to the right (\rightarrow) signify that the variables are in phase (cyclical effect on each other). (\nearrow) implies that the investors' index is leading. (\searrow) indicates that investors' index is lagging. Arrows pointing to the left (\leftarrow) mean that the variables are out of phase (countercyclical effect). (\swarrow) shows that investors' index is lagging. Finally, (\nearrow) means that investors' sentiments are leading.

The analyzed figures exhibit a significant correlation at both the high and low-frequency time scales during the period 2020–2022, with large islands of dark colors scattered along the 4–256 days bands. This correlation is much higher for Saudi Arabia, Qatar and the UAE. This result can be explained by the fact that the financial markets have experienced significant fluctuations. These have significantly affected the investor's emotions, leading to the volatility of the market index. An exception is the Islamic index of Saudi Arabia, with a higher power taking place in July 2020 and coinciding with the fear of another outbreak of COVID-19. All five cryptocurrencies, and to a lower extent Ethereum, show additional power on the 4–128 days scale in the August to September period, i.e. the middle of the second COVID-19 wave.

We study the consistency and phase between the RavenPack COVID sentiment and the market indices. The results show that the connectedness between RavenPack COVID sentiment and conventional and Islamic markets and cryptocurrencies depends on the market under consideration and the investment horizons. Moreover, the arrow analysis indicates that during the COVID-19 pandemic, RavenPack COVID sentiment and conventional and Islamic index returns are in phase for frequencies between 32 and 128 months. The arrows pointing to the right and upwards mean that RavenPack COVID sentiment is the “leader” in the sense that it drives returns toward a high correlation for most indices. However, comparing the density of the red dots, the Bahrain conventional index and Ethereum seem the least affected by RavenPack COVID sentiment. For cryptocurrencies and Islamic indices, we observe a highly significant correlation in the July–August period, which is mostly counter cyclical. In this same period, the correlation is positive (right-turning arrows) for the X8X Token. For the 64–128 days bands, the conventional indices of Bahrain and Kuwait, and Ethereum are not more affected by RavenPack COVID sentiment. This suggests that these markets can serve as a safe haven during a pandemic.



Source(s): Authors' elaborations

Figure 3.
Correlation between
RavenPack COVID
sentiment and
conventional index
returns

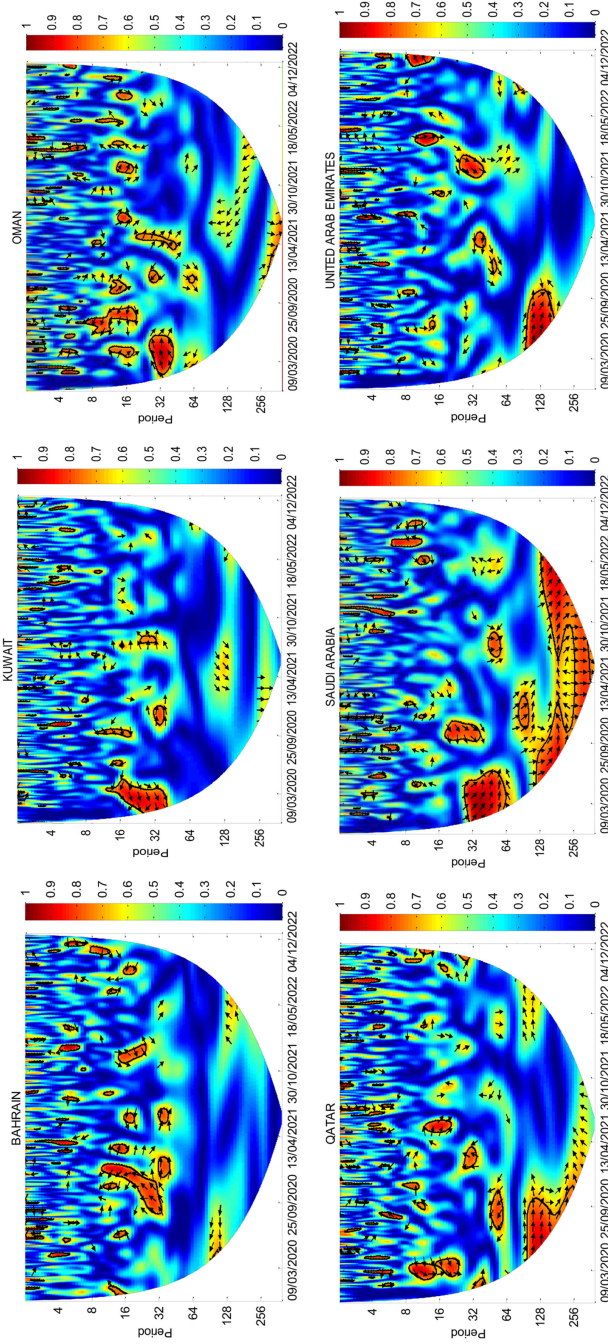
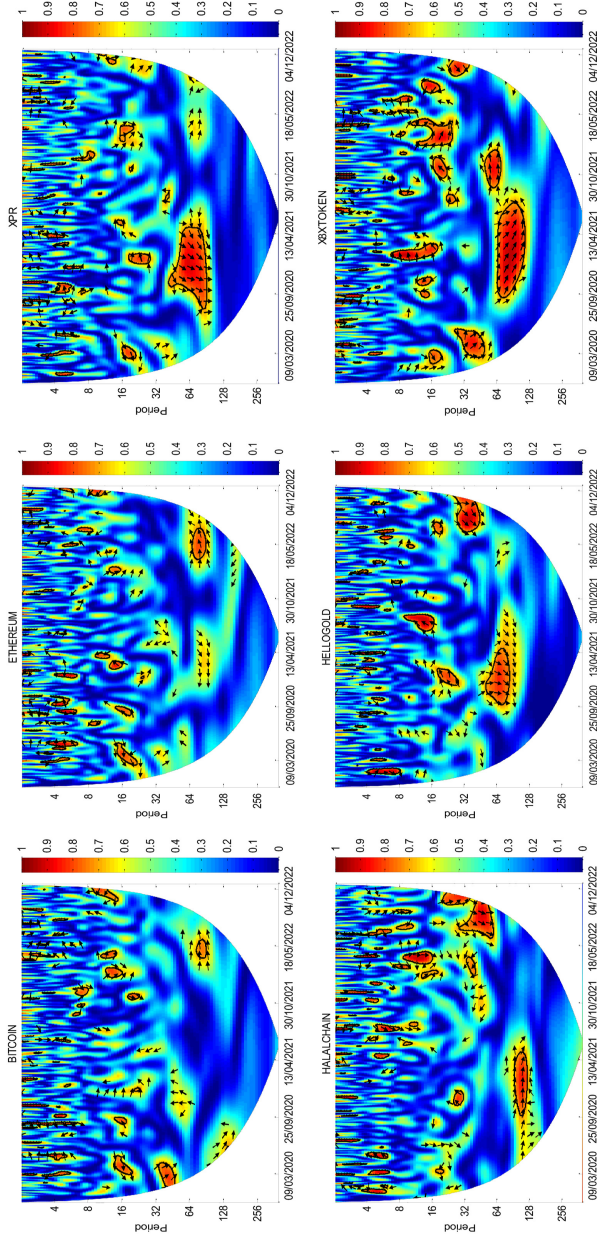


Figure 4.
Correlation between
RavenPack COVID
sentiment and Islamic
index returns

Source(s): Authors' elaborations



Source(s): Authors' elaborations

Figure 5.
Correlation between
RavenPack COVID
sentiment and
Cryptocurrencies

Although counterintuitive, this positive consistency between RavenPack COVID sentiment and the long-run financial and cryptocurrency markets is in line with the findings of Goodell and Goutte (2021) and Sharif *et al.* (2020). The difference in results regarding the investment horizon reflects the differences in perception between short-term and longer-term investors. Several studies have acknowledged that risk can decrease significantly if the asset is held for a longer period (Butler and Domian, 1991). In our case, long-term investors seem to be insulated from the short-term market fluctuations induced by the fear of COVID-19. This result confirms the severe effect of the COVID-19 pandemic on the financial markets during the study period. For instance, digital currencies can serve as a store of value during periods of market turbulence. Indeed, they also represent a source of portfolio diversification. In this context, Gil-Alana *et al.* (2020) identify that cryptocurrencies can be an important diversification option for investors, mainly Bitcoin and Ethereum.

Omame-Adjepong and Alagidede (2019) prove that all diversification benefits within cryptocurrencies are most commonly found in intra-week to intra-month time horizons for specific market pairs. However, the level of inter-market connectivity and volatility links are identified as sensitive to both liquidity and volatility. Additionally, Liu (2019) provides evidence that portfolio diversification across different cryptocurrencies can significantly improve investment outcomes. When specifically examining the market relationships between cryptocurrencies and other conventional financial variables, Bouri *et al.* (2017) find that Bitcoin is a poor hedge and only suitable for diversification purposes. This finding is echoed when examining the S&P500 exchange (Tiwari *et al.*, 2019), Eurostoxx 50, Nikkei 225 and CSI 300 (Feng *et al.*, 2018).

6. Robustness check

In order to verify the robustness of our empirical findings, we apply the time-frequency connectedness developed by Baruník and Křehlík (2018) to check the direction and scale connectedness among these markets. Specifically, we decompose the connectedness into two different frequency bands: the short and long terms, corresponding to about one–four days and more than 10 days, respectively.

Figure 6 plots the total volatility connectedness during a 100-month rolling window as the predictive horizon for the underlying decomposition. The total volatility connectedness depicts long-run fluctuations rather than short-run ones over the entire period. The total volatility connectedness peaked during the COVID-19 health crisis. It increased sharply in 2020 from 20% to 45%, which suggests that strong connectedness mainly happens in the long term. In addition, since the second half of 2020, when the pandemic was widespread, total connectedness has increased again, reaching a historical peak (45% for Saudi Arabia) in March 2020. Moreover, the TS index evolves abruptly, suggesting the existence of major shocks lowering connectivity between different GCC markets.

7. Conclusion

The COVID-19 pandemic has become a serious threat to the GCC and global economies. Given the unknown pathways of its spread and virulence, which created huge recovery and earning opportunities, it is difficult to assess its severity. Furthermore, identifying the connectedness between the Gulf Council Cooperation (GCC) stock market index and six cryptocurrencies is essential for effective risk management and portfolio diversification. Thus, in order to extend the existing literature in this field, this article mainly investigated the shock transmission between RavenPack COVID sentiment, the GCC stock market, and cryptocurrencies during the health crisis period.

Directional
spillover
effects during
COVID-19

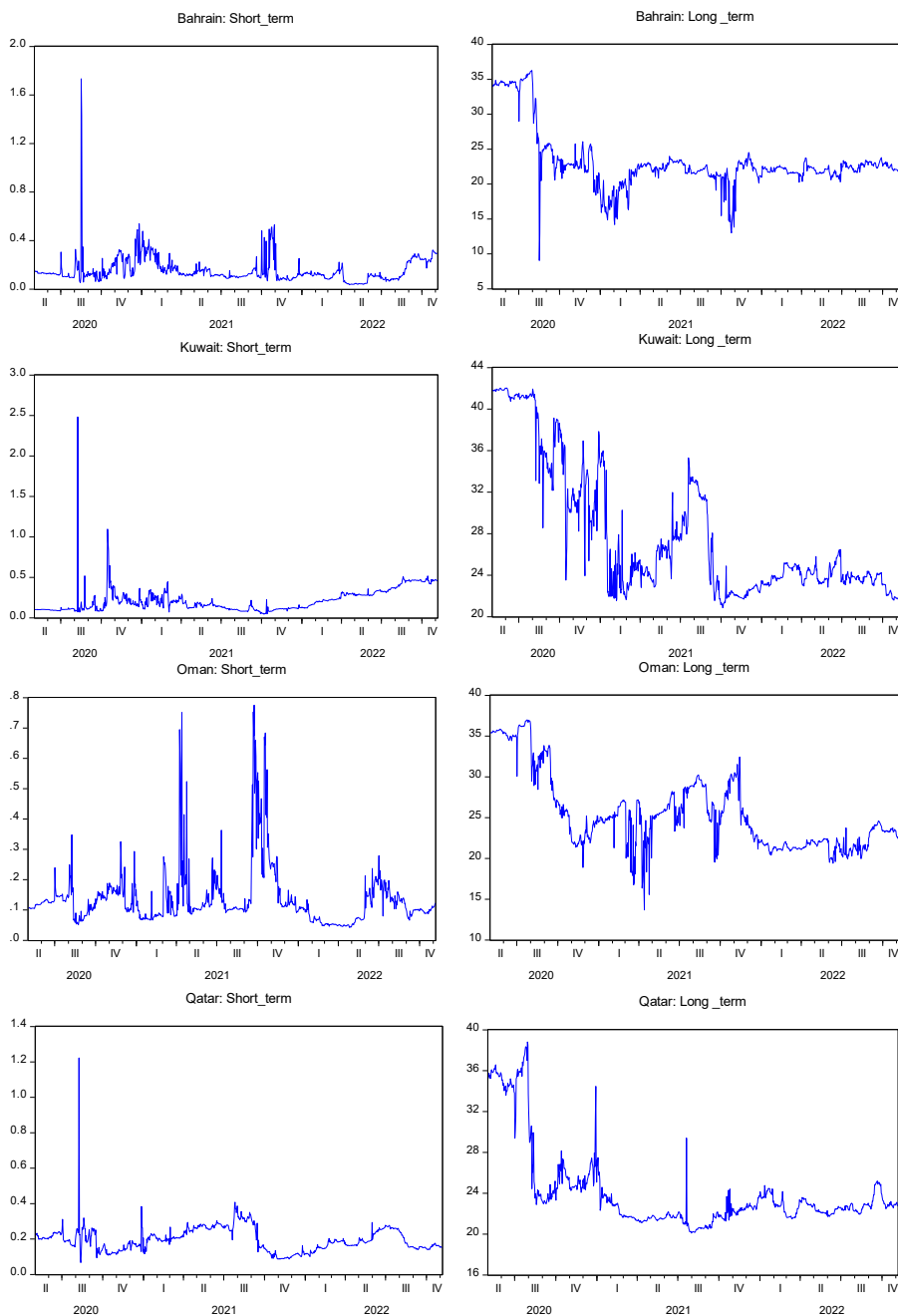


Figure 6.
Dynamic frequency
connectedness of the
RavenPack COVID
sentiment and
conventional and
Islamic stock markets
index and
cryptocurrencies
returns

(continued)

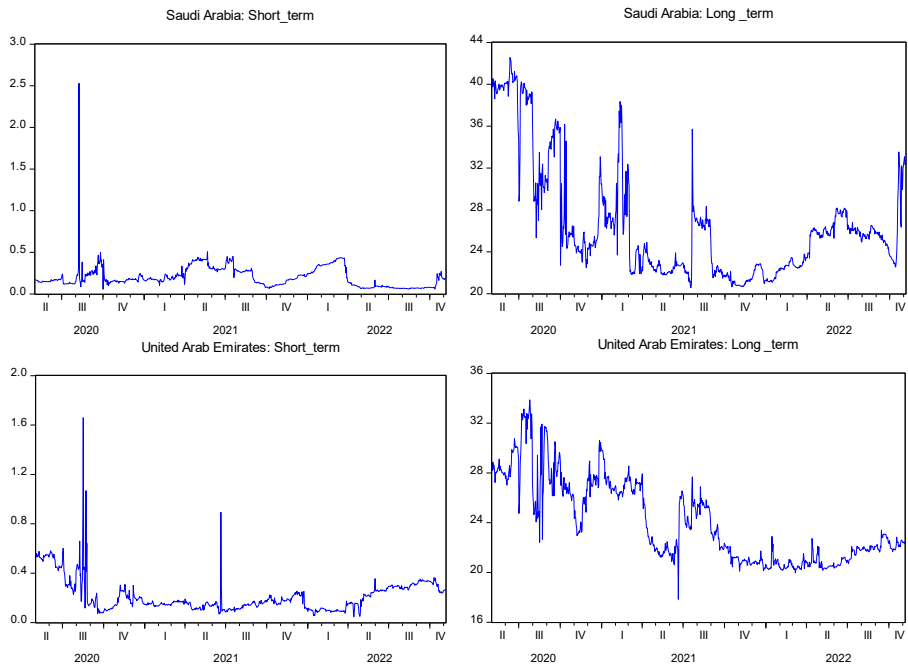


Figure 6.

Source(s): Authors' elaborations

Moreover, we relied on the methodology of [Diebold and Yilmaz \(2012, 2014\)](#) to construct network-associated measures. Then, the wavelet coherence model was applied to explore the co-movements between GCC stock markets, cryptocurrencies and RavenPack COVID sentiment. In order to check the robustness of our results, we employed the time-frequency connectedness developed by [Baruník and Křehlík \(2018\)](#). In fact, our empirical analysis illustrates the effect of COVID-19 on all cryptocurrency markets. The time variations of stock returns display stylized fat tails and volatility clustering across all return series. This stressful period increased investor pessimism and fears and generated negative emotions. Interestingly, our findings point to a high spillover of shocks between the RavenPack sentiment index, the Islamic and conventional stock return indices and cryptocurrencies.

In addition, we found that the RavenPack COVID sentiment is the main net transmitter of shocks for all conventional market indices and those most Islamic indices and cryptocurrencies are net receivers. More interestingly, our results reveal that the daily levels of positive and negative shocks in stock market indices and cryptocurrencies induced by the COVID-19 pandemic affect these variables. They also show that fear and pessimism sentiment induced by the news related to coronavirus plays a major role in driving the values of cryptocurrencies more than other indices. We also found that Ethereum can serve as a hedge against pandemic-related news. In general, news related to the COVID-19 pandemic encourages people to invest in cryptocurrencies. These results support the view of previous studies suggesting that investor sentiment performance is affected by financial markets during the bubble period (e.g. [Cheema et al., 2020](#); [Soltani and Boujelbene Abbas, 2022](#)). Therefore, this can help fund managers adjust their portfolio risk exposure by including stocks that significantly respond to COVID-19 sentiment and those that do not. In fact, the

volatility mechanism and investor sentiment can be interesting for investors as it allows them to consider the dynamics of each market and thus optimize the asset portfolio allocation.

Notes

1. <https://coinmarketcap.com/>
2. RavenPack (<https://coronavirus.ravenpack.com>) provides media data related to COVID-19 issues.

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