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Trend of Oil Prices, Gold, GCC Stocks Market during Covid-19 Pandemic: A Wavelet Approach

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ABSTRACT

This paper analyzed the co-movement among the stock indices of GCC members like Abudhabi, Bahrain, Oman, Saudi Arabia, Qatar and global oil prices as indicated by Brent, WTI. Gold, S&P 500 index and Dow Jones index has also been taken into account. Daily prices from January 2, 2020 up to September 30, 2020 were used for the analysis. In order to analyze the co-movement among the above mentioned indices in time frequency space wavelet transform approach has been used. The techniques employed in the study include wavelet correlation and wavelet coherence approach. The findings of this empirical study suggests that though there was no much interconnectedness among the above mentioned factors in the short run, the impact of the global pandemic crisis that got added to the oil price shock could be seen in the medium and long run. The study suggests that investors need to be cautious of their investment decisions with respect to the time horizon as these markets show significant co-movement in the long run when hit by global crisis.

Keywords: Oil Prices, GCC Stock Indices, Co-movement, Wavelet Analysis
JEL Classifications: G01, G15,C32

1. INTRODUCTION

The Current pandemic of COVID -19 and the global financial crisis of 2008 (GFC) exhibited similar behavior in the financial markets for both developed and emerging markets (Lustig and Mariscal, 2020). Generally Stock prices have been reacting to the public sentiment driven by economic or political news (McKibbin and Fernando, 2020).

Abundant studies in empirical finance literature are available related to the impact of US economic policy uncertainty on different financial markets (Colombo, 2013; Dakhlaoui and Aloui, 2016; Kido, 2018; Sharif et al., 2020).This emphasizes the adage that "when America sneezes, the whole world catches a cold." Decision making has also been affected due to the policy instability or uncertainty and in return has adversely affected the economies and price reactions in financial markets (Lam et al., 2020). World leading economies have significantly affected the developing countries in terms of economic and financial disturbances (Sum, 2012).

GCC economy is exposed to double shock: the spread of the COIVD-19 pandemic and the decline in the oil prices may result in the long term economic downturn as the oil markets generally are closely inter wind thus volatility in the oil market paved the way to the investors behavior and shaking the stock markets (Albulescu, 2020). GCC markets are dynamic and four out of six GCC countries Saudi, Qatar, UAE and Kuwait are now on the radar screen of global emerging markets in terms of investor engagement, disclosure levels and pro-active management access. GCC financial markets are considered to be the largest financial markets in the regions with the significant cross border effects

(Al-Maadid et al., 2020). Its members have benefited from being oil and gas producers. Being the major suppliers of oil to the World, GCC countries are segmented from the international and other emerging countries. The economic and financial structure among GCC countries are quite similar and hence prove to be very promising areas for regional investments due to the portfolio diversifications (El et al., 2011)

Previous studies indicate that the stock prices have been reacting to the public sentiments due to economic and political factors and with an addition of health now. Since the GFC 2008 period until the pandemic research studies have attempted to understand the behavior of the GCC markets and are extensively working towards the relationship between the oil price shocks and the stock markets.

Therefore, the impact of oil price shocks along with COVID 19 pandemic on GCC stock market returns emerges as an important research topic. It is expected to enable the investors to make necessary decisions and the policy makers to regulate the stock markets more efficiently.

The paper is divided into different sections as follows. The following section discusses the literature of previous studies conducted on the impact of previous epidemic, pandemic on stock markets as well as on the studies that used wavelet approach. The data collection and methodology applied are discussed following the literature review. Next section on results and empirical findings interprets the results and empirical findings of the study. Final section of the paper provides the conclusions of the study.

2. REVIEW OF LITERATURE

On March 12, 2020 GCC markets indices had a decline in international markets and oil prices. The spread of virus SARS Cov 2 caused a decline in the indices of all GCC stock markets. Dubai Financial Market (DFM) declined by 7.3% and then Abu Dhabi Securities Exchange (ADX) had a 5.9% decrease. The Saudi Stock Exchange (Tadawul) fell by 4.6% to 6251 points. Qatar Exchange dropped by 5.3% though Bahrain Bourse decreased 3.3% and thus Boursa Kuwait decided to halt trading for a day (Kamco invest research, 2020).

There has been an increased interest in analysis of fluctuations in the financial markets due to health news amidst academicians, research agencies and the policy makers. Financial news, market announcements, corporate news, and analyst forecasts affect the expectations of investors and might generate high volatility in stock markets. A report titled "Spread and Stutter" in *The Economist*[1] emphasizes that COVID-19 is a grave threat to the poise of global markets. "The Right Medicine for the World Economy"[2] also states that as fears grow about the impact of the COVID-19 virus, stock markets have slumped.

1 "Spread and Stutter - Markets Wake up with a Jolt to the Implications of Covid-19 | Finance &Economics | The Economist,"

2 Covid-19 - The Right Medicine for the World Economy | Leaders | The Economist,"

In the literature, financialization of commodity markets relationship between stock prices and oil prices has been debated at a larger extent (Balcilar et al., 2019; Wen et al., 2019). The COVID-19 impact on oil prices seems to be rather indirect, affecting first the financial markets volatility (Albulescu et al, 2019). Research studies by (Baker et al., 2020) unveiled that during the 22 trading days from 24 February 2020 to 24 March 2020 18 stock market jumps were recorded and 16 to 18 of them are perceived as a response to "bad news" attributed to either the new infectious disease or the US policy responses to the COVID-19 outbreak.

The impact of COVID -19 on the financial markets is compared with the Global Financial Crisis (GFC) of 2008 with the contagion and spillover effects. Harvey (2020) highlighted the differences between the GFC and COVID-19 crises and refers the emerging pandemic crisis as the "*Great Compression.*" Research also highlights that the Saudi stock returns and oil price changes has a bidirectional relationship, GCC markets are not directly linked to oil prices, less dependent on oil exports and influenced by their own domestic markets (Arouri et al., 2010) (Hammoudeh et al., 2004).

Earlier work done by (Hammoudeh et al., 2004.) on the long-run relationship among the GCC stock markets with respect to US oil market, the S&P 500index and the US treasury bill rate. The research concluded that the treasury bill rate has direct impact on these markets, while oil and S&P 500 have indirect effects.

From 24 to 28 February 2020, stock markets worldwide reported their largest 1-week declines since the 2008 financial crisis. Traders began to sell shares out of fear, and as a result, a market-wide circuit breaker was triggered 4 times in March (Ozili and Arun, 2020) (Hunter, 2013). The role of crude oil market is considered as significant and the biggest of all commodity markets in the world. Several studies related to the oil market and stock markets emerged to relate with the implications in international stock markets in terms of asset allocations and portfolio risk management. The stock correlation also arises across time and countries due to globalization (Masih and Majid, 2013).

The results of the available research studies on oil price and GCC stocks are heterogeneous. This is available in three different strands: research work by (Jones and Kaul, 1996; Miller and Ratti, 2009; Nandha and Faff, 2008; Papapetrou, 2001; Sadorsky, 1999) indicated the negative relationship between oil prices and Global stock indices whereas other empirical works show positive linkages between oil and stock markets (El-Sharif et al., 2005; Elyasiani et al., 2011; Narayan and Narayan, 2010). Insignificant relationships are identified as a part of third strand (Apergis and Miller, 2009; Henriques and Sadorsky, 2008). There has been an increased work on the co-movement of the GCC countries to identify the possibility of portfolio diversification in the investments. A general review of the conceptual framework on co-movements reveals that there is still a need for further studies, especially co-movements on GCC markets during the turbulent times. Based on the previous studies by (Forbes and Rigobon, 2001) and (Gallegati, 2012), the wavelet approach may allow to analyze the co-movement timing effects during the current

COVID-19 crisis, as a way to support for contagion or spillover effects.

Due to the changing times there has been an increase in shocks and volatility in the financial markets, there is an increase research through application of wavelet in economic and financial time series analysis. Wavelet approach reveals the changes of different periodic components of time series through the analysis of the spectral characteristics of time series (Aguiar-Conraria et al., 2008). This approach facilitates the analysis of frequency components and time information in time series, in contrast with the standard time series econometric models, which consider only one or at most 2 time scales (the short and the long run) and rely on model parameters (Reboredo and Rivera-Castro, 2013).Wavelet analysis reveals the potential presence of contagion through the analysis of the spillover effects across international stock and commodity markets. Moreover, the identification of timescales where correlation is lower could ensure the benefits of portfolio diversification for investors who are looking for alternative investment opportunities (Benhmad, 2013).

Main findings of research by (Akoum et al., 2012) through wavelet analysis indicated lack of market dependencies between oil and stock movement in the short term but they have co-movement over the long term providing enhanced diversification for the investors in the short term investments. (Jammazi and Aloui, 2012) applied redundant wavelet analysis to predict the movement between real stock returns and five major industries found that there is no co movement between the crude oil and stock price up to the intermediate scale but they abruptly shift their direction in unison and found that changes in crude oil and almost all the stock prices do not move together up to the intermediate scale, but since they abruptly shift their directions.

Das and Kumar (2018) employed multiple and partial wavelets to examine the interdependence of international economic policy uncertainty with the returns of 11 developed and 6 emerging market equities. The emerging economies were found to be less vulnerable to international economic policy uncertainty proxied by US economic policy uncertainty compared to the developed markets. The extent of interdependency and risk exposure varied across countries.

Wavelet-based correlations and Wavelet series decomposition was used for Stock market indexes (Germany, Japan, the United Kingdom and the United States) and continuous oil futures contract by (Martín-Barragán et al., 2015). Correlation during oil shocks and stock market crashes was higher at low frequencies during the 2008 and 2011 stock market cash which is an evidence of contagion. Strong evidence of volatility between oil and stock markets and time varying correlations for various market pairs was observed by wavelet based MGARCH approach. Wavelet coherence exhibited that oil market was leading (Khalfaoui et al., 2015). Study by (Bjorn, 1995) also appreciated the usage of wavelet decomposition to study financial time series. The study also added that this method helps to decompose a signal to multiple scales without losing the information on timing of various events.

Continuous time Morlet wavelet transform (CWT) technique was done by (Madaleno and Pinho, 2014). There was higher coherence among series for higher scales thus supporting the interdependence hypothesis, showing that long run market dynamics are more uncertain. Finally, a bidirectional relationship oil and sector equity indices for large time horizons was found. The interdependence between oil price and the stock market were more pronounced in the short and medium terms than in the long term. In addition, stock markets were more sensitive to oil shocks originating from demand shocks (Ftiti et al., 2016). Extensive empirical research has been conducted to analyze financial markets' co-movements to determine whether diversification purposes can be fulfilled by investing in international markets. Research work of (Gallegati, 2012) applied the maximal overlap discrete wavelet transform (MODWT) to analyze co-movements among the G7 stock market indices. Considering spillovers as normal interdependence in contrast to pure contagion as excessive co-movement, he argues that there was contagion from the US during the subprime crisis.

With the review of existing literature on the conceptual framework on co-movements reveals that there is a need for further studies especially on the co-movements between the GCC stock markets. Various studies during the financial crisis have highlighted the spillover effects due to the Globalization. With the changing and unprecedented times across the countries there have been different types of co-movements. This study is unique as it considers the co-movements of the GCC Stock markets as one part and the second part as Individual GCC stock index co-movements with Brent, WTI Crude, Dow Jones and Gold are taken for the period of COVID-19.This analysis helps as a significant contribution in terms of understanding and responding to the impact of COVID-19 on the GCC markets. This work will be useful for investors and will serve as the tool for decision making in the stock markets of the GCC.

3. GCC WAVELET ANALYSIS

3.1. Summary of Data and Estimations

The following is a summary of data and estimations.

3.1.1. Data

The wavelet approach of the GCC co movement analysis considered daily prices from January 2, 2020 up to September 30, 2020 with a total of 273 observations. Indices of Abu Dhabi Index (ADX), BahrainEquityIndex (Bahrain), Tadawul AllShareIndex (Tadawul), Muscat Securities Index (MSM30), Qatar Exchange Index (QE), Gold, Brent, WTI Crude, Dow Jones and S&P 500 are taken. Prices were taken from Refinitiv. Missing Data values were replaced by spline interpolation.

Daily prices were transformed into percentage changes as in expression (1):

$$Ret_t = \left(\frac{P_t}{P_{t-1}} - 1 \right) \times 100 \qquad (1)$$

The wavelet-based approach considers a process of decomposition into multiple frequency-time scales of a time series, so the analysis called multi-resolution decomposition, where each resolution level is referred to a timescale. This approach has its basis on the Fourier series analysis which the sine-cosine functions only capture the time series frequencies. Instead, the wavelet analysis allows to decompose the time series into its frequency components at different time scales, whereby means of a filtering process it is possible to separate high frequencies from low frequencies. In the first case, high frequencies mostly occur in very short time intervals, whereas the second case indicates that low frequencies may occur in long time intervals. Expression (2) represents the decomposition of a time series *f(t)* into its components occurring in different resolution levels:

$$f(t)=\sum_k s_{j,k}\phi_{j,k}(t)+\sum_k d_{j,k}\phi_{j,k}(t)+\sum_k d_{j-1,k}\psi_{j-1,k}(t)$$
$$+\cdots+\sum_k d_{1,k}\psi_{1,k}(t), \tag{2}$$

Where $\varphi(t)$ and $\psi(t)$ are the father and mother wavelet functions, respectively. The father wavelet function allows to approximate the smooth component of the time series, meanwhile the mother wavelet function approximates the detail components. On the other hand, $s_{j,k}$ are the smooth coefficients and $d_{j,k} \ldots d_{1,k}$ are the detail coefficients, where *j* and *k* are the scaling and translation parameters, obtained from the wavelet transform. Based on Daubechies (1988), expressions (3) and (4) define the discretized form of the father and mother wavelets:

$$\phi_{j,k}(t)=2^{-\frac{j}{2}}\phi\left(2^{-j}t-k\right) \tag{3}$$

$$\psi_{j,k}(t)=2^{-\frac{j}{2}}\psi\left(2^{-j}t-k\right) \tag{4}$$

An example of a mother wavelet is the Mexican hat function given in expression (5):

$$\psi(t)=\left(1-t^2\right)e^{\frac{t^2}{2}} \tag{5}$$

Then, the general decomposed form of a time series*f(t)* may be represented in terms of its smooth (S_J) and detailed (D_J) series, as in expression (6):

$$f(t)=S_J(t)+D_J(t)+D_{J-1}(t)+\cdots+D_1(t) \tag{6}$$

The interaction analysis among stock index returns is performed under the wavelet correlation and coherence. The wavelet correlation is estimated by the Maximal Overlap Discrete Wavelet Transform (MODWT) which holds the main characteristic to analyze and discretize a time series *f(t)* on a scale-based additive decomposition as shown in expression (2), with the advantage that at each scale the wavelet coefficients $s_{j,k}$ and $d_{j,k}$ have the same length as the original time series. In that context, using as mother wavelet the Least Asymmetric Daubechies function, the wavelet correlation unbiased estimator is performed as shown in expression (7):

$$\tilde{\rho}_{X,Y}\left(\lambda_j\right)=\frac{\gamma_{X,Y}\left(\lambda_j\right)}{\nu_X\left(\lambda_j\right)\nu_Y\left(\lambda_j\right)} \tag{7}$$

where $\gamma_{X,Y}$ is the covariance between time series *X* and *Y* at scale γ_j, v^2_X and v^2_Y are the variances of *X* and *Y*, respectively, at scale γ_j. Finally, $\gamma_j=2^{j-1}$ stands for the timeframe at *j*-scale; for example, if original data comes from a daily frame, then at *1*-scale it will be obtained the decomposed correlation occurring at a $\lambda_{11}=1$ day window, $\lambda_{12}=2$ day window, and successively at *J* level.

On the other hand, wavelet coherence is performed under the Continuous Wavelet Transform (CWT), which based Graps (1995) is represented as in expression (8):

$$CWT_f(j,k)=\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{j}}\overline{\psi\left(\frac{t-k}{j}\right)}dt,\ j>0, b\in\mathbb{R} \tag{8}$$

where $\overline{\psi(t)}$ stands for the complex conjugate of the mother wavelet, *j* the scaling factor, and *k* the translation factor (see expression 2). In that context, Torrence and Compo (1998) defined the cross-wavelet transform (XWT) of 2 time series *X(t)* and *Y(t)* as in expression (9):

$$W_{X,Y}=W_X W_Y^* \tag{9}$$

where *W* represents the CWT of the time series (see expression 8) and * denotes the complex conjugation. Given the XWT, Torrence and Webster (1999) define the wavelet coherence of two time series that closely match the correlation coefficient on local basis as follows:

$$R_n^2(s)=\frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right)S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{10}$$

where *S* is a smoothing operator. By such means, Grinsted et al. (2004) argue that the wavelet coherence is a powerful tool to analyze linkages between 2 time series. Also, Aloui and Hkiri (2014) consider its importance for detecting stock market co-movements.

Finally, all estimations were performed in R version 4.0.2

This Table 1 provides the basic statistics of daily crude returns for GCC stock market along with GCC – Abudhabi, Bahrain, Tadawul, MSM30, QE market indices, Dow Jones, S&P 500 indices, Brent and Gold. Data are over the period from January 2, 2020 till September 30, 2020 has been used in this study. In general, the average stock returns for all the indices are negative except that of WTI and Gold. Brent has recorded very poor returns of -0.27% followed by Abudhabi, Bahrain, MSM 30, QE and Tadawul. This indicates the impact of global pandemic on the stock markets. Skewness is negative except for WTI and gold. Highly significant kurtosis coefficients signify that outliers may occur with a probability higher than that of a normal distribution.

Table 1: Descriptive statistics of emerging Asian stock returns

	ADX	BAHRAIN	TADAWUL	MSM30	QE	SP500	DJ	WTI	BRENT	GOLD
Min	−8.77%	−6.18%	−8.41%	−5.90%	−10.75%	−13.62%	−14.85%	−32.61%	−32.28%	−4.85%
Max	7.76%	2.39%	6.60%	2.13%	3.23%	8.58%	10.21%	475.92%	17.37%	5.61%
Mean	−0.06%	−0.05%	−0.01%	−0.04%	0.03%	−0.01%	−0.04%	2.88%	−0.27%	0.07%
Var	0.00030	0.00006	0.00016	0.00005	0.00014	0.00044	0.00051	0.11444	0.00199	0.00017
Std. Dev.	1.73%	0.74%	1.26%	0.68%	1.19%	2.11%	2.26%	33.83%	4.46%	1.18%
Coef. Var.	29.10	16.27	103.99	16.94	46.43	210.20	57.82	−11.75	16.51	16.42
Skew	−0.68	−2.77	−1.61	−2.91	−3.24	−1.44	−1.43	−11.99	−2.56	0.00
Kurtosis	9.82	20.98	13.74	23.82	27.13	10.59	11.23	155.62	20.08	4.52

Figure 1: Decomposed correlation at resolution levels (scales) D1, D2, D3, and D4

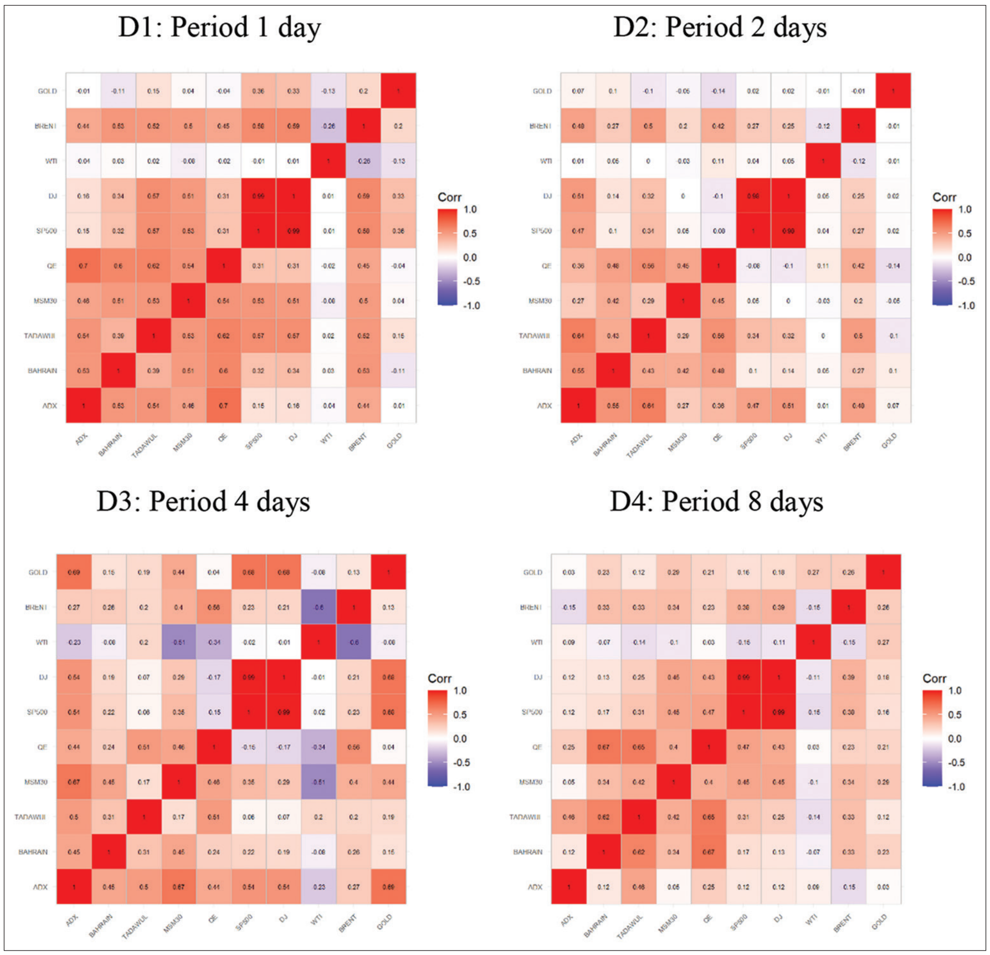
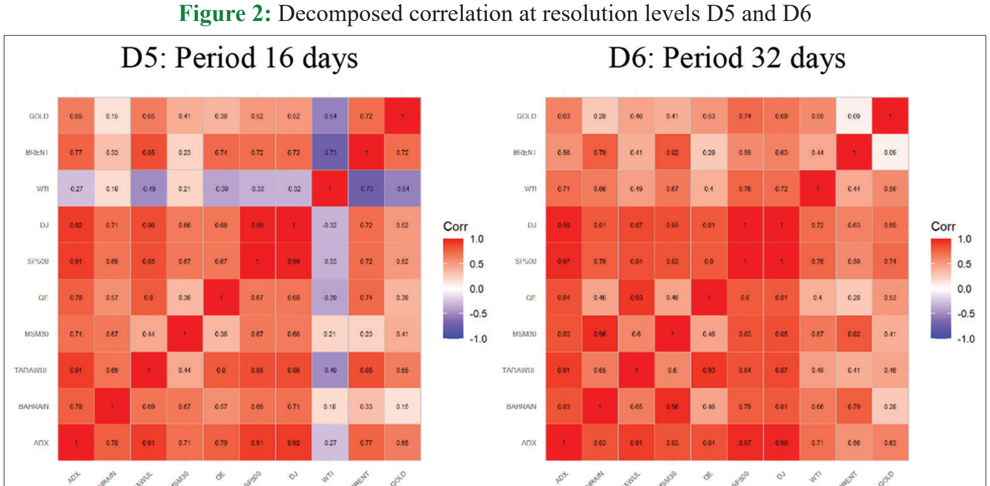


Figure 2: Decomposed correlation at resolution levels D5 and D6



4. EMPIRICAL FINDINGS

Resolution level D1 (Figure 1) related to a time frame of 1 day reveals good level of association between ADX with all other GCC indices especially with that of Bahrain, Tadawul and QE while low association with Dow Jones, WTI crude, Brent and Gold. Bahrain and Tadawul had weak association. At this level, association of GCC indices with Brent and WTI is negative. Gold has a very weak or negative correlation with all other indices.

Wave coherence map shows areas of strong association between ADX and Tadawul, QE, MSM 30 both at short term and long term. Gold has a very weak or negative correlation with all other indices.

Resolution level D2 (Figure1) related to a time frame of 2 days shows correlation of 0.54 between Bahrain and ADX and 0.64 between Tadawul and ADX while other GCC indices had a lower correlation. QE and gold recorded an exceptional negative correlation of −0.14.

Resolution level D3 (Figure1) which accounts a window time of 4 days indicated highly correlated indices pairs were Tadawul -Bahrain-, QE-Tadawul while other reveal low correlation. The GCC indices are at less association with WTI crude, Brent and Gold. Tadawul-Bahrain coherence map shows strong association at 8 days and in the long run also. The total volume of shares traded in Tadawul in February, 2020 was 15.41% less than the previous month.

Resolution level D4 (Figure 1) in the window time of 8 days, Abudhabi and MSM 30; Abudhabi and Tadawul; QE and Tadawul has shown correlation. Abudhabi has shown correlation with Dow Jones, S&P 500 and gold as well. Qatar and Brent has shown stronger association with others having weaker association. WTI recorded weaker and negative correlation with other GCC indices. Dow Jones and S&P 500 has shown stronger relation with gold.

At resolution level D5 D5 (Figure 2) related to a time frame of 16 days, strong correlation of GCC indices among themselves and with that of Dow Jones and S&P 500 could be seen. Correlation of GCC indices with that of Brent and Gold has been picking up. However, Bahrain's association with gold, Brent and WTI seemed weak. WTI consistently maintained negative correlation with other indices.

Trend of previous plot continues with a time frame of 32 days at resolution level D6 (Figure 2). Correlation among GCC indices and with that of DJ, S&P500 grew stronger. Except for Bahrain, all other indices seem to have association with gold. WTI maintained negative correlation or weak correlation with all other indices. Stronger correlation could be noticed among gold and brent.

It is shown in Figure 3 that at the resolution level D7 related to a window time of 64 days, the degree of association strengthens among GCC markets, with Dow Jones, SP500 and Brent. Nevertheless, as compared to previous resolution levels, results show an inversion of the relationship with Gold. So, in a relative long run period the negative relationship may show investors' risk aversion where Gold is considered as a safe haven security. However, at the coarse scale related to the smooth component in a time frame greater than 128 days, the relationship of the risky markets with Gold strengthens which may signal that in the whole period study Gold cannot be considered at all as a safe haven.

As observed in Figure 4 Wavelet coherence (WC) plots between pairs of Abudhabi stock index and other GCC index as well the plots between pairs of Abudhabi stock index and other indices such as Dow Jones, S&P 500, Brent, Crude and Gold indicated strong positive association at lower frequency (long-time horizon). Additionally there were interspersed areas of positive association at higher frequencies (short time horizon) indicating co-movement of stocks. Association of Abudhabi stock index and Brent seemed to reduce at lower frequency (long time horizon).

The association with gold looks weak at higher frequency (Short time horizon), however stronger association emerged at lower frequency (long time horizon). Same pattern could be observed with that of Dow Jones and S&P 500. There were associations with that of crude both at high and lower frequencies.

Figure 3: Decomposed correlation at resolution levels D7 and S7

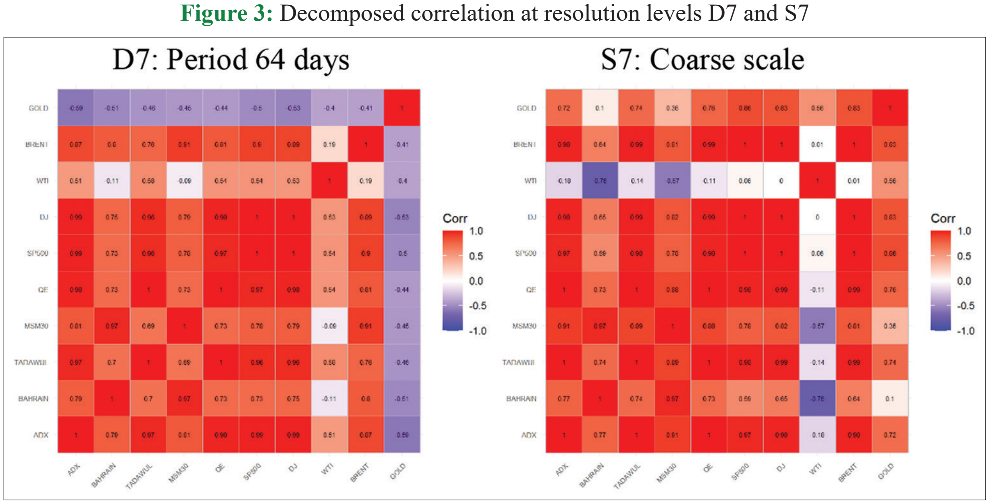
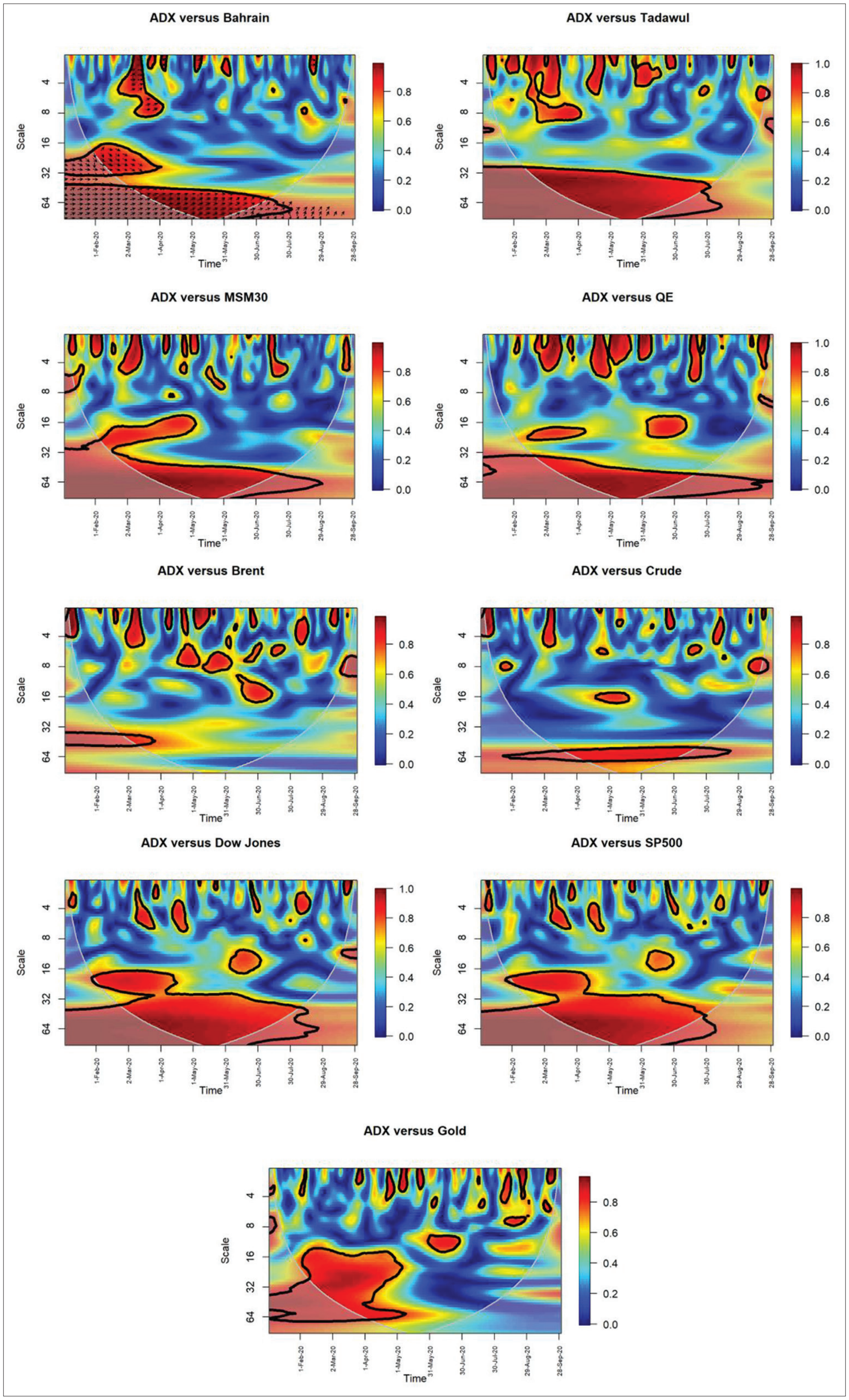
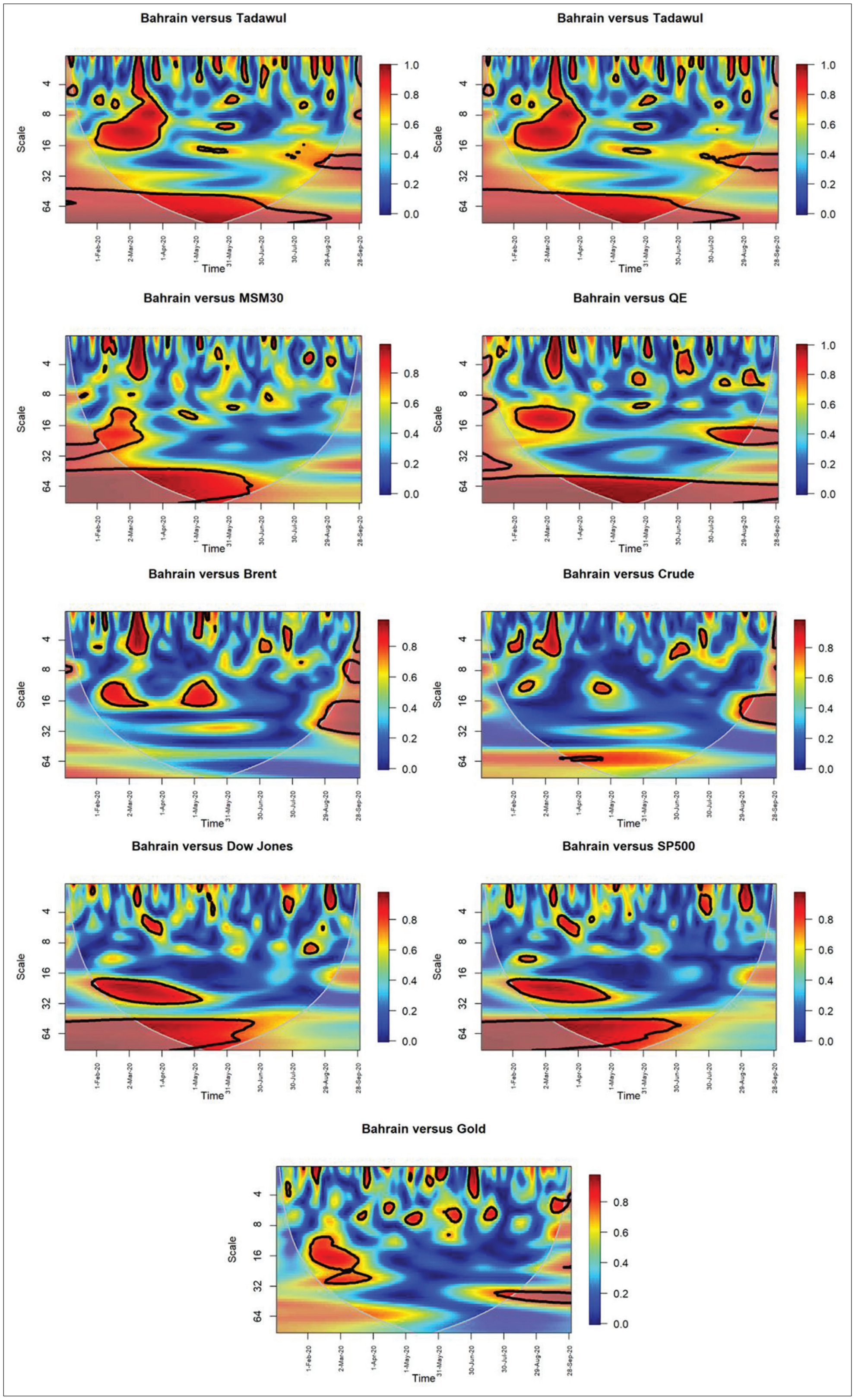


Figure 4: Wavelet coherence analysis of Abudhabi versus Bahrain, MSM 30, Tadawul, QE, Brent, Crude, Dow Jones, S&P500, and Gold



Wavelet coherence plots of Bahrain paired with other GCC indices indicated strong association both at high frequency (short time horizon) and at medium frequency (medium time horizon) Figure 5. Although the association of Bahrain stock index with Brent and gold could be seen at high and medium frequencies, it was absent at the shorter frequency (long time horizon). Some level of association with crude could be found interspersed at high and low frequencies. Co movements of Bahrain stock index with Dow Jones and S&P 500 could be identified at medium and lower frequencies.

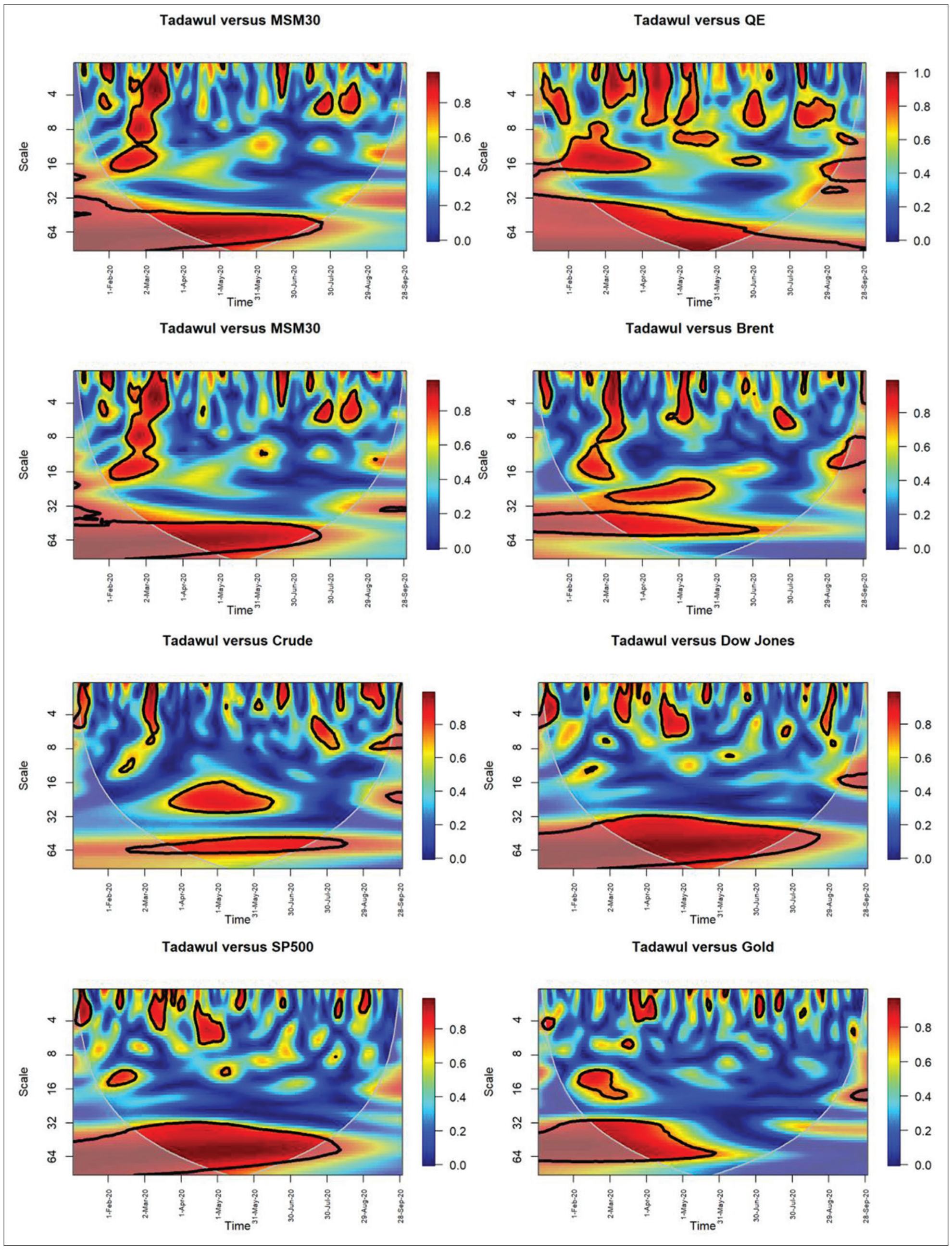
Figure 5: Wavelet Coherence maps of Bahrain Index with Tadawul, MSM30, QE, Brent, Crude, Dow Jones, S&P500, and Gold



Tadawul stock index (Figure 6) has shown significant associations with all other GCC indices both at short (long time horizon) and at high frequency (short time horizon) especially with that of Qatar and Bahrain. When it comes to Brent, Crude, Gold, Dow Jones, S&P 500 Tadawul has shown association both at short and longer frequency indicating significant co-movements with all other indices.

Like other GCC indices, MSM 30 (Figure 7) has shown significant associations with other GCC indices both at short frequency

Figure 6: Wavelet coherence maps of Tadawul, MSM 30, Brent, Crude, Gold, DowJones, S&P500



(long time horizon) and at higher frequency (short time horizon). Association of MSM 30 with Brent and Crude is weak or absent with Gold and Brent. Significant co-movement could be observed between MSM 30 with that of S&P 500 and Dow Jones at short frequency.

Similar to Tadawul stock market, QE has significant association with that of other GCC indices both at short frequency (long time horizon) and at higher frequency (short time horizon) (Figure 8). Brent, Crude, Gold have shown association with QE at both short and long frequency. S&P 500 and Dow Jones have significant association with that of QE at short frequency.

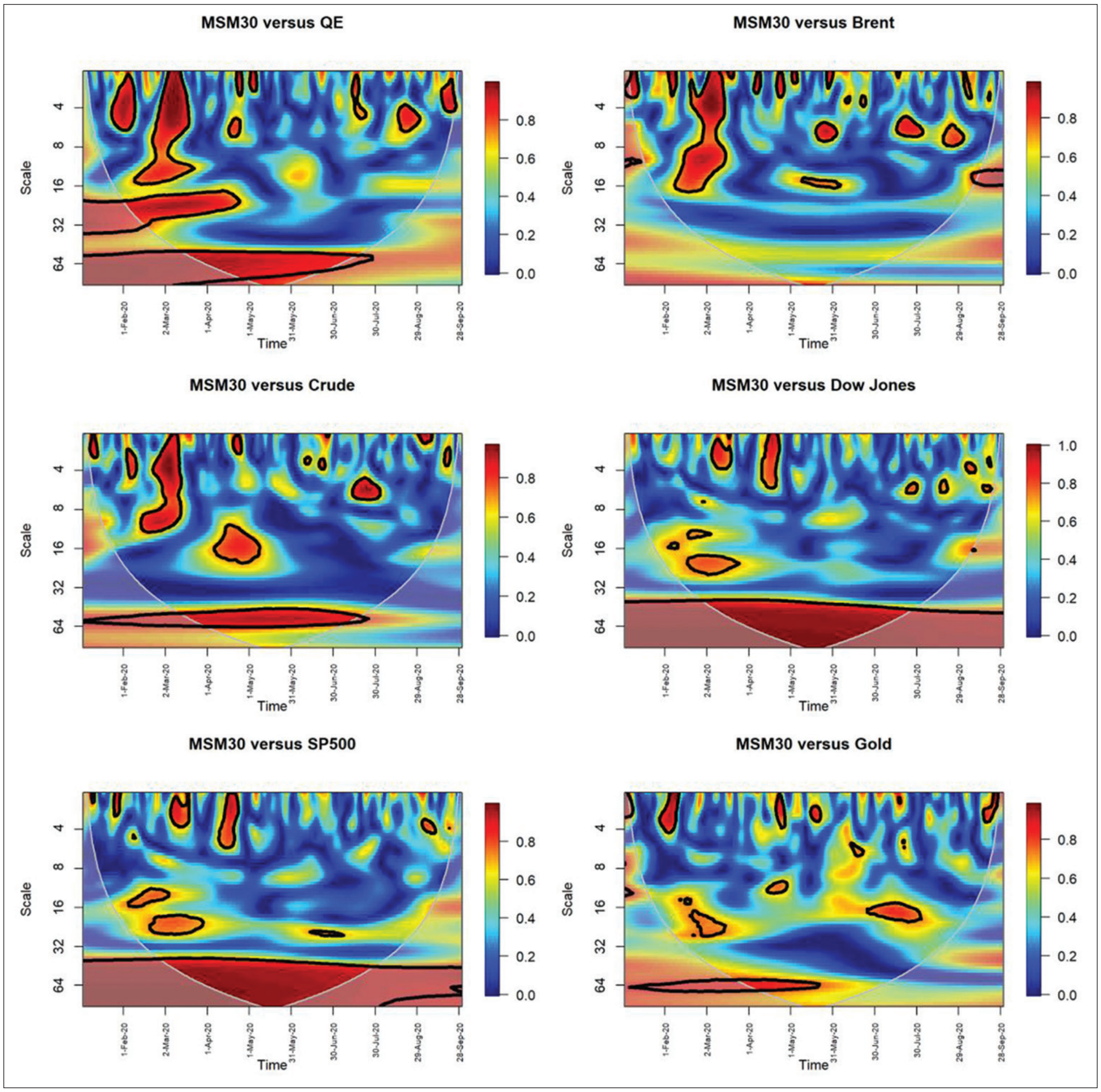
Overall, GCC have shown co-movements with each other as well as with Dow Jones and S&P 500. Bahrain and MSM 30 have shown less dependence on Brent and Gold in the long run.

Brent has shown co-movement with gold, Dow Jones and S&P 500 at higher frequency (short time horizon) (Figure 9). Compared to Dow Jones and S&P 500, Gold has shown more association at lower frequency (long run time horizon).

5. DISCUSSION

This study has chosen time period from January 2, 2020 up to September 30, 2020 to understand posible co-movement among

Figure 7: Wavelet Coherence maps of MSM 30 with QE, Brent, Crude, Dow Jones, S&P500, and Gold



GCC índices, Brent, Crude, Dow Jones and S&P500 due to the impact of COVID 19.

Analysis of 276 days' stock data, shows co-movement among GCC índices, Brent, Dow Jones and S&P 500 in the long run time horizon. This clearly shows that the pandemic has had its effect on stock market especially that of GCC markets.

The multi resolution decomposition of the time series presented in the study illustrates that there are spillover and co-movement existence among the investigated GCC market indices due to the negativities caused by COVID-19.

Initially, there were positive correlation of 0.6 and above among indices like Abudhabi and Qatar, Bahrain and Qatar, Tadawul and Qatar. These GCC indices had negative correlation with gold and Brent had weak correlation with all other GCC indices. The correlation among the GCC indices seemed to reduce by Day 4 and the association of GCC indices with that of Crude (WTI) was negative. By Day 4, Abudhabi and Oman has some positive correlation. By Day 8, positive association among Bahrain, Qatar and Saudi started picking up. Association of gold and crude remained with other GCC indices remained weak. Day 16 has shown negative correlation among WTI and GCC indices and Gold; Bahrain and Gold as well as negative correlation among WTI and Brent. There was negative correlation among Oman and Saudi as well as among Oman and Qatar.

Though GCC indices had weak association with S&P 500 and Dow Jones initially, by Day 32 there was co-movement among all the paired indices. The strength of association among all the indices looked higher by day 32. However, the association of Bahrain and Qatar and that of Oman and Qatar remained weak.

At Day 64 except for Abudhabi and crude; Oman and Crude all other markets show stronger association indicating potential risk for the investors. Though Gold has shown a negative relationship with all other indices at this stage, coarse scale indicates correlation of gold with other risky markets. Hence gold cannot be considered as safe haven.

Figure 8: Wavelet Coherence maps of QE with Brent, Crude, DowJones, S&P500, and Gold

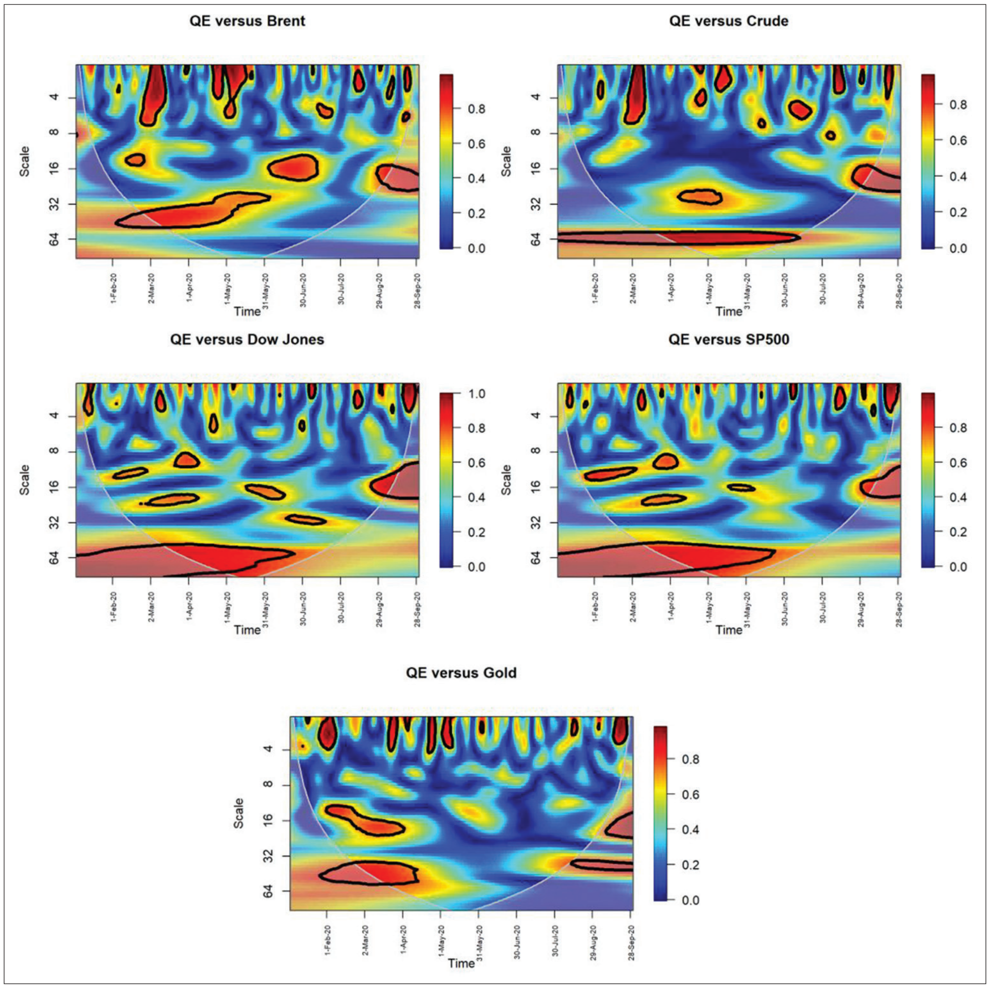
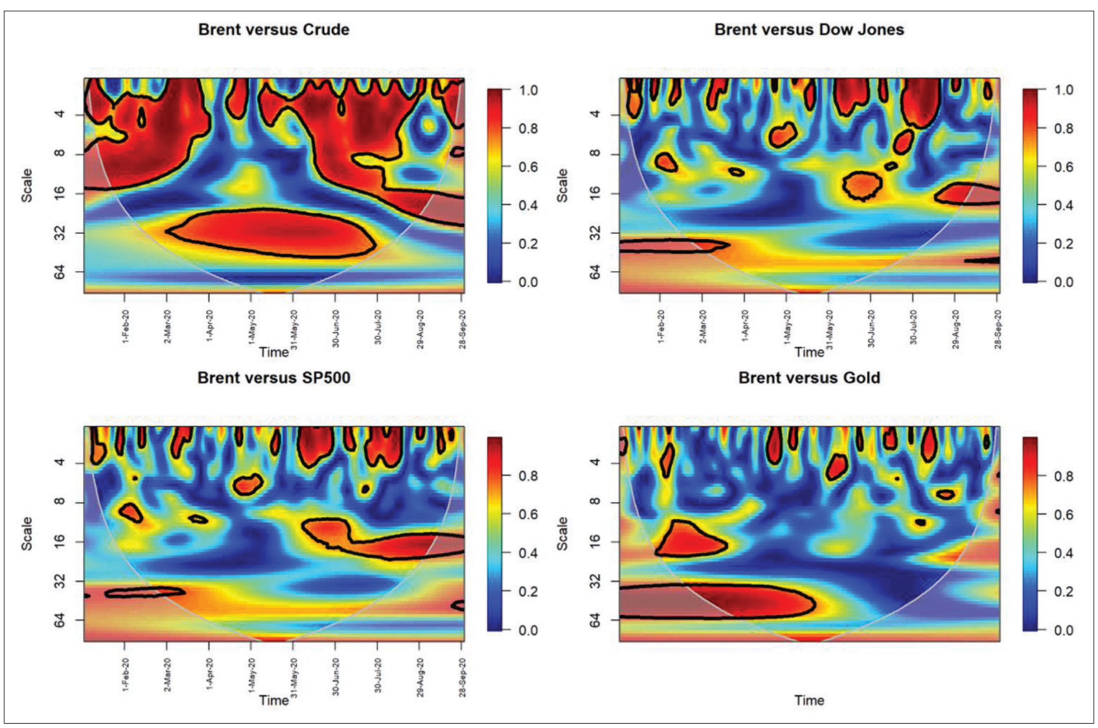


Figure 9: Wavelet Coherence maps of Brent with Crude, Dow Jones, S&P500, and Gold



Hence, it could be understood that the impact of economic crisis has penetrated all the markets considered for this study.

6. CONCLUSION

The study reveals that timing is a strong determinant of the co-movement effect after economic shocks and crisis. This can be observed during the long term window when the correlation increases for all paired indices. As a result, authors proposed that, due to the integration of the GCC markets, these indices have a tendency to show strong co-movement after major economic events or crises. Hence, investors that are considering investing in emerging GCC countries should not only consider possible co-movement, but also the timing of their investment.

Therefore, strong indices shown in the analysis might be fruitful to support the investors that are wishing to internationally diversify their portfolio among emerging GCC markets.

The study suffers the limitation of analysis of short term data over a period of 9 months. The authors propose further research that analyzes the pre COVID 19 and post COVID 19 data for further insights.

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