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The Granger Causality of Bahrain Stocks, Bitcoin, and Other Commodity Asset Returns:

Evidence of Short-Term Return Spillover Before and During the COVID-19 Pandemic

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ABSTRACT

This study examines the tendency of short-term return spillover across Bahrain stocks, bitcoin, and other commodity assets factoring in the dynamic effect of the COVID-19 pandemic. The study employed vector autoregression (VAR) model using the daily returns of Bahrain All Shares Index, bitcoin, crude oil, and gold futures from January 2018 to March 2022. The results showed a persistent unidirectional short-term spillover of return from the Bahrain stock market to the futures gold market for both the period before and during the pandemic. Moreover, the results also showed that the significant positive shock in the bitcoin returns as granger-caused by the returns of the Bahrain stock market is only during the period before the pandemic. Finally, a significant negative contemporaneous short-term effect on the crude oil market returns can be statistically explained by the shocks in the Bahrain stock market only during the COVID-19 period.

KEYWORDS

Bahrain Stock Exchange, Bitcoin, COVID-19, Granger Causality, Vector Autoregression

INTRODUCTION

The immense disruption of financial markets caused by the 2008 financial crisis has exposed the level of integration across different markets and economies around the globe (Kim et al., 2015). This experience has opened up a lot of valid arguments and debates about how returns, including volatility, are spilled over across different equity and commodity markets which are undeniably more complex and overwhelmed with information due to technological developments. However, the primary motivation in the arguments and debates related to market spillovers is anchored on hedging risk and finding a suitable financial asset that will provide a safer haven for investors and market regulators alike.

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On the other hand, with the emergence of cryptocurrencies, academics, investors, and policymakers have speculated on the role of bitcoins in financial markets and its possible implications for trading and policies related to the management and regulation of market risk and liquidity (Kyriazis, 2019). Urquhart (2017) added that investors' growing interest in participating in the Bitcoin market had increased market efficiency and undeniable speculative bubbles. Despite being relatively new, Watcharaporn et al. (2021) argued that the growing interest in cryptocurrency may result in short- and long-term spillovers that are worthy of analysis and evaluation.

While there are several definitions of return spillover, Dewi et al. (2021) referred to it as the transmission of returns between markets primarily due to information transfer. Looking at this subject from the Gulf Cooperation Council (GCC) market expands the analysis to factor in the dependence of spillover effects on the varying market and economic conditions and level of integration and monetary policy. For example, Arouri and Rault (2010) noted that spillover or transmission of price shocks, especially oil-related, should be different in GCC markets compared to relatively oil-importing economies. GCC countries' economies highly affect their fiscal and monetary policy, leading to a different structural spillover effect. Interestingly enough, other countries in the GCC, like UAE and Bahrain, are more liberal in terms of market and economic policies and are less dependent on oil (Arouri et al., 2011). For example, Bahrain's more liberal market and economic policies are even more prevalent in its Central Bank's effort to digitally transform the Kingdom's financial services (Central Bank of Bahrain, n.d.), leading to a more cryptocurrency-integrated economy.

With the growing interest in the complexity of market spillover on the one hand and the unique economic and monetary policy implications, it is surprising that very few studies have explored the market spillover in the Kingdom of Bahrain. On the other hand, the decentralized nature of blockchain technology provides varying risk and reward characteristics (Urom et al., 2020), which has tremendous implications for investment portfolio management in a thriving economy. In addition, Baker et al. (2020) observed that the recent COVID-19 pandemic had provided another layer to the already challenging aspect of market spillover and financial contagion.

Thus, the contribution of this paper to emerging research can be seen in two folds. First, this study offers fresh empirical evidence on the varying direction of spillover across the Bahrain Stock Market, Bitcoin Market, and other major commodity markets during and before crises. This investigation is crucial in market regulation and policymaking, especially in an economy that intends to expand its involvement in financial technology and diversify outside an oil-based economy. In addition, the unique market condition and level of regional integration in an oil-exporting economy like Bahrain provide more insight into price spillovers since these characteristics were noted to be relevant factors, especially during periods of economic unrest (Arouri et al., 2011). Second, Granger causality statistics paired with the Cholesky variance decomposition allow the structural analysis of the modeled directional shocks. This process results in a more educated and evidence-based approach to developing policies for market regulation and investment and portfolio management.

LITERATURE REVIEW

Three significant strands in the literature explain the spillover effect focused on this study: studies that explore market return spillover in general, the direction of spillover, and time-varying spillover during periods of crisis. These strands also served as the basis for developing the study's hypothesis and the decision to use the model to assess the said spillover dynamics. Thus, the first section of this review will look at studies focused on the development and treatment of market return spillover and other studies that explored market return spillover involving stock markets, bitcoins, and other commodity assets. The second section of the review will look at studies that propose the direction of the spillover. In contrast, the third section will close by providing the landscape of studies converging on spillover dynamics during crises like the COVID-19 pandemic.

Market Return Spillover

In its earliest roots, Engle et al. (1990) used meteorological analogies to test a form of market efficiency they termed *market dexterity*, which posits that the equilibrium price of a given market instantaneously responds to news. Thus, old prices compound with other news resulting in price movements. The same study deviates from the traditional efficient market hypothesis, which attributes the determination of prices of financial assets to the expected cash flows from the same discount over time. Instead, Engle and colleagues suggest that prices of assets fluctuate in response to factors not related to future dividend expectations.

The pioneering study mentioned in the previous section kicked up succeeding studies supporting the *meteor shower hypothesis*, contending that innovations in one market are spilled over to another market. For example, studies associating new york, tokyo, and london stock exchanges were conducted during the 1990s, documenting significant spillover of returns and volatility across countries' stock markets (Hamao et al., 1991; Barclay et al., 1990; Shiller et al., 1991). Consequently, the interest in spillover effects and market contagion encouraged efforts to model these interactions among economies and different assets. Some of the most pervasively recognized multivariate models assume that *spillover* is a portion of the error variance response to a shock or innovation from another market (Gillaizeau et al., 2019). The models closely under this assumption include vector autoregression models (var), the vector error correction model (vecm), forecast error variance decomposition (fevd), structural vector autoregressive (svar), and granger causality statistics.

On the other hand, univariate models also gained popularity in modeling spillover effects and market contagion primarily because of their ability to capture volatility clustering effects. This model includes ARCH models and the family of GARCH models such as Glosten-Jagannathan-Runkle (GJR)-GARCH, (DCC)-GARCH, Baba-Engle-Kraft-Kroner (BEKK) GARCH, and integrated GARCH (IGARCH). Finally, even recent studies have incorporated classic correlation statistics in investigating the connectedness of financial markets and economies (Ciaian & Rajcaniova, 2018; Luu Duc Huynh, 2019).

In terms of return spillover across different asset markets, corbet et al., 2018 found that there is very little evidence to prove the connectedness between the cryptocurrency market and other financial markets like gold, bonds, and other major stock markets, at least in the perspective of a generalized variance autoregressive framework. Nevertheless, their findings suggest that, with the lack of short-term connectedness, investors with short-term investment horizons could take advantage of cryptocurrency to improve their investment portfolio's risk and return characteristics. However, in a later study using the method of diebold and Yilmaz, Corbet et al. (2018) stumbled upon a different finding. By analyzing spillover effects across famous cryptocurrencies (bitcoin, ripple, and litecoin), bonds, gold, currencies, commodities, and S&P 500 S&P 500, they found that while the significant cryptocurrencies understudy showed significant price spillover effects, the linkage between them and other financial assets was very low.

In addition, a study by Zwick and Syed (2019) found that gold had a weak negative impact on bitcoin returns in the long run from October 2017, which, however, significantly changed to a positive long-term effect after October 2017. Their findings suggest that the increase in gold's demand results in a long-run increase in the demand for Bitcoins.

Direction of Spillover

Balcilar, Demirer, and Hammoudeh (2019) found that european countries tend to exhibit asymmetries of spillover from the oil market to emerging stock markets during periods of increasing returns and prices. Their results suggest that oil prices could be feasible signals of stock market activity, including responses to global shocks because of the bidirectional effect.

In another study, Lundgren et al. (2018) found a strong connection between technology-based assets and stocks and common or traditional stocks. In terms of the direction of shocks, the same study found that the spillover emanates primarily from the emerging stock market, followed by the Bitcoin market and Nasdaq Financial Technology Index. Gold and oil, among others, are recipients of the observed innovations from the latter.

In a more recent study, Bouri et al. (2021) used a TVP-VAR approach to investigate the dynamic spillovers across several asset indices, including S&P GSCI gold, Investment Grade Corporate bond index Exchange-Traded Fund, and USD index. The study found that the interactions of the markets are significantly higher during the COVID-19 pandemic. The same study also showed that the US stock market and US dollar exchange markets are the primary sources of the spillover before the pandemic, while bond markets are the sources of shocks during the pandemic. The results also showed that the US dollar exchange markets primarily absorbed the shocks caused by the innovations in the bond market during the COVID-19 outbreak.

Moreover, Li et al. (2021) built on the previous study by investigating the associations of financial and commodity assets in the US and China during the COVID outbreak to expand their results. Their study found a strong dynamic return spillover across commodities and financial assets in both countries. This spillover also significantly increased during the pandemic period. Among the results observed, several assets also shifted roles from receivers of shocks to sources of shocks during and before the pandemic. Notably, the persistence of the US Bond market as a source of shock is observed in both periods. Their findings suggest that the dynamics of the direction of spillover varies according to the economic conditions at the time of the investigation. For this reason, spillover effects during periods of crisis like the recent pandemic have caught the interest of investors, policymakers, and academics alike.

Spillovers During Periods of Crisis

The proliferation of evidence of significant spillover effects in the academic literature during crises can be primarily traced to the global financial crisis in 2008 (Shahzad et al., 2021). To illustrate, Karanasos et al. (2014) found that volatility spillovers were more evident during the 2008 financial crisis as they discovered breaks in price variances associated with the observed economic event. Similarly, Lundgren et al. (2018) found that European stocks respond to renewable energy stocks' shocks. This nonlinear connectedness was pervasively observed during the 2008 global financial crisis and the European sovereign debt crisis in 2009.

Maitra and Dawar (2019) used the returns of commodity futures, stock indexes, and exchange rates to investigate the return spillover effects across diverse asset classes as an effect of the 2008 financial crisis. The study found that commodity futures, stock indexes, and exchange rates do not exhibit long-term stochastic associations. On the other hand, the commodity futures market unidirectionally responds to the shocks in the stock market only after the observed financial crises due to a market that is more sensitive to the transmission of relevant economic and financial information.

Using the stock market of the epicenter of the first registered COVID-19 case, Corbet et al. (2020) argued that primarily because of the "flight to safety" phenomenon, the volatility spillover between the Chinese stock market and the Bitcoin market is significantly higher during the pandemic period. The study results debunk the assumption that other assets like cryptocurrency and gold can act as hedging assets during times of crisis. Instead, these assets with stocks in an investment portfolio only amplify risk exposure.

In one of the pioneering studies relating to COVID-19 as an economic event, Sharif et al. (2020) used several wavelet-based approaches to study the association between the shock in crude oil prices and the stock market during the COVID-19 outbreak. Their study found that, together with the disruptions brought about by the volatility of oil prices and COVID-19, the US stock market experienced an unparalleled sensitivity to the studied exogenous variables.

Finally, Le et al. (2021) also analyzed the spillover effects during the COVID-19 pandemic, emphasizing Fintech assets and Bitcoins and how it associated with usual assets such as gold, oil, and equities. Their study found a high spillover during the pandemic, with the US dollar exchange and gold exhibiting relative stability during the crisis. Bitcoin and financial technology stocks tend to absorb most of the shocks during the COVID outbreak dispelling their perceived value as a haven for safety during economic uncertainty.

The results of the studies discussed confound several themes. First, the direction of the spillover effect is a matter of significant interest despite the overwhelming evidence supporting the establishment of spillover effects of returns across different asset markets. Second, the studies also proved time-varying structural dynamics in market spillover. These structure variations are most heightened during periods of crisis. Thus, based on the mentioned studies, this research is grounded on the following two hypotheses.

Hypothesis 1: There is a bidirectional Granger causality between Bahrain stock exchange market returns, Bitcoin, crude oil, and futures gold.
Hypothesis 2: The observed Granger causality was more significant during the pandemic.

DATA AND RESEARCH METHODS

Data

The study sample comprises the daily returns of RBHB (rate of return for Bahrain All Shares Index), RBT (rate of return for Bitcoin), RO (rate of return for Crude Oil), and RG (rate of return for gold) before the pandemic (i.e., January 2, 2018, to January 30, 2020) and during the pandemic (i.e., February 3, 2020, to March 15, 2022). The start of the pandemic period was determined based on the first identified COVID-19 case in Bahrain recorded on February 21, 2020 (Al Shurafa, 2020). Intuitively, the researcher opted to start the pandemic during the first overlapping trading period of February 2020. All time-series data were obtained from Investing.com, a publicly available database providing one of the most comprehensive economic and financial information about several global financial markets. Due to the variation of trading days of the observed market, the data was harmonized by excluding returns of trading days that do not overlap among all markets. In addition, daily returns for all markets were paired to improve the accuracy of results (Hung, 2018).

Method of Analysis

Vector Autoregressive Model

The study will utilize a multivariate linear model that utilizes the autoregressive nature of the time series and the present and past values of other variables of interest. This multivariate model is called Vector autoregressive model (VAR), which Christopher Sims first introduced in 1980 (Stock & Watson, 2001). VAR is designed to effectively capture structural inferences to allow efficient model description, forecasting, and policy analysis (Stock & Watson, 2001). To investigate the possible return spillover of the RBHB (rate of return for Bahrain All Shares Index), RBT (rate of return for Bitcoin), RO (rate of return for Crude Oil), and RG (rate of return for gold), the following equations were used:

$$RBHB_{t,1} = \alpha_1 + \theta_{11} RBHB_{t-1,1} + \theta_{12} RBHB_{t-1,2} + \theta_{13} RBHB_{t-1,3} + \theta_{14} RBHB_{t-1,4} + \omega_{t,1} \tag{1}$$

$$RBT_{t,2} = \alpha_2 + \theta_{21} RBT_{t-1,1} + \theta_{22} RBT_{t-1,2} + \theta_{23} RBT_{t-1,3} + \theta_{24} RBT_{t-1,4} + \omega_{t,2} \tag{2}$$

$$RO_{t,3} = \alpha_3 + \theta_{31} RO_{t-1,1} + \theta_{32} RO_{t-1,2} + \theta_{33} RO_{t-1,3} + \theta_{34} RO_{t-1,4} + \omega_{t,3} \tag{3}$$

$$RG_{t,4} = \alpha_4 + \theta_{41} RBHB_{t-1,1} + \theta_{42} RBHB_{t-1,2} + \theta_{43} RBHB_{t-1,3} + \theta_{44} RBHB_{t-1,4} + \omega_{t,4} \tag{4}$$

$RBHB_{t,1}$, $RBT_{t,2}$, $RO_{t,3}$, and $RG_{t,4}$ are the time-series daily returns of Bahrain All Shares Index, Bitcoin, crude oil, and gold, respectively, explained by lag values for all variables under study. Moreover, the number of lags utilized in the model will be determined using the final prediction error (FPE) and the Akaike information criterion (AIC). These criteria were found by Liew (2004) to be less sensitive to sample size and maximize the possibility of acquiring the real lag length while minimizing the possibility of generating estimates under true value. FPE and AIC are estimated as follows:

$$FPE_p = \sigma_p^2 \left(T - p\right)^{-1} \left(T - p\right) \tag{5}$$

$$AIC_p = -2T[\ln\left(\sigma_p^2\right) + 2p \tag{6}$$

where σ_p^2 and p are the model's residuals, and T is the sample size utilized in the data set.

Granger Causality Test

Granger causality statistics were employed in the analysis to test whether lagged values of the variables under study help predict another variable within the data set in the short run. This method provides a way to determine the direction of the causality and explain the spillover effects among the variables in the observed data set. The specification of the causality is shown in the previous Equations 1–4.

Impulse Response Function

Recursive and structural VARs will be developed to calculate the impulse response of each value in the data set, one unit at a time ceteris paribus. This calculation allows the estimation of the response of one variable in another system to the shock of another variable in a separate system. Assuming all errors are uncorrelated across equations considered in the study, IRF can capture the short-run dynamic interactions and spillover effect considering shocks in different time series. The impulse response function is estimated as follows:

$$RBHB_{t,1} = \mu_1 + \varphi_{11} RBHB_{t-1,1} + \varphi_{12} RBHB_{t-1,2} + \varphi_{13} RBHB_{t-1,3} + \varphi_{14} RBHB_{t-1,4} + \varepsilon_{t,1} \tag{7}$$

$$RBT_{t,2} = \mu_2 + \varphi_{21} RBT_{t-1,1} + \varphi_{22} RBT_{t-1,2} + \varphi_{23} RBT_{t-1,3} + \varphi_{24} RBT_{t-1,4} + \varepsilon_{t,2} \tag{8}$$

$$RO_{t,3} = \mu_3 + \varphi_{31} RO_{t-1,1} + \varphi_{32} RO_{t-1,2} + \varphi_{33} RO_{t-1,3} + \varphi_{34} RO_{t-1,4} + \varepsilon_{t,3} \tag{9}$$

$$RG_{t,4} = \mu_4 + \varphi_{41} RG_{t-1,1} + \varphi_{42} RG_{t-1,2} + \varphi_{43} RG_{t-1,3} + \varphi_{44} RG_{t-1,4} + \varepsilon_{t,4} \tag{10}$$

where $RBHB_{t,1}$, $RBT_{t,2}$, $RO_{t,3}$, and $RG_{t,4}$ represent the endogenous variables in the structural model at time *t*, φ_{ij} denotes the matrix in the backshift operator. In addition, μ_i denotes the constant value while the error terms are denoted by $\varepsilon_{j,t}$.

Cholesky Variance Decomposition

The forecast error decomposition will support the impulse response function. This process allows estimating the variance error percentage exhibited by forecasting one variable as a response to a specific shock of another variable in an identified forecast horizon. These factors in both effect size and time dimension of the structural VAR model are considered. After all the data were gathered, data cleansing and diagnostics, including all statistical analyses, were carried out using STATA 14.

EMPIRICAL RESULTS

Descriptive Statistics and Other Diagnostic Tests

This section presents the empirical results of the study. Figure 1 shows the daily raw observations of RBHB (rate of return for Bahrain All Shares Index), RBT (rate of return for Bitcoin), RO (rate of return for Crude Oil), and RG (rate of return for gold) before the pandemic (i.e., January 2, 2018, to January 30, 2020) and during the pandemic (i.e., February 3, 2020, to March 15, 2022).

It can be seen that daily fluctuations are observable across all the time series, both before and during the pandemic. Interestingly, the daily returns for oil during the pandemic significantly behave differently than other observed assets in the study. RBHB, RBT, and RO tend to exhibit a negative response shock in return during the early stages of the pandemic but eventually revert to a state of lesser variance in the subsequent periods after that. Moreover, RO exhibits the slightest variation in returns during the pandemic period.

Table 1 presents the variables' descriptive statistics, ARCH test, unit root test during and after the pandemic, and the entire study period. As shown in panel A, the sample means for RBHB and RG are positive before and during the pandemic, while RO has an overall negative mean during both periods. On the other hand, RBT only had a positive sample mean during the pandemic. The unconditional variance of returns is relatively similar across all variables both before and during the pandemic.

The Jarque–Bera test statistics show that all observed returns are highly leptokurtic, evidenced by significant *p*-values in the normality test. The Augmented Dickey-Fuller tests (ADF) and Philipps-Perron (PP) test for both periods were also examined. The results show that all variables are stationary ($p < 0.05$) for both periods. Moreover, the autoregressive conditional heteroskedasticity (ARCH)

Figure 1. In-sample RBHB, RBT, RO, AND RG daily returns before pandemic (left) and during the pandemic (right)

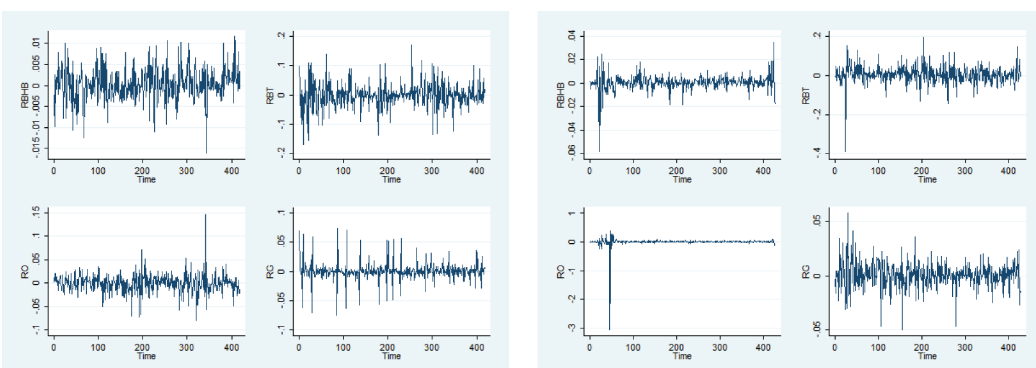


Table 1. Descriptive statistics of returns for Bahrain All Shares Index (RBHB), Bitcoin (RBT), oil (RO), and gold (RG) January 2018–March 2022

	RBHB	RBT	RO	RG
Panel A. Pre-Pandemic				
Mean	.0003056	-.0018454	-.0004508	.0004847
Std. Dev	.0040194	.0427217	.0200768	.015183
Minimum	-.0162227	-.1705056	-.0790372	-.0747577
Maximum	.0117007	.1722998	.1467639	.0740598
Skewness	-.1057664	-.0362389	.482262	.3014721
Kurtosis	3.947905	5.250636	10.92996	12.94923
Jarque-Bera	9.19**	21.68**	68.50**	69.89**
ARCH Test	6.657**	2.706*	2.765*	0.615
ADF Test	-17.898**	-20.648**	-21.127**	-22.913**
PP Test	-18.060**	-20.646**	-21.116**	-25.007**
Observations	418	418	418	418
Panel B. Pandemic				
Mean	.0004609	.003868	-.0059093	.000744
Std. Dev	.006478	.0458717	.1669256	.0118546
Minimum	-.0582476	-.3918161	-3.059661	-.0494685
Maximum	.0348257	.1941374	.3766234	.0578793
Skewness	-1.69357	-1.211728	-15.31641	.0749113
Kurtosis	23.00997	16.54098	270.7011	6.594433
Jarque-Bera	0.00**	0.00**	0.00**	33.79**
ARCH Test	1.905	0.055	11.637**	16.528**
ADF Test	-19.407**	-20.053**	-15.345**	-20.241**
PP Test	-19.509**	-20.044**	-15.081**	-20.264**
Observations	428	428	428	428
Panel C. Whole Period				
Mean	.0003842	.0010451	-.0032123	.0006159
Std. Dev	.0054022	.0444092	.1195276	.0135939
Minimum	-.0582476	-.3918161	-3.059661	-.0747577
Maximum	.0348257	.1941374	.3766234	.0740598
Skewness	-1.477192	-.6767072	-21.13355	.22529
Kurtosis	-1.477192	11.57807	521.641	11.85096
Jarque-Bera	0.00**	0.00**	0.00**	0.00**
ARCH Test	4.817**	0.415	23.545**	3.919**
ADF Test	-26.815**	-28.657**	-21.707**	-30.987**
PP Test	-27.053**	-28.655**	-21.299**	-32.210**
Observations	846	846	846	846

*significant at 0.10 ; **significant at 0.05

Table 2. Correlations belonging to variables used in the model

Variable	BHB	RBT	RO	RG
Panel A. Pre-Pandemic				
BHB	1.00			
RBT	0.553*	1.00		
RO	0.505*	0.453*	1.00	
RG	0.490*	0.435*	0.884*	1.00
Panel B. Pandemic				
BHB	1.00			
RBT	0.0940*	1.00		
RO	0.0871*	0.0864*	1.00	
RG	-0.0200	0.1805*	0.0287	1.00
Panel C. Whole Period				
RBHB	1.00			
RBT	0.0829*	1.00		
RO	0.0751*	0.0618*	1.00	
RG	-0.0084	0.1230*	0.0177	1.00

* Significant at 0.10

test showed that conditional heteroskedasticity is not consistently observed across returns, with RG and RBHB, and RBT having no ARCH effect before and during the pandemic, respectively. This observation would imply that the ARCH model and its variations (e.g., GARCH, GARCH-BEKK) may not be suitable to model return volatility interactions between assets considered in the study. Instead, a vector autoregression (VAR) model may best capture the estimated response to structural shocks among the variables under study.

The pairwise correlation for all time series is presented in Table 2. All observed correlations are only significant at the 10% level, as observed from the same table. The highest correlation can be observed between RG and RO (0.884) before the pandemic, while RG and RBT can be said during the pandemic (0.1805). Overall, the data shows that the markets for the assets observed were more integrated before the pandemic exhibiting higher correlation coefficient values relative to the pandemic period.

Vector Autoregressive Estimation

Lag Length Criterion

The estimation will commence with identifying the number of lags needed to capture the relevant structural component of the VAR. This process is done to ensure that the lag length is not too small that it results in misspecification while not too large that it will result in the waste of degrees of freedom. Therefore, the lag length criterion utilized in this study will have to be less susceptible to sample size and maximizes the possibility of acquiring the real lag length while minimizing the possibility of generating estimates under true value. Thus, final prediction error (FPE) and the Akaike Information Criterion (AIC) were used (Liew, 2004). Table 3 shows the lag length criterion with their corresponding estimates. Following the decision rule mentioned earlier, it is apparent that FPE and AIC are significant in the third lag for both periods. Thus, the lag length selected for the data set was

Table 3. Lag selection criterion

	LL	LR	*df*	*p*	FPE	AIC	HQIC	SBIC
Panel A. Pre-Pandemic								
Lag								
0	4608.34				2.6e-15	-22.2432	-22.2278*	-22.2043*
1	4620.66	24.654	16	0.076	2.6e-15	-22.2254	-22.1485	-22.0309
2	4647.55	53.772	16	0.000	2.5e-15	-22.278	-22.1396	-21.9279
3	4665.01	34.916*	16	0.004	2.5e-15*	-22.285*	-22.0851	-21.7794
4	4673.43	16.837	16	0.396	2.6e-15	-22.2484	-21.9869	-21.5872
Panel B. Pandemic								
0	3684.67				3.4e-13	-17.3616	-17.3465*	-17.3234*
1	3710.32	51.306	16	0.000	3.2e-13	-17.4072	-17.3317	-17.2161
2	3734.16	47.69	16	0.000	3.1e-13	-17.4442	-17.3083	-17.1003
3	3750.9	33.472*	16	0.006	3.1e-13*	-17.447*	-17.2514	-16.951
4	3759.27	16.734	16	0.403	3.2e-13	-17.4116	-17.155	-16.7621

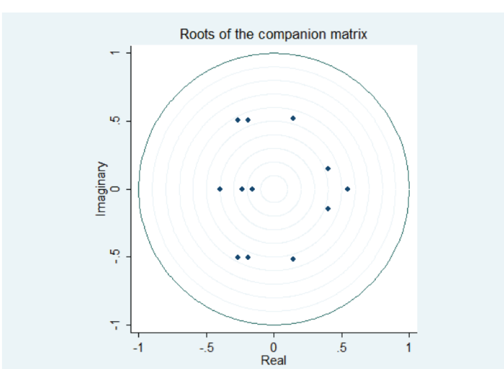
* Endogenous: RBHB RBT RO RG; Exogenous: _cons

3. This result would mean that a VAR (3) multivariate model best fits the structural characteristics of the time series of interest for both the periods before and during the COVID-19 pandemic.

Model Stability and Residual Diagnostics

The model developed in the previous section will have to exhibit system stability. All eigenvalues should lie within the unit circle having modulus values less than one (Lütkepohl, 2005). Therefore, the stability of the VAR model is a prerequisite for the interpretation of the impulse response standard errors. In addition, residual diagnostics will also be conducted using the Lagrange multiplier test to ensure no autocorrelation at the lag orders utilized in the model. Figure 2 shows the eigenvalue stability test of the VAR model specified. The same figure shows that all eigenvalues lie within the unit circle for both periods. Thus, the estimated VAR (3) model exhibits dynamic stability and meets the stationary conditions in a system. The residuals at the model's identified lag order should not

Figure 2. Eigenvalue stability condition pre-pandemic (left) and during pandemic (right)



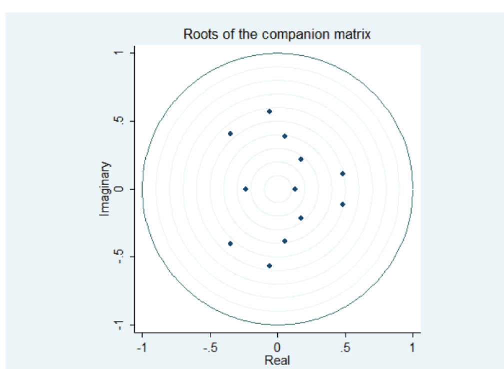


exhibit autocorrelation (Krolzig, 2001). Therefore, the null hypothesis suggests no serial correlation at the identified lag orders. Furthermore, the Lagrange multiplier test in Table 4 shows insufficient evidence to reject the null hypothesis for both periods. Thus, the VAR model developed does not exhibit autocorrelation at three lags and can be used for structural analysis for both periods of interest.

Granger Causality Test

The application of the Granger causality test helps define the causality direction of VAR models by examining the correlation between the present value of a time series and the lagged value of another time series (Sajwan & Chetty, 2018). In this process, the causality of variables may either be unidirectional or bidirectional. The general hypothesis of the Granger causality test is expressed as follows:

$$Y_t = \beta_0 + \sum_{i=l}^{n} \beta_{1i} Y_{t-i} + \sum_{i=l}^{m} \beta_{2i} X_{t-i} + \varepsilon_{1t} \tag{11}$$

$$X_t = \alpha_0 + \sum_{i=l}^{n} \alpha_{1i} Y_{t-i} + \sum_{i=l}^{m} \alpha_{2i} Y_{t-i} + \varepsilon_{1t} \tag{12}$$

where β_{1i} and α_{1i} represents the measures of causation of assets *Y* and *X* return at $t - i$, respectively. Thus, the null hypothesis that asset *X*'s return does not Granger cause the return of Asset *Y* is confirmed when $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$. Similarly, the null hypothesis that *asset Y*'s return does not Granger cause the return of asset *X* is confirmed when $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$. For this study, the causality between RBHB, RBT, RO, and RG will be examined by probing the co-movements of the four variables' time-series of the individual reduced VAR with a recursive VAR, alternately.

It can be seen in the pre-pandemic column in Table 5 that the lagged values of RBHB Granger causes RBT as the computed p-value is significant at the 10% level. It can also be seen that RG Granger causes RO, and RBHB Granger causes RG at the 10% level of significance. Based on the Granger Causality Test during the period before the pandemic, it can be derived that there are three unidirectional causalities: (1) from RBHB to RBT, (2) from RG to RO, and (3) from RBHB to RG.

As may be explained by economic shock, the causality dynamics are illustrated when attention is shifted to the period during the pandemic. Only the Granger causality from RBHB to RG is maintained during the pandemic period at a 10% significance level, while the null hypothesis of no causality is rejected in the direction from RBHB to RO at a 5% level of significance. The previously observed Granger causality of RBHB to RBT and RG to RO was non-existent during the COVID-19 pandemic. For the pandemic period, unidirectional Granger causality is observed at (1) RBHB to RO and (2) RBHB to RG. RBHB tends to have a contemporaneous effect on two of the three comparative markets during and before the pandemic.

Table 4. Lagrange-multiplier test

Step	Pre-Pandemic			Pandemic		
	chi^2	df	Prob > chi^2	chi^2	df	Prob > chi^2
1	18.7973	16	0.27931	13.0974	16	0.66562
2	21.4612	16	0.16146	13.7270	16	0.61904
3	14.3654	16	0.57151	12.3770	16	0.71765

H_0: no autocorrelation at lag order

Table 5. Granger causality Wald tests

Equation	Pre-Pandemic			Prob.	Pandemic		
	Excluded	chi²	*df*		chi²	*df*	Prob.
RBHB	RBT	1.3384	3	0.720	1.0127	3	0.798
	RO	2.4297	3	0.488	.51543	3	0.915
	RG	4.383	3	0.223	11.395	3	0.010
	ALL	8.0368	9	0.530	12.467	9	0.188
RBT	RBHB	7.5421*	3	0.056	5.3643	3	0.147
	RO	2.3879	3	0.496	2.7664	3	0.429
	RG	3.2359	3	0.357	2.4364	3	0.487
	ALL	12.748	9	0.174	12.308	9	0.197
RO	RBHB	1.0564	3	0.788	9.4067**	3	0.024
	RBT	5.009	3	0.171	2.9334	3	0.402
	RG	7.6959*	3	0.053	3.3491	3	0.341
	ALL	13.882	9	0.127	15.014*	9	0.091
RG	RBHB	8.2328*	3	0.041	6.6037*	3	0.086
	RBT	1.5288	3	0.676	4.9773	3	0.173
	RO	3.2846	3	0.350	6.1315	3	0.105
	ALL	13.216	9	0.153	19.634**	9	0.020

With this, we could reject the hypothesis that there is a bidirectional Granger causality between Bahrain stock exchange market returns, Bitcoin, crude oil, and futures gold. While Granger causality was observed with some asset classes' returns, all causality is unidirectional, mainly from the Bahrain stock market for both periods. The persistent unidirectional effect of Bahrain stock returns significantly proves the role of the kingdom's equity market as the primary yardstick for the general economic and financial condition of the country.

Impulse Response Function

The recursive VAR's impulse responses are plotted in Figure 4. Considering that the consistent Granger cause is observed from RBHB, the focus of the analysis will be channeled on IRF RBHB to RBT and RBHB RG pre-pandemic and IRF to RG and RBHB to RO during the pandemic. The response functions are plotted with the 95% confidence bands. While there are multiple IRFs, the analysis will zero in the significant unidirectional Granger cause identified in the previous section.

It can be inferred from Figures 3 and 4 that, while the direction of the mean return spillover from RBHB to the Granger caused markets are relatively similar for both periods, it is apparent that the magnitude shock is relatively greater during the pandemic period. This result supports the study's second hypothesis, which posits that the Granger causality will be more significant during the pandemic. The observation is consistent with Bissoondoyal-Bheenick et al. (2020) and Bouri et al. (2021), who proved that different major asset markets are more connected during periods of crisis. The results prove that the association of markets is not the same across time (Gulzar et al., 2019) and that structural breaks occur depending on the varying levels of economic and financial circumstances.

Looking at Figure 3, the contemporaneous shock caused by RBHB to RBT before the pandemic suggests that a first period/day negative impact of BHBH on RBT is observed. In contrast, a significant asymmetric positive jump in RBT is observed on day three, which eventually dies down to zero in

Figure 3. Impulse response function pre-pandemic

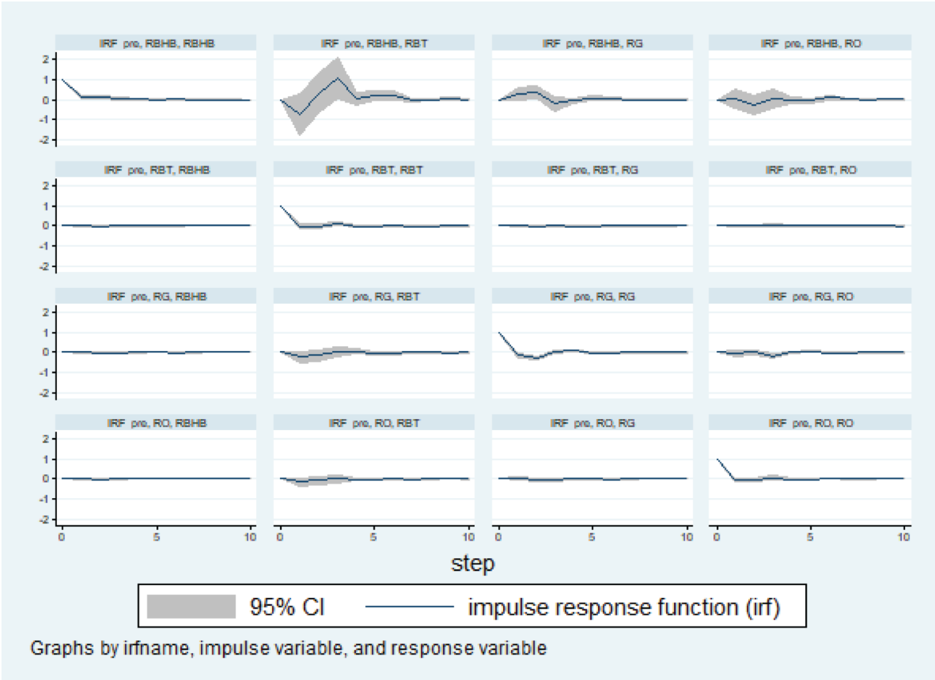
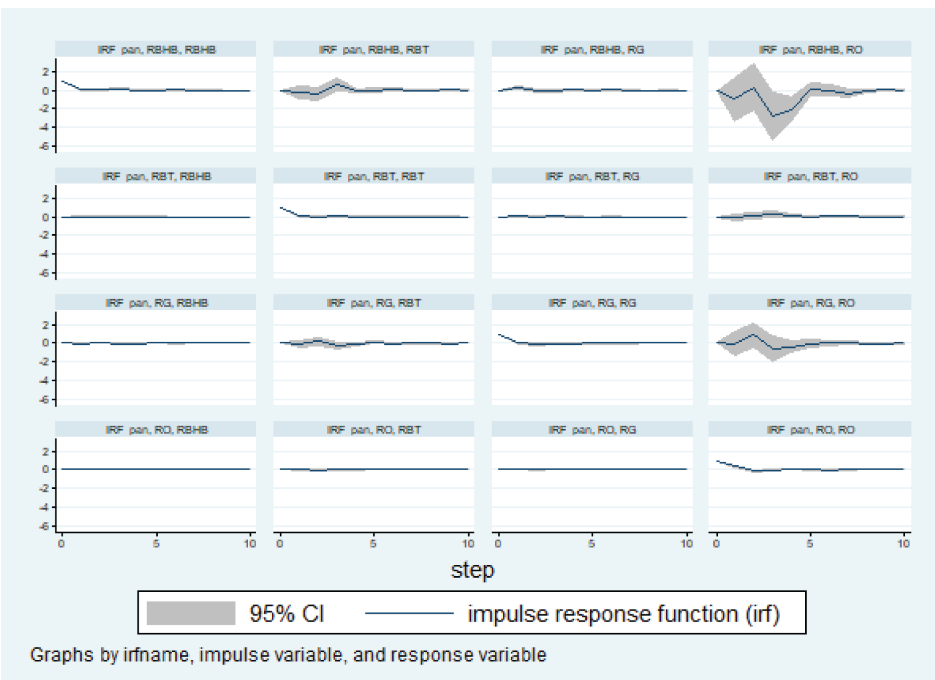


Figure 4. Impulse response function during the pandemic



the fourth period. Furthermore, a brief period of positive impact was observed during Days 5–6, but the impact converges back to zero after that. Finally, a slightly positive impact is observed around day two regarding RBHB to RG before the pandemic, but this immediately dips to less than zero the day after. In summary, the impact of RBHB on both RBT and RG before the pandemic is primarily positive, except for the early period of negative shock on RBT.

On the other hand, the significant negative impact of BHB on RO is glaring, reaching its extreme low around the third period, as seen in Figure 4. This extreme negative impact is a slow response to the previously observed low immediately during the first day. The negative shock eventually decays around Day 5, with a minor dip around Day 7. The exact opposite can be observed in the impact of RBHB on Gold during the pandemic. Looking at the exact figure, not only that the innovation in the stock market of Bahrain has a positive impact on RG, but it is also substantially lesser in magnitude compared to the observed impact on RO during the pandemic period. In summary, it can be said that RBHB has a significantly high negative impact on RO while maintaining a positive contemporaneous effect on RG during the pandemic.

Cholesky Variance Decomposition Matrix

The variance decomposition matrix will show how other variables explain other variables in the non-restrictive VAR model. Put differently, the variance decomposition matrix estimates the extent to which the exogenous shocks of one variable contribute to the forecast error variance of the other variable in the model (Floyd, 2005). The mentioned data are shown in Tables 6 and 7 for the period before and during the pandemic, respectively.

Notice that all variables are stationary at the first step (Day 1) because the Cholesky decomposition imposes no response during the first step or, in the case of the study, Day 1. Also, recall that the returns for all assets are expressed daily, so one step means one day. Moreover, considering that VAR models capture more short-run causal relationships (Kantaphayao & Sukcharoensin, 2021), the forecast decomposition will only expand to 10 days. This observation is supported by the decay of shocks occurring in less than ten days in the IRF for both periods.

Panel 1 in Table 6 shows the variance decomposition of RBT under VAR (3) with three endogenous variables: RBHB, RO, and RG. The results in the same panel show that, before the pandemic, 96.35% of the variation in RBT within the ten days is due to its own shock. Looking at

Table 6. Cholesky variance decomposition and forecast error decomposition pre-pandemic

	Panel 1. Variance Decomposition of RBT				Panel 2. Variance Decomposition of RO				Panel 3. Variance Decomposition of RG			
Step	RBHB*	RBT	RO	RG	RBHB	RBT	RO	RG*	RBHB*	RBT	RO	RG
0	0	0	0	0	0	0	0	0	0	0	0	0
1	0.005619	0.994381	0	0	0.000146	0.000167	0.999687	0	3.20E-06	0.001101	0.000068	0.998828
2	0.010497	0.979954	0.004563	0.004986	0.00029	0.003163	0.995244	0.001303	0.005624	0.001095	0.000491	0.992791
3	0.011245	0.976263	0.005651	0.006841	0.003104	0.004325	0.991058	0.001513	0.014431	0.00136	0.002978	0.981231
4	0.022286	0.965275	0.005696	0.006743	0.003242	0.009688	0.970912	0.016158	0.016999	0.004656	0.007696	0.970649
5	0.022285	0.964739	0.005762	0.007215	0.003276	0.009704	0.970773	0.016247	0.017262	0.004681	0.008215	0.969842
6	0.02256	0.96433	0.005809	0.0073	0.003381	0.009694	0.969039	0.017885	0.017518	0.005018	0.008788	0.968676
7	0.022908	0.963651	0.005826	0.007615	0.003707	0.00973	0.968513	0.01805	0.017619	0.00502	0.008931	0.96843
8	0.022911	0.963621	0.00584	0.007628	0.003725	0.009729	0.968385	0.018161	0.017637	0.005042	0.008958	0.968362
9	0.022911	0.963608	0.00584	0.007642	0.00373	0.009732	0.968358	0.01818	0.017638	0.005043	0.008968	0.968351
10	0.022925	0.963577	0.005847	0.007651	0.003732	0.009734	0.968354	0.01818	0.017638	0.005043	0.008968	0.96835

* Exogenous variable with significant Granger causality

the unidirectional Granger causality from RBHB, which was found significant, the same panel shows that RBHB can explain 2.29% of the 10-day shock in RBT.

On the other hand, Panel 2 of Table 6 shows the variance decomposition of RO 10 days before the pandemic. The innovations within the same time series cause 96.83% of RO fluctuations. Moreover, the significant Granger causality from RG explains 1.8% of RO changes. The final panel in Table 6 shows the variance decomposition of RG before the pandemic. The results show that its shock causes 96.83% of the variations within the system, while 1.7% of the changes in the same are accounted for the significant Granger causality from RBHB.

Table 7 shows the Cholesky variance decomposition matrix for the period of the COVID-19 pandemic involving the response variables that were found to exhibit Granger causality with another endogenous variable in the unrestricted VAR (3) model. Panel 1 of Table 7 shows the variance decomposition of RO during the pandemic. Of the total fluctuations in RO within the ten days, 96% account for its shock, while 2.3% can be traced to the significant Granger causality from RBHB.

Finally, Panel 2 of Table 7 shows the Cholesky variance decomposition of RG during the pandemic. As can be seen from the same panel, 92.63% of the shocks in RG within the ten days can be explained by its innovations, while 1.9% of the variations can be traced to the significant Granger causality from RBHB.

DISCUSSION AND RESEARCH IMPLICATIONS

It has been established that the results of this investigation would provide fresh empirical evidence on the varying degree and direction of spillover across different asset classes, including Bahrain stocks and bitcoins. Furthermore, this investigation is done to shed light on developing policies for market regulation and investment and portfolio management. Therefore, it is essential to discuss the findings' theoretical and practical implications with the results. First, the findings showed that the Granger causality for both periods is transmitted primarily from the Bahrain stock market to most of the assets under investigation except for the association of the gold market to the oil market prior to the COVID-19 crisis. In addition, there was no bidirectional causality observed for both periods. This result is not consistent with Arouri and Rault (2010). They found

Table 7. Cholesky variance decomposition and forecast error decomposition, during the pandemic

Step	Panel 1. Variance Decomposition of RO				Panel 2. Variance Decomposition of RG			
	RBHB*	RBT	RO	RG	RBHB*	RBT	RO	RG
0	0	0	0	0	0	0	0	0
1	0.009374	0.005107	0.98552	0	0.000141	0.031874	0.000293	0.967692
2	0.008166	0.004484	0.987343	7.40E-06	0.015068	0.036937	0.003131	0.944864
3	0.008019	0.004662	0.983822	0.003497	0.018585	0.036371	0.010553	0.934491
4	0.018228	0.010428	0.96628	0.005064	0.018888	0.040969	0.012871	0.927272
5	0.023055	0.010722	0.960579	0.005644	0.018937	0.040927	0.01335	0.926786
6	0.023057	0.010766	0.960516	0.005661	0.018933	0.041069	0.013366	0.926632
7	0.023053	0.010768	0.960519	0.00566	0.019125	0.04106	0.013444	0.926371
8	0.023217	0.010806	0.960314	0.005664	0.019125	0.04106	0.013447	0.926368
9	0.023223	0.010805	0.960308	0.005664	0.01913	0.04106	0.013451	0.926359
10	0.023223	0.010807	0.960303	0.005665	0.019136	0.04106	0.013452	0.926352

* Exogenous variable with significant Granger causality

significant bi-directional causality in stocks and oil prices, at least in an oil-importing country like Saudi Arabia. However, the observed unidirectional causality from Bahrain stocks to crude oil was only significant during the pandemic, together with gold. A possible explanation would be that the demand for crude oil and gold is sensitive to macroeconomic conditions that are significantly associated with stock prices (Zeng et al., 2020). Moreover, the persistent Granger causality observed between Bahrain stocks and gold strongly suggests that gold is not a viable hedging asset against general equity market conditions in Bahrain.

Another significant finding of the study is associated with the dynamics of the causality of asset prices dependent on the varying levels of economic and financial circumstances, which is consistent with the findings of previous studies (Bissoondoyal-Bheenick et al., 2020); Bouri et al., 2021); Gulzar et al., 2019). This observation has significant implications for market regulation and investment and portfolio management. First, the assumption that bitcoins are safety havens during periods of crisis (Trabelsi, 2018; Bissoondoyal-Bheenick et al., 2020; Naeem et al., 2021; Demir et al., 2018) is supported by this study.

This observation proves that bitcoins exhibit varying responses to different economic events (Qarni et al., 2019,) which could value portfolio managers who want to exploit the observed return spillover dynamics for strategic hedging. However, the same cannot be said during normal conditions, as Bitcoins were sensitive to innovations in the Bahrain stock market before the pandemic, not supporting several studies like those of Corbet et al. (2018) and Trabelsi (2018), among others. In addition, since the short-term spillover from the Bahrain stock market to the bitcoins market is supported, the analysis used in evaluating the fundamental movements of the stock market could also be applied in the Bitcoin market. Furthermore, the movements in the Bahrain market could serve as a valuable signal for those trading in the bitcoin market—at least in terms of trading.

Finally, the observed independence of Bahrain's stock market returns from the crude oil market prior to the pandemic and the unidirectional shock measured from the former to the latter suggests that the Kingdom's economic policy to lessen its dependence on oil is paying off. The mentioned findings significantly differ from the results obtained by Arouri, Lahiani, and Nguyen (2011). They compared the spillovers of oil and stock prices across GCC countries during and after the 2008 Financial crisis. While the authors found significant spillover effects between oil prices and stock returns of Bahrain for both periods, this cannot be said anymore based on the findings of this study. In addition, the unidirectional spillover from Bahrain stocks to crude oil prices suggests the dominance of the Bahrain stock market over other markets, including crude oil. A possible explanation for the independence of Bahrain's stock market from oil prices during regular periods is offered by the same authors (Arouri et al., 2011), pointing to the role of increasing presence in the stock market of companies in the banking and service sectors similar to Kuwait. However, policymakers should be cautious of the dominance of financial firms in the stock market as a factor in price and volatility spillovers during crises (Akhtaruzzaman, Boubaker, & Sensoy, 2021). As aptly demonstrated in the results of this study, the Granger causality between Bahrain stocks and crude oil prices seems to be apparent only during the pandemic. Thus, market regulators should be mindful that while policies that increase the dominance of banking financial services in the stock market improve independence from the oil market during normal periods, the same policy does the exact opposite during crises.

While several explanations could be attributed to the mentioned observation, one possible explanation could be the susceptibility of economies that experience a faster pace of financial deepening. These economies are more exposed to greater risk during crises (Beck, 2014). Thus, during crises, an economy has no choice but to revert to its primary industry (oil) when the benefits of financial deepening fail. The results of this study may suggest that if an economy aims to be less reliant on oil and be more sustainable, other sectors, such as agriculture, are better alternatives.

CONCLUSION

This study offers fresh empirical evidence of the dynamics of market spillover during regular periods and periods of crisis. The authors argue that the information derived from the investigation holds tremendous value for policymakers and investment managers alike. The study concludes that Granger causality is unidirectional in which shocks from Bahrain's equity market persistently explain the shocks of most of the leading asset markets, including Bitcoins, at least during normal conditions. The study also concludes that return spillover is more significant during crises exhibiting conditional spillover effects. Considering the presence of crises, the varying effect of the Bahrain stock market returns on gold, bitcoin, and oil is helpful to policymakers and investment managers in designing strategies and policies that will serve their respective interests. Future studies may consider conducting a further study on the role of banking and financial services sectors in the dynamics of return spillover using different countries' markets.

DATA AVAILABILITY STATEMENT

The datasets generated by the survey research and analyzed during the current study are publicly available in the Investing.com repository at https://www.investing.com.

COMPETING INTERESTS

The authors have no competing interests to declare relevant to this article's content.

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