Understanding the Dynamic Correlation between Bitcoin, Gold, Oil, and Stock Market Indices in the selected Arab countries: Application of the DCC-GARCH Model to the Banking and Insurance Sectors

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Table of contents

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Abstract

Understanding the association between virtual assets and other financial assets is attracting the attention of global investors, regulators, and market analysts alike. Since crypto assets and equity markets move in tandem, shocks and financial instability are transmitted, and low correlation offers portfolio diversification and risk management opportunities. In this study, the primary objective is to examine the dynamic conditional variance among Bitcoin, gold, oil, and stock market indices in the Arab world over the period of 05/01/2016 to 11/11/2021 using dynamic conditional correlation DCC-GARCH model, with a special focus on banking and insurance sectors. The overall findings of the study suggest that a variety of financial assets (including bitcoin currency, gold, and oil) have varying conditional variance associations in relation to stock market returns in different countries in the Arab region. Further, the findings show that the conditional variance of Bitcoin currency market returns is statistically insignificant when compared with most stock markets conditional variances indices in the Arab region. These findings have implications for portfolio managers operating in the Arab region who are inclined to construct their portfolios by utilizing a diverse set of assets from different countries in the region. For decision makers, these results are critical for monitoring the use of cryptocurrency dealers, especially since many Arab countries prohibit the trading of Bitcoin.

Keywords: Bitcoin, Gold, oil, stock market indices, banking sector, insurance sector, Arab region, DCC GARCH model.

1. Introduction

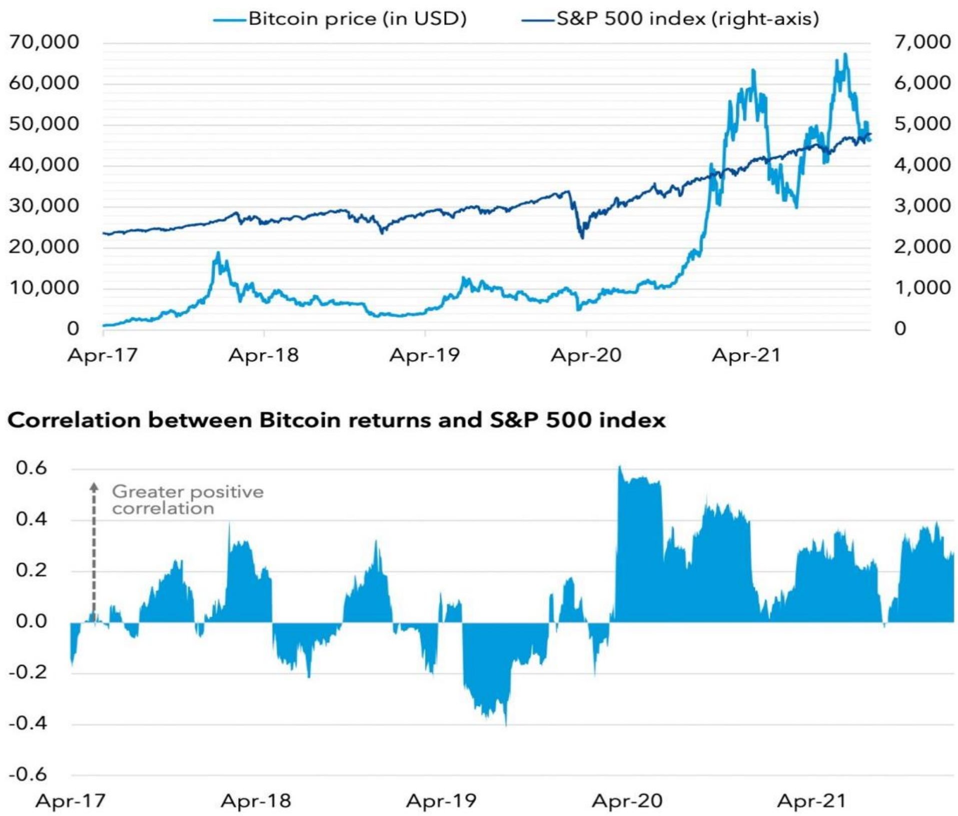
As the world experiences dramatic technological progress, the financial sector has been able to take advantage of these advancements. Cryptocurrencies, as a by-product of technological advancement, could be seen as a valuable contribution to financial markets and the global economy. Among all cryptocurrencies, Bitcoin has the most famed market capitalization, estimated at $930 billion on 28th December 2021 (CoinMarketCap, 2021) [1]. The exchange or trade in Bitcoin and other types of cryptocurrencies has become very widespread in financial markets around the world and gained the attention of practitioners. Equally, cryptocurrencies and their interactions with financial markets indicators have earned the interest of market research analysts. A major part of technological progress in recent years has been used by the financial sector. As a by-product of technological advancement, cryptocurrency can be viewed as a valuable contribution to financial markets and the world economy. The exchange or trade in Bitcoin and other types of cryptocurrencies has become common in financial markets around the world and attracted practitioners. Financial analysts are equally interested in cryptocurrencies and their interactions with financial market indicators.

There have been several studies investigating the relationship between oil prices and stock markets (Jiang and Yoon, 2020), and gold prices and stock markets (Ghorbel and Jeribi, 2021). It is interesting to see that there is a strong correlation between energy prices and financial assets regardless of the COVID-19 period. The degree of independence of commodity prices, cryptocurrencies, and financial markets may vary depending on the country and economic conditions. As an example, gold is perceived as a safe-haven investment because it has the ability to hedge risks, especially in times of crisis (Kakinuma, 2021; Ghorbel and Jeribi, 2021). In spite of this, Bouri et al. (2020) found evidence supporting Bitcoin as a superior investment compared with gold and stock returns. Accordingly, investment portfolios are getting increasingly diversified or changed as a result of shifting investor perspectives due to the changes the world is experiencing, which affects the economy and hence returns on investment.

As a consequence of co-movements between virtual assets and stock indices, new risks arise in the stock market and real assets market as a result of volatility transmission from the wildly volatile cryptocurrency market. In contrast, if the correlation is weak, the benefits of diversification between crypto assets and stocks increase, as opposed to if the correlation is strong, which reduces the benefits of diversification. As shown in the figure (1), the daily correlation between the S&P 50 and bitcoin was 0.01 during the 2017-2019 period, but this coefficient increased to 0.36 during the period 2020-2021, and on the level of emerging markets, the correlation between returns on the MSCI Emerging Markets Index and bitcoin was 0.34 in 2020-2021, an increase of 17 times that of previous years. In terms of volatility, Bitcoin's volatility explains about one-sixth of the S&P 50's volatility during the pandemic and about a tenth during other periods. The relationship between the stock market and the crypto market is also about the same size.

[1] https://coinmarketcap.com/

Figure 1: Correlation Between Bitcoin Price Index and S&P 500 Index



Source: https://blogs.imf.org (12/01/2021)

When the stock market and the high crypto market co-move at a time of high volatility, dealers' behavior is transferred from one market to another, destabilizing the stock market, particularly in countries that adopt crypto on a large scale. In light of this situation, decision makers should adopt a compliant and coordinated global regulatory framework that will guide regulation and supervision. This will ensure that financial stability will be enhanced as a result. Therefore, the current study investigates the co-movement among Bitcoin, gold, oil, and stock market returns. A focus will be placed on the stock market returns of the banking and insurance sectors in selected Arab countries.

Following are the ways in which the current study contributes to the body of literature. An analysis of the interdependency of Bitcoin, gold, oil, and stock market returns is quite relevant to both academics and investors, given recent evidence that Bitcoin and gold commodities are safe-haven investments. Additionally, the study explores the stock market returns of financial institutions, including the banking and insurance sectors, which is highly relevant to those industries. As a third goal, the study seeks to shed light on the relationship between equity returns and Bitcoins, gold, and oil prices in the Arab region, considering the lack of studies in this area. To achieve the study's objectives, GARCH was used as an innovative conditional correlation method.

The remainder of our study is organized as follows. In section 2, we review relevant empirical literature. The data used in Section 3 and its sources, together with the econometric methodology, are explained. In Section 4, the empirical findings are discussed considering the related studies. Section 5 concludes the analysis and provides some recommendations for policy and future research.

2. Literature review

The last decade has witnessed the emergence of various financial technological innovations such as cryptocurrency that is shown to be quite useful in many aspects, and most importantly as a medium of exchange. Recently, various cryptocurrencies have shown a massive increase in their attractiveness and market capitalization due to the great demand by individuals and institutions, however, the markets for crypto are quite volatile (Goel and Mittal, 2020; Tanwar et al., 2021; Singh and Singh, 2021). The word cryptocurrency emerges from crypto which means encryption and currency. The cryptocurrency was developed using blockchain technology that provides a secure platform, and the transactions are recorded into every computer as a digital medium (Islam et al., 2021). Although there might be some challenges limiting cryptocurrency from being more widely accepted as a method of payment such as legal, economic, and social factors, the outcomes of distributed ledger technologies could be the optimal allocation of resources (Ather et al., 2021). Therefore, the macroeconomic consequences and mechanism of cryptocurrency, and the legal aspects of digital currency are becoming main concerns for researchers and policymakers (Yue et al., 2021).

As a new trend of new investments, many individuals new or old investors started to participate in buying and selling cryptocurrencies (Zhao and Zhang, 2021). Aslan (2021) suggested that the cryptocurrencies risk spillovers to the financial markets are sensitive to economic slowdowns and perhaps to social and political events. During the COVID-19 crisis most of the stock markets have been affected negatively, and therefore, many investors are looking for safe alternatives. In the same context, Gunawan and Anggono (2021) attempted to explore whether cryptocurrency could be safe assets compared to the stock market in Indonesia during the period of COVID-19 using GARCH and DCC-GARCH models. Their findings predicted that the most profitable asset was "Bitcoin" and the riskiest one was "Ripple". The authors argued that the cryptocurrency was not a safe-haven investment, at least in the case of Indonesia.

It is widely believed that the volatility of energy prices is strongly linked to financial assets during the COVID-19 crisis. In a study conducted by Ghorbel and Jeribi (2021), the interconnection among stock indexes, Bitcoin, Gold, and energy assets was studied in the G7 countries using a Markov–Switching GARCH model. Their results revealed that volatility spillover effect from energy to financial assets especially during the era of COVID-19. Moreover, they argued that investing in Gold is a safe haven for all energy and financial assets during the COVID-19 crisis. Nevertheless, cryptocurrencies such as Bitcoin were considered high-risk investments, especially during the study period. Moreover, Kakinuma (2021) tested spillover effects between return and volatility in the Southeast Asian stock markets (Singapore and Thailand), i.e., bitcoin and gold before and during the COVID-19 pandemic period. The findings revealed that bitcoin and gold were interdependent during the pandemic and the contagion effect was unavoidable. Overall, the results suggested that gold assets be less risker compared to bitcoin. Another study conducted by Caferra and Vidal-Tomás (2021) investigated the performance of cryptocurrencies and stock markets throughout the COVID-19 crisis using autoregressive Markov switching. Their results showed evidence of financial contagion initially, as cryptocurrency and stock prices dropped sharply. However, the cryptocurrency prices have recovered, unlike stock prices.

Ho (2020) aimed to show how the cryptocurrency in a country affects the value of stocks exchanged. The study suggested that the development of cryptocurrency has led to a structural change in the financial sector after examining 67,166-panel data sets from stock markets in China and Taiwan. The study pointed out that the Chinese stocks markets experience substantially higher effects from the cryptocurrency exposure than the markets in Taiwan. Furthermore, Singh and Singh (2021) examined the relationship between the value of Bitcoin and the Dow Jones Industrial Index. They found that there was a strong association between cryptocurrency and stock prices, which suggested the possibility of an entry and exit strategy for capitalizing on cryptocurrencies. However, Wang et al. (2021) suggested potential asymmetric contagion effects between cryptocurrency and stock markets. The findings provided intuitions on risk hedging in establishing portfolios.

Several new studies have explored the link between cryptocurrency and the performance of stock markets. For example, Sami and Abdallah (2020) investigated how cryptocurrency affects the performance of the stock markets in MENA countries using daily data between 2014 – 2018. The study used panel cointegration analysis to examine the effect of cryptocurrency volume, cryptocurrency returns, and other control variables on the stock market performance. Their instrumental variable technique results showed that both measures of cryptocurrency (volume and returns) are negatively linked to the performance of the stock market in the Gulf countries. However, for non-Gulf countries, the cryptocurrency returns affected the stock market negatively, whereas the effect of cryptocurrency volume was insignificant.

The current study aims to further highlight the relationship between volatility of crypto currencies, gold, oil, stock market index, bank sector stock index, and insurance sector stock index in the Arab countries in the first section, in the second section we present the literature review, in the third section the data and methodology. The fourth section we analysis the results, finally in the fifth section conclusion and recommendation for further research.

3. Data and methodology

3.1. Data

The study's data consists of the daily stock market general indices of selected Arab countries, specifically indices for the banking and insurance sectors, as well as the daily market returns for Bitcoin, gold and oil price from 05/01/2016 to 11/11/2021. These data were collected from www.coindesk.com and finance.yahoo.com. An analysis of the proposed relationship between the variables under study was conducted using the dynamic conditional correlation Generalized Autoregressive Conditional Heteroscidasticity DCC GARCH model.

3.2. The econometric model

Engle & Bollerslev (1986) developed the univariate GARCH model. Since GARCH allows for conditional variances to be dependant on previous own lags, the conditional variance equation can be written as follows:

$$y_t = \sigma_t \ \varepsilon_t \qquad (01)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (02)$$

Where

y_t: the expected value of series.

ε_t: the standard error, its IID,

σ_t : the conditional standard deviation.

GARCH multivariate model and Dynamic Conditional Correlation model (DCC-GARCH (p.q)) are part of the class of models of variances and correlations with conditional variances (see NAAS et al., 2021). Engle and Sheppard (2001) proposed this model, which decomposes the covariance matrix into conditional standard deviations, Dt, and a correlation matrix, Rt. In the DCC-GARCH model both D_t and R_t are designed to be time-varying (Brooks, 2014, p. 428).

The Dynamic Conditional Correlation (DCC) GARCH model is defined as:

$$r_t = \mu_t + \varepsilon_t \qquad (03)$$

$$\varepsilon_t = {H_t}^{1/2} z_t \qquad (04)$$

$$H_t = D_t R_t D_t \qquad (05)$$

where :

μ_t: Vector (n×1) of conditional expectation of Y_t at t,

ε_t: Vector (n×1) conditionals errors of n actifs at t, with E(ε_t)=0 and Cov(ε_t)= H_t.

H_t: is the matrix (n×n) of conditional variances and covariances of ε_t at t,

D_t: diagonal matrix (n×n) of conditional standard errors of εt at t, which is always positive,

R_t: Matrix (n×n) of conditional correlations of εt at t.

The DCC-GARCH (1.1) model is based on the hypothesis that the conditional (Orskaug E, 2009,pp 15) returns are normally distributed with zero mean and conditional covariance matrix $H_t = E[r_t r_t' | I_t - 1]$ the covariance matrix is expressed as follow:

$$H_t = D_t R_t D_t$$

Where $D_t = diag\left[\sqrt{h_{1t}}, \sqrt{h_{2t}}\right]$ is a diagonal matrix of time-varying standard deviations issued from the estimation of univariate GARCH processes:

$$H_{i,t} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{t-1} \qquad (06)$$

Where ω_i is a constant term, $\alpha_i$captures the ARCH effect, i.e., conditional volatility and $\beta_i$measures the persistent of the volatility.

R_t is the conditional correlation matrix of the standardized returns ε_t, with $\varepsilon_t = D_t^{-1} r_t$

$$R_t = \begin{bmatrix} 1 & q_{21t} \\ q_{21t} & 1 \end{bmatrix} \qquad (07)$$

This matrix is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (08)$$

With Q_t is the positive definite matrix containing the conditional variances-covariances of ε_t, and Q_t^{*-1} is the inverted diagonal matrix with the square root of the diagonal elements of Q_t:

$$Q_t = \begin{bmatrix} q_{11t} & 0 \\ 0 & q_{22t} \end{bmatrix} \qquad (09)$$

$$Q_t^{*-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & 0 \\ 0 & 1/\sqrt{q_{22t}} \end{bmatrix} \qquad (10)$$

We can write the DCC-GARCH (1,1) as follow:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} + \beta Q_{t-1} \qquad (11)$$

Where: $\omega = (1 - \alpha - \beta)\bar{Q}$ and,

Q_t is treated as the second moment of ε_t, and is peroxide by the sample moment of the estimated returns in large systems. (Creti et al, 2013 , pp 19)

4. Findings and Analysis

4.1. Descriptive statistics

Table (1) summarizes the logarithmic returns for Bitcoin currency, Gold, Oil, and stock market indices of selected countries: the UAE (Abu Dhabi and Dubai), Amman, Bahrain, Kuwait, Morocco, Oman, Palestine, Qatar, Saudi Arabia, And Tunisia. The selected series of variables data show diversity in returns, volatility (standard deviation), and normality distribution. Bitcoin currency experienced the highest average return of 0.00513 of the selected variables, while the Abu-Dhabi stock market had the highest average return of 0.00069 among the selected countries, while the Oman stock market recorded the lowest return of -0.00064. Standard deviation is a measure of a variable's risk or volatility. Bitcoin currency has the highest standard deviation at 0.06091, followed by the oil and gold return index, which have values of 0.02869 and 0.01615, respectively. This indicates that bitcoin returns are more volatile than those of other assets like gold or oil, as well as those of selected stock market indices for chosen countries. In addition, the standard deviation of Kuwait's stock market returns is 0.01573, which is the highest among the selected countries; meanwhile, the standard deviation of the Palestine stock market returns of 0.00555 is the lowest among the selected countries. Furthermore, the Kuwait stock market returns are subjected to the highest standard deviation of 0.01573 among selected countries, while the Palestine stock market returns are subjected to the lowest standard deviation of 0.00555. In Table (1) the skewness values indicate that the variable series distribution is not normally distributed as they exceed the rule (-1 to +1) as recommended by Hair et al. (2006), except for Bitcoin, Gold, and the stock market return of Oman and Palestine. Also, all stock market return series presented in Table (1) are negatively skewed, except for Amman's stock market return, indicating overall weak performance during the study period and asymmetry in the given return series. Furthermore, the kurtosis values, which are a measure of the fatness of the tails, the number of values is greater than the rule of thumb of 3 that Stock and Watson (2006) recommend, which confirms that the data are not normally distributed. The Jarque-Bera normality test rejects the null hypothesis of normality at a significance level of 1% for the variables under study.

In Table (2), we report the logarithmic returns of the Bitcoin currency, Gold, Oil, and banks' stock market indices of selected countries, including the United Arab Emirates (Dubai and Abu Dhabi), Amman, Bahrain, Kuwait, Morocco, Oman, Palestine, Qatar, Saudi Arabia, And Tunisia. With the exception of the Amman banks' stock market that records a negative mean of -0.00012, all the selected variables show positive means. A return of 0.0048 on the Bitcoin currency was the greatest among the selected variables, whereas a return of -0.00012 was the lowest and recorded on the Oman bank's stock market. According to the standard deviation and volatility, Bitcoin currency has the highest standard deviation, with a value of 0.06141, followed by gold and oil return indices at 0.02913 and 0.01647, respectively. These results indicate bitcoin returns are volatile in comparison to other assets such as gold and oil and selected Banks' stock market indices for specific countries. In addition, 0.01676 is the standard deviation of Abu Dhabi banks' stock market returns, which is the highest among these selected countries. On the other hand, 0.00639 represents the standard deviation of Palestine banks' stock market returns which was the lowest among selected countries. In Table (2), the skewness values indicate that the variable series distributions are not normally distributed, except for bitcoin, gold, and the stock market returns for Oman and Palestine, as well as Tunisia, which are found to be normally distributed. In addition, the skewness test indicates that all stock market return series are negatively skewed, except for Amman's stock market return, and Bitcoin and gold return indexes have positive signs. According to Table (2), all variables under study have kurtosis values greater than 3, which confirms that the series returns of the variables are not normally distributed. With Jarque-Bera normality testing, the null hypothesis of normality for all variables is rejected also at a significance level of 1%.

In Table (3), we report the logarithmic returns of the Bitcoin currency, Gold, Oil, and Insurance stock market indices of selected countries, including the United Arab Emirates (Dubai and Abu Dhabi), Kuwait, Morocco, Palestine, Qatar, Saudi Arabia, Tunisia. Table (3) displays that unless the Qatar Insurance stock market shows a negative mean of -0.00056, all the other selected variables show positive means. Similarly, a return of 0.00603 on the Bitcoin currency was the highest among the variables under study, whereas a return of -0.00056 on Qatar insurance's stock market was the lowest. In the same manner, Table (3) indicates that Bitcoin currency has the highest standard deviation, with a value of 0.06465, followed by gold and oil return indices at 0.0318 and 0.01749, respectively. By using the standard deviation values shown in Table (3), the results suggest that bitcoin returns, oil, and gold have higher volatility than selected insurance stock market indices for specific countries. In addition, in order to compare the level of volatility of Insurance stock markets across selected countries, Table (3) indicates that Saudi Arabia had the highest standard deviation followed by Qatar and Dubai with statistical values of 0.01994, 0.01914, and 0.01734, respectively. The skewness values in Table (3) indicate that most of the variable data are not normally distributed, except for Bitcoin and the stock market returns of Dubai, Kuwait, Palestine, Qatar, Saudi Arabia, and Tunisia, which are found to be normally distributed. Further, the skewness test reveals a variety of skewed indicators, such as Bitcoin, gold, the insurance stock market returns of Abu Dhabi, Dubai, Kuwait, Palestine, and Tunisia, all of which are positively skewed, while variables such as the oil return and the insurance stock market returns for Morocco, Qatar, and Saudi Arabia are negatively skewed. Further, according to Table (3), the kurtosis value for all variables is greater than 3, indicating that the returns for all variables are not normally distributed. More so, at a 1% significance level, Jarque-Bera normality testing also rejects the null hypothesis of normality for all variables under study.

4.2. ARCH effect Results

The presence of the ARCH effect in the return series is captured by the parameters in equation (1) and a prerequisite for using the univariate and multivariate GARCH models. From the last line of the table (1), that the ARCH test is statistically significant at the level 1, 5 and 10 percent, of all stock indices of the studied Arab countries, as well as for oil, gold, and bitcoin. The same result is also observed at the level of the banking sector and the insurance sector, in the last line of the table (2) and the table (3) respectively, where the presence of ARCH effect in the series of returns.

4.3. Volatility Clustering Analysis

Figure 1 shows a graphic representation of the volatility structure of the variables under study. The figure shows that the return series for bitcoin, gold, oil, and stock markets for selected countries show clustering of volatility over the study period. A long period of high volatility follows a long period of low volatility. The reverse is also true. Time varies rather than being constant for all variables' return series. Specifically, Figure 2 illustrates the varying volatility of Bitcoin, gold, oil, and stock market returns for each selected country. According to Figure 2, Bitcoin, oil, and gold returns are generally more volatile than stock market returns for the selected countries. Figure 2 shows high volatility in 2020, particularly during the global pandemic crisis.

Table (1): Descriptive Statistics for Bitcoin, Gold, Oil, and **overall** stock market return indices for selected countries

	BITCOIN	GOLD	OIL	ABU	AMMAN	BAHRAIN	DUBAI	KUWAIT	MOROCCO	OMAN	PALESTINE	QATAR	SAUDI	TUNISIA
Mean	**0.00513**	0.00051	0.00082	0.00069	0.00000	0.0004	0.00002	0.00036	0.00042	-0.00064	0.00016	0.00019	0.00058	0.00033
Median	0.00325	0.00049	0.00231	0.00067	-0.00009	0.0003	-0.00004	0.00088	0.00026	-0.00047	-0.00002	0.00033	0.00071	0.00019
Maximum	0.52545	0.14352	0.13374	0.14959	0.06321	0.03348	0.07064	0.09391	0.05305	0.0269	0.04605	0.05368	0.10265	0.0302
Minimum	-0.45456	-0.10033	-0.37493	-0.17711	-0.0743	-0.10801	-0.18089	-0.30396	-0.16694	-0.08053	-0.06233	-0.13175	-0.16755	-0.0849
Std. Dev.	0.06091	0.01615	0.02869	0.01323	0.00654	0.00761	0.01441	0.01573	0.00953	0.00667	0.00555	0.01238	0.01402	0.00617
Skewness	0.12546	0.37054	-2.46122	-2.19476	0.27321	-5.35434	-3.74309	-10.39899	-5.9141	-2.55563	-0.70824	-1.98127	-2.01826	-2.7976
Kurtosis	16.66915	16.2693	35.19807	65.41339	35.56906	75.23788	49.58864	185.1361	109.8868	30.93704	27.24507	23.30473	32.2463	42.91395
Jarque-Bera	7600.9***	7182.6***	43145.1***	159197.8***	43149.1***	216874.8***	90546.1***	1366649***	470297.8***	32801.88***	23986.4***	17404.6***	35446.6***	66060.1***
Observations	976	976	976	976	976	976	976	976	976	976	976	976	976	976
ARCH effect	98.636***	179.427***	11.964***	170.367***	6.404**	47.496***	5.741*	4.341*	28.174***	3.973*	16.548***	8.610***	45.094***	3.375*

Significant at: ***1, * *5, and * 10 percent levels.

Table (2): Descriptive Statistics for Bitcoin, Gold, Oil, and overall stock market return indices in **Banking** industry for selected countries

	BITCOIN	GOLD	OIL	ABU DHABI	AMMAN	BAHRAIN	DUBAI	KUWAIT	MOROCCO	OMAN	PALESTINE	QATAR	SAUDI ARABIA	TUNISIA
Mean	0.0048	0.00048	0.00079	0.00037	-0.00012	0.00041	0.00021	0.00051	0.00018	0.00000	0.00007	0.00054	0.00082	0.00029
Median	0.0032	0.00046	0.00244	0.0004	-0.00011	0.00039	0.00014	0.0008	0.00000	-0.00035	0.00000	0.0005	0.00066	-0.00004
Maximum	0.52545	0.14352	0.13374	0.12282	0.09527	0.04309	0.07443	0.05514	0.06564	0.06414	0.03612	0.05302	0.09178	0.04357
Minimum	-0.45456	-0.10033	-0.37493	-0.1994	-0.08643	-0.14404	-0.18199	-0.1965	-0.1766	-0.0666	-0.048	-0.13673	-0.18204	-0.07725
Std. Dev.	0.06141	0.01647	0.02913	0.01676	0.00809	0.01158	0.01492	0.0132	0.01181	0.00868	0.00639	0.01329	0.01639	0.00833
Skewness	0.11909	0.38176	-2.5015	-1.96973	1.32554	-4.0118	-3.34139	-4.98232	-4.60649	-0.43991	-0.1968	-1.46589	-1.53144	-0.46787
Kurtosis	17.03582	15.97621	35.1792	39.22918	46.42169	51.3912	47.47548	69.07287	70.90462	17.66595	12.27901	18.96073	24.57563	16.41473
J-Bera	7529.3***	6455.8***	40521.1***	50743.4***	72308.1***	91932.5***	77285.1***	170597.1***	179423.1***	8247.8***	3295.6***	10061.7***	18144.7***	6909.2***
Observations	917	917	917	917	917	917	917	917	917	917	917	917	917	917
ARCH	93.913***	167.888***	11.208***	59.337***	4.687**	32.969***	8.532***	25.610***	100.686***	21.230***	19.634***	8.002**	19.741***	17.822***

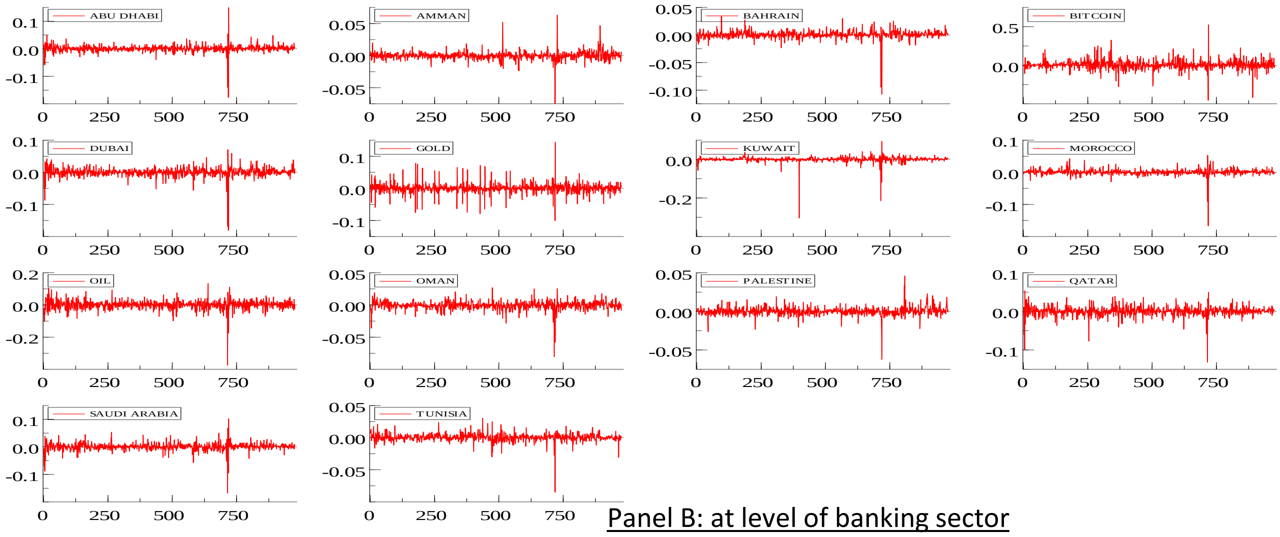
Significant at: ***1, * *5, and * 10 percent levels.

Table (3): Descriptive Statistics for Bitcoin, Gold, Oil, and overall stock market return indices in the **Insurance** industry for selected countries

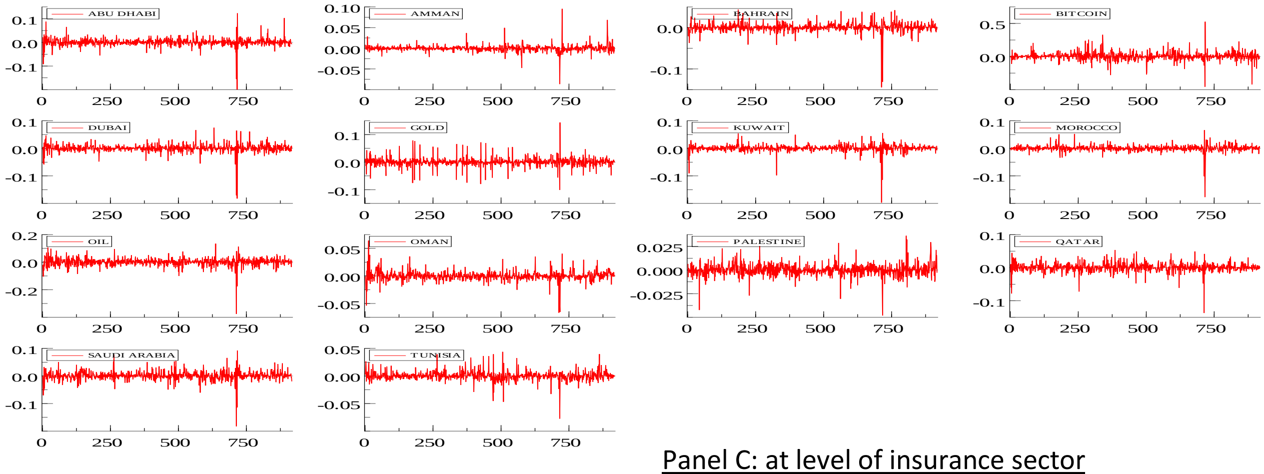
	BITCOIN	GOLD	OIL	ABU DHABI	DUBAI	KUWAIT	MOROCCO	PALESTINE	QATAR	SAUDI	TUNISIA
Mean	0.00603	0.00061	0.001	0.00018	0.00054	0.00043	0.00053	0.00097	-0.00056	0.0004	0.00028
Median	0.00331	0.00059	0.00212	0.0000	-0.00039	0.00000	0.00065	0.0000	-0.00068	0.00037	0.00000
Maximum	0.37921	0.15058	0.28309	0.09743	0.14334	0.07941	0.08782	0.05979	0.07943	0.15841	0.06192
Minimum	-0.39944	-0.07895	-0.37493	-0.05111	-0.08761	-0.07354	-0.18593	-0.03738	-0.12611	-0.1574	-0.04377
Std. Dev.	0.06465	0.01749	0.0318	0.00961	0.01734	0.01482	0.01709	0.00759	0.01914	0.01994	0.0113
Skewness	0.23792	1.21982	-1.72997	2.47368	0.83975	0.09128	-2.30332	0.58484	-0.09462	-0.85894	0.86723
Kurtosis	9.7495	17.60063	37.14749	26.4343	13.9518	7.63873	26.36602	10.3498	7.97518	17.64422	7.919
Jarque-Bera	1550.8***	7423.1***	39905.5***	19432.2***	4158.5***	730.1***	19213.6***	1876.2***	839.7***	7364.5***	921.5***
Observations	813	813	813	813	813	813	813	813	813	813	813
ARCH effect	4.190**	20.159***	17.520***	4.585**	4.693**	4.601**	10.385***	5.015***	3.759**	25.040***	5.404**

Significant at: ***1, * *5, and * 10 percent levels.

Panel A: at level of Stock index



Panel B: at level of banking sector



Panel C: at level of insurance sector

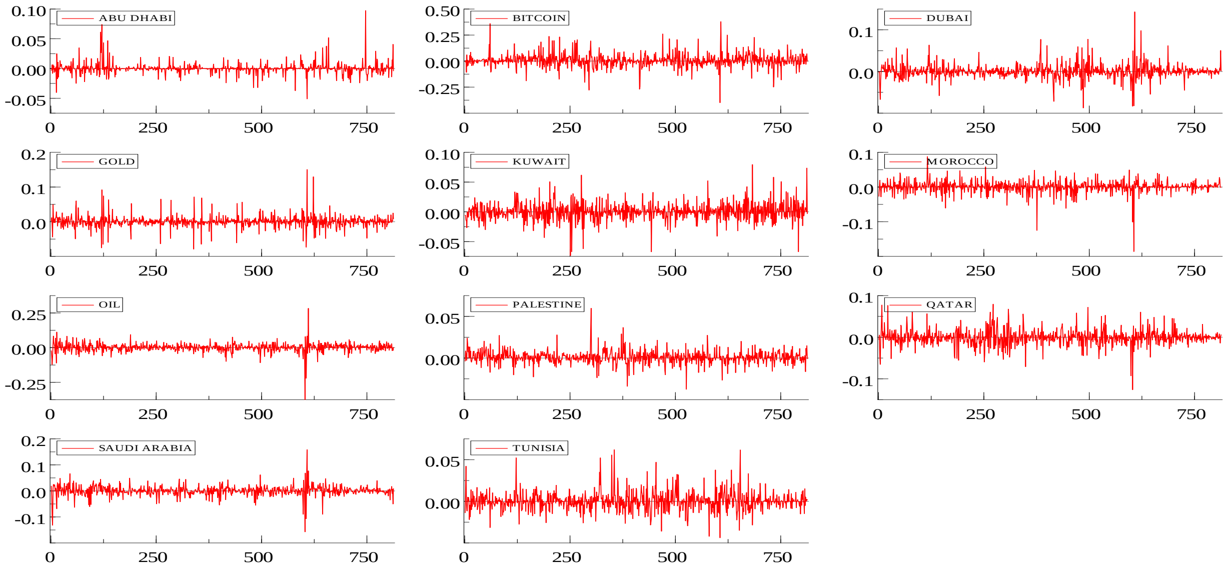


Figure (2); volatility clustering for all the variables under study.

4.4 *Conditional Variance: Dynamic conditional Correlation Analysis Results*

In Table (4), we analyze the relationship between the conditional volatility of the Bitcoin currency, gold, oil, and stock market indices for selected countries: the UAE (Abu Dhabi and Dubai), Amman, Bahrain, Kuwait, Morocco, Oman, Palestine, Qatar, Saudi Arabia, and Tunisia. The study found that there was a positive association between the conditional variance of Bitcoin currency and the conditional variance of Abu Dhabi, Dubai, Bahrain, Oman, Morocco, and Qatar stock market returns, but the association was not statistically significant. However, the results indicate that the conditional variance of bitcoin currency is positively correlated with the conditional variance of stock market returns in Amman, Kuwait, Palestine, Saudi Arabia, and Tunisia. In addition, the findings in Table (4) show that there is a positive conditional variance association between Bitcoin currency returns and the conditional variance of gold. Further, Table (4) reports that the conditional variance of Bitcoin currency returns was found positively associated with the conditional variance of oil market returns at a statistically significant level of 10 percent. The overall results indicate that the conditional variance of Bitcoin currency market returns is statistically insignificant when compared with most of the conditional variance of stock market returns in the Arab region, which suggests that bitcoin currency may be used for hedging and diversifying the portfolio investment strategy in the future.

In addition, Table (4) indicates there is a significant association between the conditional variance of gold market returns and the conditional variance of Abu Dhabi and Dubai stock market returns at a significant level of 5 percent and 10 percent, respectively. Additionally, gold's conditional variance was positively associated with the conditional variance of stock market returns in Amman, Bahrain, Morocco, Palestine, Oman, Qatar, and Tunisia. The conditional variance of gold market returns in Table (4) also shows that it is negatively related to the conditional variance of Kuwait and Saudi Arabia stock market returns indices. Furthermore, Table (4) reports the conditional variance association outcomes between global oil market return and the conditional variance of the stock market index in the Arab region. The results of the study indicate a significant association between the conditional variance of global oil market returns and the conditional variance of stock market returns of Abu Dhabi, Dubai, Kuwait, Saudi Arabia, Qatar, and Morocco at a significant level of 1, 1, 5, 1, 1,5 percent, respectively. Further, the findings in Table (4) indicate that global oil's conditional variance is positively associated with the conditional variance of stock market return indices in Amman, Bahrain, Oman, and Tunisia. On the other hand, the results of the study indicate that the conditional variance of global oil returns is negatively correlated with the conditional variance of Palestinian stock market returns over the studied period. In general, there are a few association relationships between the conditional variance of gold return, oil return, and stock markets return for the selected countries in the Arab region. These results suggest that investment portfolio diversification strategies among studied assets may be improved by their negative and insignificant associations.

We analyse in Table (5) the relationship between the conditional volatility of the Bitcoin currency, gold, oil, and the banking sectors stock market returns indices for several countries:

the UAE (Abu Dhabi and Dubai), Amman, Bahrain, Kuwait, Morocco, Oman, Palestine, Qatar, Saudi Arabia, and Tunisia. The study found that there was a positive association between the conditional variance of Bitcoin currency and the conditional variance of Abu Dhabi, Dubai, Bahrain, Oman, Morocco, and Qatar stock market returns, but the association was not statistically significant. It was found that there was a positive correlation between the conditional variance of Bitcoin currency and the conditional variance of Dubai, Amman, Bahrain, Oman, Morocco, Palestine, Saudi Arabia, and Tunisian stock market returns, but the correlations were not statistically significant for all markets except for Saudi Arabia that found significant at 10%. This suggests the possibility of using cryptocurrency as an alternative investment asset to diversify portfolios and invest in the Arab world. On the other hand, the findings indicate that the conditional variance of the cryptocurrency industry found negatively correlated with conditional variance of the banks' sector stock market returns indices of Abu Dhabi and Qatar. This may indicate that the banking investment operators are very conservative and not eager to get involved in the crypto industry.
The results of Table (5) additionally demonstrate that there was a significant positive correlation between the conditional variance of gold market returns and the conditional variance of all bank stock market indices, with the exception of Saudi Arabia bank stock market return, which was found to have a negative relationship with gold market return. Further, the results in Table (5) indicate that the conditional variance of global oil market returns is significantly correlated with the conditional variance of banking stock markets in GCC countries such as Abu Dhabi, Dubai, Qatar, and Saudi Arabia at a significant level of 1, 1, 5, 1, 5 percent respectively. Similarly, Table (5) shows that oil market returns are positively correlated with banking stock market returns in Amman, Bahrain, Kuwait, Morocco, Palestine, and Tunisia, however the correlation is not statistically significant.

As shown in Table (6), we examine the relationship between the conditional volatility of the Bitcoin currency, gold, oil, and stock market returns indices within the Insurance sector for several countries: the UAE (Dubai), Palestine, Kuwait, Morocco, Qatar, Saudi Arabia, and Tunisia. According to Table (6), the conditional variance of bitcoin currency returns has an insignificant positive correlation with the stock markets return in the insurance industry of Palestine, Qatar, Saudi Arabia, and Tunisia, with the exception of the Dubai market, which showed a statistically significant positive correlation. Meanwhile, the conditional variance of bitcoin currency was negatively and insignificantly associated with stock market returns in Kuwait and Morocco's insurance industry. This my suggest that the insurance industry could benefit from portfolio diversification between crypto and stock markets.

The Table (6) also shows that the conditional variance of gold market returns is positively and significantly correlated with the conditional variance of stock market returns for the insurance industry in Dubai, Qatar, at a significant level of 5, 1 percent, respectively. Further, the findings of the study indicate that gold market's conditional variance is positively correlated with the conditional variance of Kuwaiti, Saudi Arabia, and Tunisian insurance market returns, but it was not statistically significant. In contrast, Table (6) shows that the conditional variance of gold market return, and the conditional variance of stock market returns in the insurance industry for Abu Dhabi, Morocco, and Palestine are negatively associated. By using these

negative associations, one might be able to plan a suitable portfolio diversification strategy between the insurance market and the global gold market in these countries.
Additionally, Table (6) presents the conditional variance correlation for stock market returns in the Insurance industries for selected countries and the conditional variance of oil market returns. All stock market returns' conditional variances for the insurance industries in selected countries are positively associated with conditional variances of oil market returns at different levels of significance, with the exception of Kuwait's insurance industry, which had a negative correlation. Hence, there is a lack of potential portfolio diversification between the global oil market and stock market indexes in these specific countries.

The overall findings of the study suggest that a variety of financial assets (including bitcoin currency, gold, and oil) have different conditional variance associations in relation to stock market returns in different countries. Thus, the findings have implications for portfolio managers operating in the Arab region who are inclined to take advantage of a diverse set of financial assets across a variety of countries when constructing their portfolio investments.

Figure 03 shows the conditional correlation between the stock indices of the studied Arab stock exchanges and bitcoin, taking into account the time dimension. Before the outbreak of the pandemic, the conditional correlation was practically fixed and stable on all stock exchanges, which suggests that dealers in the financial market may use cryptocurrencies as a hedge and to reduce portfolio risk. The correlation during the pandemic was somewhat strong at the level of most stock exchanges, which is in line with the studies of Dyhberg (2016), Guesmi et al. (2019), Tiwari et al. (2019).

4.1. Diagnostic Test Results

Finally, we performed diagnostic ARCH-LM tests to identify any ARCH effect in residuals from the Dynamic Conditional Correlation models. In view of the null hypothesis that "there is no ARCH effect" being accepted at the significance level of 5 percent as illustrated in Table (5, 6, and 7), all residuals of the Dynamic Conditional Correlation Model are free of ARCH effects; therefore, all conditional variance equations for all volatility specifications are well identified and estimated.

5. Conclusion And Recommendation

With a focus on the banking and insurance sectors indices, this paper examines the dynamic conditional variance between Bitcoin, gold, oil, and stock market indices on Arab stock exchanges. In this study, DCC GARCH model was used to analyze conditional variance association among variables examined from 05/01/2016 to 11/11/2021. The conditional variance of Bitcoin currency market returns was found to be statistically insignificant when compared with most conditional variances of stock market returns in the Arab region. In the future, it is feasible for the Arab region to use bitcoin for portfolio investment hedging and diversification. Furthermore, the conditional variance of gold returns, oil returns, and stock market returns are associated with the selected countries in the Arab region. By their negative and insignificant associations, these results suggest that portfolio diversification strategies among studied assets may be improved. Furthermore, the findings of this study imply that the financial assets under investigation have different relationships with stock market returns, particularly in the banking and insurance sectors. As a result, investors in the chosen countries can benefit from the findings, which are useful for portfolio construction. In other words, the study argues that investors can diversify their portfolios by investing in stock markets such as the banking and insurance sectors. This is because both are independent and fluctuations in the one does not affect the other. We conclude that these results are critical for investors to diversify in their portfolios, reduce risk, and hedge effectively. Policymakers should monitor the use of cryptocurrency dealers, especially since many Arab countries do not allow Bitcoin trading.

In future research, this study could be extended to compare conditional variance associations between crypto-assets, gold, and oil indexes with other international stock markets for the purposes of diversifying investment strategies across different regions. The scope of conditional variance of crypto assets may also be extended beyond bitcoin currency to include other cryptocurrencies and to examine their association with stock market indices in the Arab region for further portfolio diversity enhancements and risk mitigation.

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Estimate output of models

Table (4) DCC estimation between stock index, cryptocurrency, gold, and oil.

```
********************************
 ** MG@RCH( 1) SPECIFICATIONS **
 ********************************
Conditional Variance : Dynamic Correlation Model (Engle)
Multivariate Normal distribution.
Strong convergence using numerical derivatives
Log-likelihood = 43663.6
Please wait : Computing the Std Errors ...
 Robust Standard Errors (Sandwich formula)
```

	ABUDHABI	AMMAN	BAHRA	BTC	DUBAI	GOLD	KUWAIT	MOROCCO	OIL	OMAN	PALESTINE	QATAR	SAUDI ARABIA	TUNISIA
ABUDHABI	1.00	0.10**	0.19***	-0.05	0.55***	0.10**	0.18	0.17*	0.19***	0.18***	0.08	0.39***	0.31***	0.03
AMMAN		1.00	0.06	0.04	0.12**	0.10	0.05	0.14***	0.02	0.01	0.11**	0.07	0.03	0.07
BAHRA			1.00	-0.01	0.30***	0.02	0.41***	0.17**	0.07	0.12	0.07*	0.19***	0.21***	0.09
BTC				1.00	-0.02	0.06	0.01	-0.06	0.08	-0.07	0.06	-0.01	0.01	0.04
DUBAI					1.00	0.08*	0.24*	0.16***	0.15***	0.18***	0.09**	0.47***	0.38***	0.01
GOLD						1.00	0.00	0.03	0.00	0.06	0.01	0.07	0.00	0.02
KUWAIT							1.00	0.13	0.15**	0.05	0.02	0.18	0.27***	0.00
MOROCCO								1.00	0.14**	0.09	0.02	0.12**	0.18***	0.10*
OIL									1.00	0.08	-0.05	0.24***	0.27***	0.02
OMAN										1.00	0.04	0.18***	0.12*	0.03
PALESTINE											1.00	-0.02	-0.02	0.10**
QATAR												1.00	0.33***	-0.02
SAUDI ARABIA													1.00	0.05
TUNISISA														1.00

Significant at: * * *1, * *5, and * 10 percent levels;

```
No. Observations :      976  No. Parameters  :      149
No. Series       :       14  Log Likelihood  : 43663.576
```

Table (5) DCC estimation between banking sector index, cryptocurrency, gold, and oil

****
** MG@RCH(1) SPECIFICATIONS **
****
Conditional Variance: Dynamic Correlation Model (Engle)
Multivariate Normal distribution.
Strong convergence using numerical derivatives
Log-likelihood = 38997.5
Please wait: Computing the Std Errors ...
Robust Standard Errors (Sandwich formula)

	ABUDHABIBANK	AMMANBANK	BAHRAINBANK	BTC	DUBAIBANK	GOLD	KUWAITBANK	MOROCBANK	OIL	OMANBANK	PALESTINBANK	QATARBANK	SAUDIBANK	TUNISBANK
ABUDHABIBANK	1.00	0.12***	0.17***	-0.08	0.39***	0.11***	0.21***	0.05	0.19***	0.23***	0.09***	0.31***	0.05	0.03
AMMANBANK		1.00	0.10**	0.09	0.15***	0.11***	0.09**	0.07	0.08	0.06	0.13**	0.11***	0.06**	0.07
BAHRAINBANK			1.00	0.06	0.28***	0.04	0.50***	0.05	0.10	0.13*	0.06	0.18***	0.05	0.08
BTC				1.00	0.01	0.08	0.02	0.07**	0.08**	0.03	0.04	-0.03	0.05*	0.02
DUBAIBANK					1.00	0.08*	0.30***	0.00	0.20***	0.22***	0.06*	0.37***	0.05	0.02
GOLD						1.00	0.08**	0.06**	0.02	0.10**	0.01	0.08*	0.00	0.04
KUWAITBANK							1.00	0.04	0.09	0.16*	0.02	0.24***	0.09	0.07
MOROCBANK								1.00	0.04	0.04	0.01	0.01	-0.01	0.04
OIL									1.00	0.15***	0.04	0.22***	0.17**	0.02
OMANBANK										1.00	0.09	0.16***	0.05	0.10**
PALESTINBANK											1.00	0.04	-0.01	0.06
QATARBANK												1.00	0.11	0.03
SAUDIBANK													1.00	0.05
TUNISBANK														1.00

Significant at: ***1, * *5, and * 10 percent levels.

No. Observations : 976 No. Parameters : 149
No. Series : 14 Log Likelihood : 43663.576

Table (6) DCC estimation between insurance sector index, cryptocurrency, gold and oil

****

Conditional Variance: Dynamic Correlation Model (Engle)

Multivariate Normal distribution.

Strong convergence using numerical derivatives

Log-likelihood = 24227.319

Please wait: Computing the Std Errors ...

Robust Standard Errors (Sandwich formula)

	ABUDHABIINSUR	BTC	DUBAIINSUR	GOLD	KUWAITINSUR	MOROCINSUR	OIL	PALESTINSUR	QATARINSUR	SAUDINSUR	TUNISINSUR
ABUDHABIINSUR	1.00	0.026	0.045	-0.003	0.045	0.066*	0.016	0.051*	-0.012	-0.033	0.0167
BTC		**1.00**	**0.139*****	**0.135****	**-0.027**	**-0.014**	**0.10****	**0.053**	**0.016**	**0.032**	**0.05**
DUBAIINSUR			1.00	0.113**	0.105**	0.04	0.121**	0.0482	0.173***	0.148**	-0.014
GOLD				1.00	0.0336	-0.0043	0.0095	-0.0151	0.0798***	0.0393	0.0669
KUWAITINSUR					1.00	-0.0741**	-0.0217	0.0484	0.0272	0.0654	-0.0013
MOROCINSUR						1.00	0.1246*	-0.0455	0.0681	0.1321***	0.0356
OIL							1.00	0.0086	0.1483**	0.1521***	0.0045
PALESTINSUR								1.00	0.0327	-0.1009**	-0.0090
QATARINSUR									1.00	0.2183***	0.0549
SAUDINSUR										1.00	0.0642
TUNISINSUR											1.00

Significant at: ***1, * *5, and * 10 percent levels..

No. Observations : 813 No. Parameters : 101

No. Series : 11 Log Likelihood : 24227.319

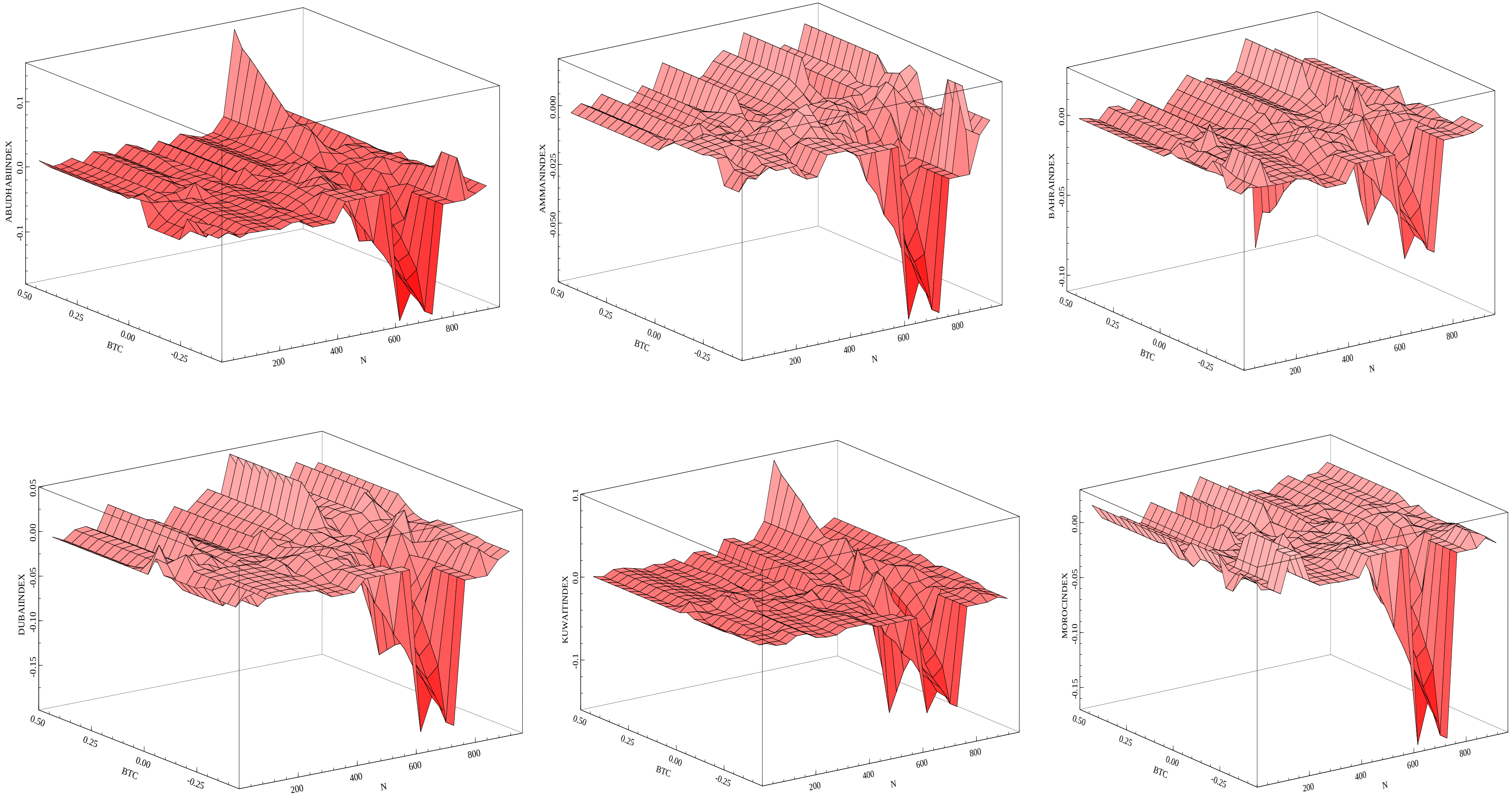

Figure (03): 3D plot of relationship between Arab stock index and Bitcoin.

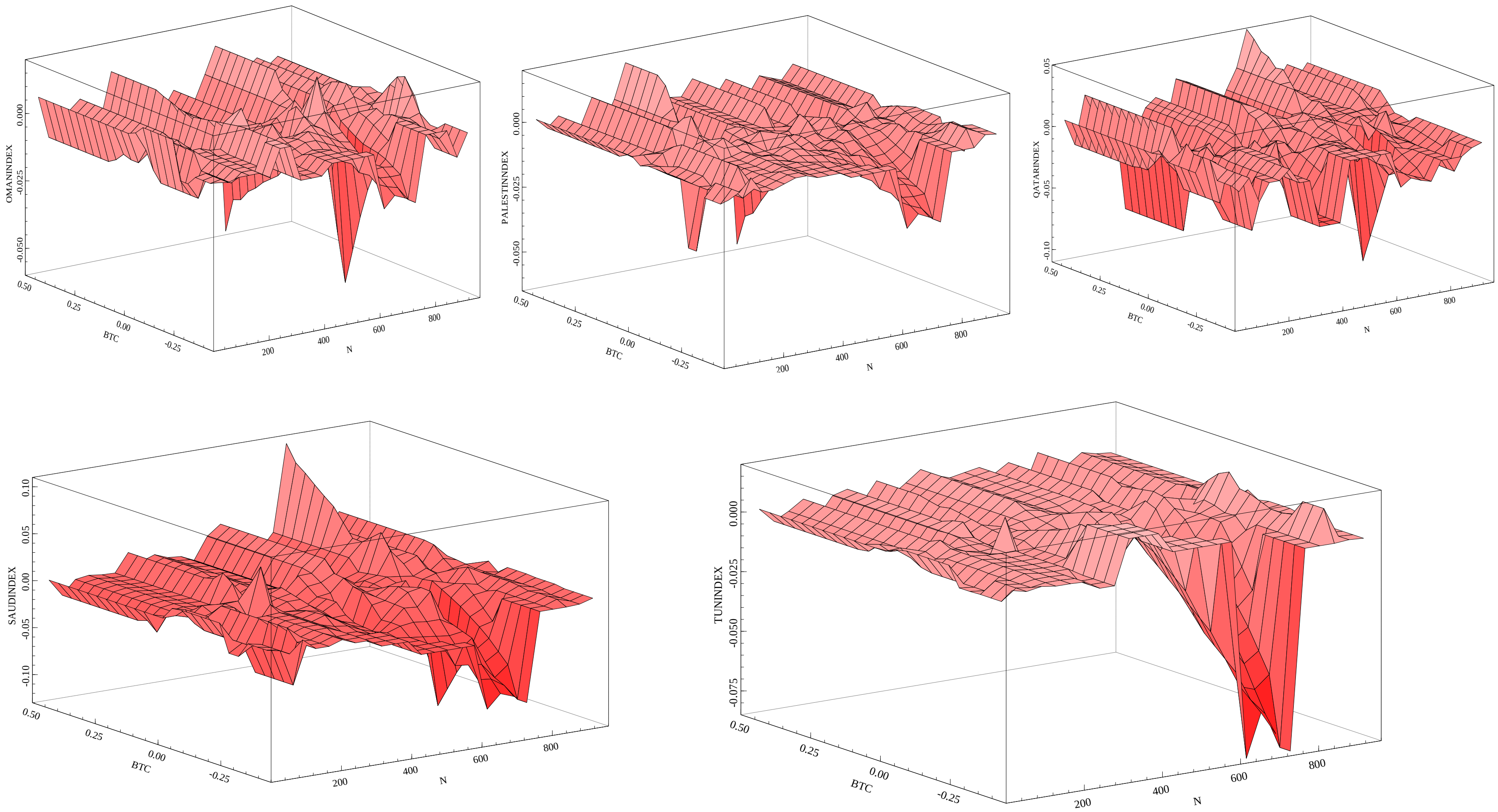

Figure (3): 3D plot of relationship between Arab stock index and Bitcoin(Continued).