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Time and Frequency Dynamics of Connectedness among Emerging MENA Stock Markets, Brent Crude Oil, and Gold Market

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Abstract
This study investigates the return connectedness across the major Middle East and North Africa (MENA) stock markets, Brent crude oil, and Gold, from April 2008 to July 2019 using the frequency-domain framework and causality among these markets. Three different periods, including the short term, medium term, and long term are considered to analyze the interconnectedness of markets. The results of the study indicate that the markets are more connected and speculative in the short term, thus there is less chance of portfolio diversification among these markets in the short term. The QE general contributes more to the Brent crude oil market in the short term, and Tadawul has more connectedness with this market in other timeframes. Moreover, among MENA stock markets, the QE general contributes more to the short term and medium term and ADX general has more influence on other markets in the long term. The financial crisis of 2008 and the oil price crash during 2014 increased the total return connectedness of these markets with the shocks having long-lasting effects. The findings of this study can offer new insights to policymakers and investors.

Keywords: Brent Crude oil, Frequency Return Connectedness, MENA Stock Markets.
JEL Classification: C18, C32, G15

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1. Introduction

The Middle East and North Africa (MENA) is a diverse region consisting of 19 countries. The MENA region accounts for approximately 6% of the world's population, 60% of the world's oil, 45% of the natural gas reserved, and 4.5% of the global GDP. Considering such figures, MENA countries have an essential role in the global economy (The World Bank Group, 2020).

Researchers use various models to investigate the connectedness of markets (Billio et al., 2012; Diebold & Yilmaz 2014; Bagheri & Ebrahimi 2020; and Bagheri et al., 2021). The connectedness among financial markets is not only important for the regulatory view but is also vital for the portfolio management and risk management. Therefore, a model is needed to measure the connectedness between markets. Here, we examine the interdependence between the Brent crude oil market, Gold market, and stock exchanges in some MENA countries.

Diebold and Yilmaz (2012, 2014) presented a new connectedness measurement based on the generalized variance decomposition to analyze volatility spillovers across US equity, bond, and exchange markets and found out that it existed among all these markets and the level of these spillovers was different during the financial crisis. Barunik and Kocenda (2019) expanded the DY methodology using spectral variance decomposition decomposing connectedness into various frequency ranges. They argue that variables, which have an impact on economic shocks, have various effects of frequencies and thus it is necessary to understand the mechanism of shocks and information transition to have a better perception of the source of connectedness. Moreover, this framework determines the direction and intensity of cross-market connectedness in different frequency domains simultaneously.

This paper provides a new empirical view to illustrate the short, medium, and long-term Return connectedness among MENA, Brent crude oil, and Gold stock markets. Moreover, to solve the drawback of the Barunik and Krehlik model, which does not consider the causality of markets, we utilize a causality test to understand the evidence of causal links between these markets and obtain more insightful and complementary results. The findings could be useful for investors, portfolio managers, and authorities.

The rest of the paper is organized as follows: Section 2 deals with a literature review of previous investigations about this subject, Section 3 introduces the research methodology, Section 4 presents research findings, and finally, Section 5 summarizes the results and conclusions.

2. Literature Review

2.1 MENA Economic Situation

The MENA zone consists of mainly developing countries that are rich in natural and human resources, labor, GDP, and population, although these countries considerably vary in some cases (Guetat & Serranito, 2007). The region mostly confronts high inflation and unemployment rates. Due to a remarkable positive population growth rate in this region, however, these countries have a favorable population structure of young people.

One important advantage of the concentration on MENA is that these emerging markets are interesting for investors around the world due to the recently liberalized investment regulation, removed ownership restrictions, and trade and capital flow barriers (Alqaralleh, Awadallah, & Al-Ma'aitah, 2019). According to Bakhshi Dastjerdi and Dallali Isfahani (2011), there is a significant potential for having considerable economic growth in the MENA region. Moreover, some of these countries reached a high-level financial development. However, the main drawback of investment in this region is related to the lack of security and unfair policies to protect investment in some of these countries.

Most of the equity markets in MENA countries have only come to the fore in the 1990s. Despite their small market capitalization during the past 10 years, equity markets in MENA countries have exhibited performance characteristics parallel to other emerging markets in similar stages of financial development (Neaime, 2012). However, many investors have been motivated to contribute to these markets by increasing the efficiency and liquidity of some of these markets.

2.2 Interconnectedness of Financial Markets

Researchers have used various models to study the interconnection of markets. Some researchers have focused on correlation-based measures. Pal and Mitra (2018) use a de-trended cross-correlation analysis to indicate the interconnectedness among oil-food markets.

Ladonit et al. (2003) proposed a new method to estimate time-dependent covariance matrices in the Diagonal Vech framework, which is a state of multivariable GARCH model. After the introduction of the dynamic conditional correlation (DCC)-GARCH models, many studies used Multivariate GARCH (MGARCH) to measure volatility spillovers (e.g., Sadorsky 2014; Mimouni et al., 2016). Lee (2007) focused on the interconnection between stock markets of China, Hong Kong, and the U.S. using BEKK models. Billio et al. (2012) and Bondia, Ghosh, and Kanjilal (2016) utilized Granger causality approaches. Dutta, Bouri, and Roubaud (2019) used ARDL methods to measure the volatility connection between crude oil and precious metals. Acharya et al. (2017) examined marginal expected shortfall methods (MES) to measure systematic risk. Another group of researchers tried to use the conditional value at risk (CoVaR) (Shahzad et al., 2018; Adrian & Brunnermeier 2016; Reboredo 2015). Diebold and Yilmaz (2009) proposed a new measurement model called the volatility spillover index. This approach is based on the generalized variance decomposition. Diebold and Yilmaz could obtain a volatility spillover table for 19 selected markets of different countries and introduce a quantitative measure. Three years later, Diebold and Yilmaz (2012) tried to improve their connectedness measure framework by introducing the generalized forecast error variance decomposition (GFEVD), which not only measured volatility aggregation but also determined their direction. They used it to study the U.S. stock, bond, foreign exchange, and commodities markets from 1999 to 2010 to determine net transmitters and receivers in the time variation of volatility spillovers.

Diebold and Yilmaz (2014) represented a network connectedness that used variance decomposition of VAR as the measurement of strength. They measured the connectedness of 11 main U.S. financial institutions and formed a network based on the aggregation and direction of connections with a given weight. Klößner & Wagner (2012) introduced a robust spillover index of Diebold and Yilmaz (2009). They used the Economic Policy Uncertainty Index of Baker et al. (2013) along with the spillover index to measure spillovers of policy uncertainty during 1997-2013. They found that the U.S. and U.K. are strongly connected as net transmitters while other countries are net receivers, especially in crisis periods. Yoon et al. (2019) used the findings of Diebold and Yilmaz to investigate the connectedness among gold, currencies, and bonds from 1999 to 2016. They reported that markets reached the highest connectedness during the 2008 financial crisis, and gold and diversification in the portfolio could reduce systematic risk. Lin and Li (2015) focused on regional differences using monthly data of the U.S., German, and Japanese, markets. Their results revealed a strong bidirectional spillover effect between the U.S. and Germany. Antonakakis and Kizys (2015) used the variance decomposition to measure spillovers and volatilities of currencies and commodity markets. The results showed that gold, silver platinum, and pound could send major shocks to other markets. On the other hand, the euro and crude oil could be considered the major shock receivers.

Greenwood-Nimmo et al. (2016) worked on risk-return spillovers between G10 currencies from 1999 to 2014. They found that volatility spillovers would rise massively across currencies during financial crisis periods. Barunik and Krehlik (2018) introduced a new spectral method and improved Diebold and Yilmaz's framework to the frequency domain, which is based on the spectral representation of the forecast error variance decomposition leading to different frequency domains. Therefore, this new measurement can compute the aggregate connectedness with different frequencies and diagnose the direction of information transmission at different times. They used it to measure the volatility shocks transmission across oil, gasoline, and heating oil futures. The results showed that the connectedness at high frequencies could be crucial. This new measure has been used in many studies.

Restrepo Uribe, and Manotas (2018) investigated the return of 20 Oil Companies in NYSE and reported a high similarity score in the correlation dynamics between crude oil stock volatility series from January 2002 to November 2016. Baur, Dimpfl, and Kuck (2018) worked on crypto-currencies, especially Bitcoin, from 2010 to 2015 and documented that Bitcoin had different volatility characteristics compared to dollar and gold. Ferrer et al. (2018) worked on the connectedness among oil price, financial market, and stock prices of renewable energies from January 2003 to September 2017. They observed no connection between the oil and stock prices. Wang et al. (2019a) focused on the future trends of electricity, coal, natural gas, and crude oil markets using a novel frequency connectedness method across with the MF-DCCA method. The results showed that connectedness in the short term was strong and each market played various roles in the system based on periods.

Wang et al. (2019b) investigated the gold, wheat, WTI crude oil, and copper future markets to measure return spillovers among them. They found that copper was an information transmitter while the others were receivers of return spillovers. Maghyereh, Abdoh and Awartani (2019) worked on the dynamic connectedness between gold, Sukuk, and Islamic equities from 2005 to 2018. The results confirmed the hedging role of Gold in different investment horizons and showd that the diversification of Islamic equities with the risk hedge character of gold could be very effective in Islamic stock markets, especially in the short term. Lovcha and Perez-Laborda (2019) studied the dynamic volatility connectedness and frequency dynamics of the transmission in the oil and natural gas market from 1994 to 2018. They showed that connectedness usually happened at low frequencies, with volatility shocks across markets having long-lasting effects.

In the region of this study (MENA), many studies have tried to measure the dependency between these countries. For example, Noomen Ajmi et al. (2014) focused on the connection between the world oil price and MENA stock markets during crisis periods using the nonlinear and asymmetric causality test of Kyrtson and Labys (2006). Elsayed and Yarovaya (2019) used the method of Diebold and Yilmaz (2012) to measure the influence of Arab Spring on the MENA region. Mensi et al. (2019) used a combined wavelet and the dependence-switching copula approach to study the roles of oil, Bitcoin, gold, and VIX (the volatility index) in MENA stock markets. Their results showed a significant tail dependency between MENA stock markets and global financial factors. This dependence structure varies across different regimes and time horizons. This paper used the finding of Diebold and Yilmaz (2012) along with Barunik and Krehlik (2018) to measure time-frequency dynamics of connectedness and documented that a long-run component had the strongest effect on total volatility spillovers. The results also showed that commodities and Islamic finance instruments could reduce the volatility spillover.

3. Research Methodology

The present study aims to measure the shares of forecast error variation in an asset "k" due to shock to an asset "j" at specific frequency bands. First, we summarize the generalized forecast error variance decomposition (FEVD) framework introduced by Diebold and Yilmaz (2012).

By assuming the n-variate stationary process $Y_t = (y_{t,1}, \dots, y_{t,n})$, the VAR (p) at t = 1,..., T is defined as:

$$\Phi(L)Y_t = \varepsilon_t$$

where $\Phi(L) = \sum_h \Phi_h L^h$ is a n×n, p-th order lag-polynomial and ε_t is White-noise. Following MA (∞) representation:

$$Y_t = \Psi(L)\varepsilon_t$$

where $\Psi(L)$ is an n×n infinite lag polynomial matrix of coefficients.

Based on the FEVD, we have:

$$(\Theta_H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} ((\Psi_h \Sigma)_{j,k})^2}{\sum_{h=0}^{H-1} (\Psi_h \Sigma \Psi_h^{'})_{j,j}}$$

where Ψ_h is an n×n matrix of coefficients corresponding to lag h and $\sigma_{kk} = (\Sigma)_{kk}$.

The $(\Theta_H)_{j,k}$ measures the share of the kth variable of the system to the variance of forecast error of the asset j. We know that the effect does not add up to one $(\sum_{h=0}^{H} \theta_{j,k} \neq 1)$ within columns by definition in the generalized VAR process of FEVDs, then we use measuring the pairwise-directional connectedness to standardize the effects by $(\widetilde{\Theta}_H)_{j,k}$:

$$(\widetilde{\Theta}_H)_{j,k} = (\Theta_H)_{j,k} / \sum_k (\Theta_H)_{j,k}$$

The total directional connectedness from asset k to other assets is defined as:

$$C_{j\leftarrow}(H) = 100 \times \sum_{j\neq k, j=1}^{n} C_{j,k}(H) \Big/ \sum_{j,k=1}^{n} C_{j,k}(H)$$

and the total directional connectedness of other variables to j market is measured with:

$$C_{\leftarrow k}(H) = 100 \times \sum_{j\neq k, k=1}^{n} C_{j,k}(H) \Big/ \sum_{j,k=1}^{n} C_{j,k}(H)$$

Therefore, the connectedness of the whole system is defined as:

$$C_H = 100 \times \frac{\sum_{j\neq k} (\sim\Theta_H)_{j,k}}{\sum (\sim\Theta_H)_{j,k}} = 100\left(1 - \frac{Tr\{\sim\Theta_H\}}{\sum (\sim\Theta_H)_{j,k}}\right) \quad (1)$$

where Tr {.} is the trace operator and C_H shows the connectedness of the whole system.

Now, we follow the methodology of Barunik and Krehlik (2018) to measure connectedness in the frequency domains. As, the generalized FEVDs (GFEVD) are the core of connectedness, a frequency response function is needed:

$$\Psi(e^{-iw}) = \sum_h e^{-iwh} \Psi_h \quad (2)$$

which is obtained from the Fourier transform of the coefficients Ψ, with $i = \sqrt{-1}$.

We assume $d = (a, b): a, b \in (-\pi, \pi), a < b$ as a frequency band. Hence, the generalized variance decompositions on this frequency band are defined as:

$$(\Theta_{j,k}) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \Gamma(\omega) (\mathfrak{f}(\omega))_{j,k}$$

where $(\mathfrak{f}(\omega))_{j,k}$ shows the generalized causation spectrum over frequency $\omega = (-\pi, \pi)$, with $\Gamma(\omega)$ as the weighting function. When we use the frequency share of the variance of variable j as the weighting function of $(\mathfrak{f}(\omega))_{j,k}$, we can measure a natural decomposition of original GFEVD to frequencies.

"d_s" demonstrates an interval on the real line from the set of intervals Ɗ that form a partition of the Interval $(-\pi, \pi)$, such that $\cap_{d_s=Ɗ}\ d_s = \emptyset$ and $\cap_{d_s=Ɗ}\ d_s = (-\pi, \pi)$. Due to the linearity of the integral and the construction of "d_s", we have:

$$(\Theta_\infty)_{j,k} = \sum_{d_s \epsilon Ɗ} (\Theta_{d_s})_{j,k}$$

Spectral representation of (GFEVD) can help describe the time-varying frequency of the connectedness. The scaled generalized variance decomposition on the frequency band $d = (a, b): a, b\ \epsilon\ (-\pi, \pi), a < b$ is defined as:

$$(\widetilde{\Theta}_d)_{j,k} = (\Theta_d)_{j,k} \Big/ \sum_k (\Theta_\infty)_{j,k}$$

Therefore, the within connectedness on the frequency band d is measured as:

$$C_d^W = 100\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \widetilde{\Theta}_d}\right)$$

and the frequency connectedness on the band d is also defined as:

$$C_d^F = 100\left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum (\widetilde{\Theta}_d)_{j,k}}\right) = C_d^W \cdot \left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty}\right)$$

It should be mentioned that the within connectedness leads us to the connectedness effect of the frequency band, which is exclusively weighted by the power of the series on the specific frequency band. Moreover, the frequency connectedness decomposes the original connectedness into distinct parts that in sum gives the original connectedness measure.

Moreover, we use the Granger causality test to measure the ability to predict the future values using prior values of another time series. The main idea behind GC is that X "Granger causes" Y if X contains information that helps predict the future of Y better than information in the past of Y or predicts information in the past of other conditioning variables. For the recognition of Granger causality between two time series X and Y, we need two linear regressions:

$$Y(t) = \sum_{i=1}^{L} \alpha_i Y(t-i) + \varepsilon_1(t) \quad (9)$$

$$Y(t) = \sum_{i=1}^{L} \alpha_i Y(t-i) + \sum_{i=1}^{L} \beta_i X(t-i) + \varepsilon_2(t) \quad (10)$$

If the second model is significantly better for predicting the time series Y, we can argue that process X is the cause of process Y.

4. Research Findings

In the present study, the authors employed weekly global crude oil market data and six stock markets of MENA countries, including Iran (TEPIX), Saudi Arabia (Tadawul), Qatar (QE General), Egypt (EXG100), Turkey (BIST100), and United Arab Emirates (ADX General) from April 2008 to July 2019, all of which were gathered from Thomson Reuters and the Tehran stock exchange databases. We calculated the weekly return using $Ln(p_t) - Ln(p_{t-1})$. Table 1 shows the descriptive statistics for the weekly return series. We utilized the Jarque-Bera test to analyze the normality of variables. The normality assumption was rejected in all series. Moreover, the Augmented Dickey-Fuller unit root test was also rejected at the 1% significance, indicating that all series were stationary. Given the degree of Kurtosis in each time series, they can be described to be a fat tail.

Granger defined the causality relationship based on two principles:

- The cause happens before its effect.
- The cause has unique information about the future values of its effect (Eichler, 2012).

Table 1. Descriptive Statistics and Preliminary Tests for Return

	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera	ADF
BIST100	0.00149	0.00352	0.1576	-0.1927	-0.444	6.097	255.580	-25.29
BRENT	-0.00089	0.00178	0.2010	-0.2971	-0.652	7.235	483.447	-24.53
ADX GENERAL	0.00016	0.00156	0.1032	-0.2100	-1.944	15.711	4351.006	-24.47
EGX 100	-0.00344	0.00076	0.1764	-0.2483	-2.001	11.952	2367.646	-11.15
GOLD	0.00080	0.00099	0.1239	-0.1013	-0.160	5.542	161.709	-24.37
QE GENERAL	0.00011	0.00169	0.1198	-0.2297	-1.274	12.060	2181.491	-23.41
TADAWUL	-0.00010	0.00196	0.1376	-0.1912	-0.985	9.207	1044.380	-25.16
TEPIX	0.00545	0.00269	0.1381	-0.0704	1.223	7.997	762.053	-10.11

Source: Authors

Table 2. Granger Casualty Test for Return Series

Null Hypothesis:	F-Statistic	Prob.
GOLD does not Granger Cause TEPIX	2727.4	6.00E-297
BRENT does not Granger Cause TEPIX	13.7555	1.00E-06
ADX-GENERAL does not Granger Cause TEPIX	4.03743	0.0181
QE GENERAL does not Granger Cause TADAWUL	3.83509	0.0221
TADAWUL does not Granger Cause QE GENERAL	3.4265	0.0332
BRENT does not Granger Cause TADAWUL	17.1724	6.00E-08
TADAWUL does not Granger Cause BRENT	4.96868	0.0072
BIST100 does not Granger Cause TADAWUL	13.6688	2.00E-06
BRENT does not Granger Cause QE GENERAL	12.7682	4.00E-06
BIST100 does not Granger Cause QE GENERAL	11.4304	1.00E-05
GOLD does not Granger Cause EGX 100	4.50532	0.0114
BIST100 does not Granger Cause EGX 100	4.63498	0.0101
BIST100 does not Granger Cause GOLD	6.79386	0.0012
GOLD does not Granger Cause ADX GENERAL	3.99739	0.0189
BRENT does not Granger Cause ADX GENERAL	15.1496	4.00E-07
BIST100 does not Granger Cause ADX GENERAL	4.61609	0.0103

Source: Authors

We investigated the possibility that one of the two variables could cause the other. Table 2 shows the markets that reject the first hypothesis of the causality test. Brent crude oil is the Granger cause of stock markets of oil-producing countries, thus there is a potential predictability power for these markets while only Tadawul is the Granger cause of Brent crude oil market. Considering the Tehran stock exchange, Gold and ADX general contribute to the prediction of TEPIX while no reciprocal relations could be observed here. Among stock markets, BIST100 is the Granger cause of Gold while Gold is the Granger cause of ADX General, EGX100 and as mentioned before, TEPIX. Moreover, BIST100 has the potential of predictability of ADX General, QE General, and EGX100.

Considering the methodology described in Section 3, the vector auto-regression starts here with assessing the Schwarz information criterion (SIC) to select the slack length and to construct the frequency connectedness tables. We use a 100-period ahead forecasting horizon. Table 3 shows a time frame of 1-4 weeks (short-term), whereas Table 4 generally corresponds to 4-10 weeks (medium-term), and Table 5 roughly presents 10-50 weeks (long-term). The total connectedness of returns is 33.08% showing that the returns in these markets are connected to some extent, and the total connectedness of the short term (23.04%) has the highest contribution to all frequencies. This shows that the markets are highly speculative in the short term, thus there is less chance of portfolio diversification among these markets in the short term. Moreover, the variance of forecast error in all frequencies in most markets is due to the shocks themselves, especially for the Tehran stock exchange.

Considering the pairwise frequency connectedness, QE general contributes more to the Brent market in the short term. In contrast, Tadawul has more connectedness with the Brent crude oil market in the medium and long terms. A remarkable return connectedness is also observed between QE General and Tadawul, especially in the short term.

ADX General has a considerable return connectedness with QE General and Tadawul, especially in the short term, which are 13.79% and 7.97%, respectively. BIST100 is more connected with Brent crude oil in the short term, while QE General and EGX100 are more connected in the medium term and long term with 1.23% and 1.88%, respectively.

TEPIX and EGX 100 have less contribution to the other markets in all timeframes. Nevertheless, EGX100 is significantly affected by Tadawul and QE general, especially in the short term. On the other hand, TEPIX has more return connectedness with BIST 100 in the short term and with ADX General in the medium and long terms, which are 1.22%, 0.39%, and 0.74%, respectively.

The gold market has an insignificant return connectedness with MENA stock markets, suggesting that this market is a suitable choice for portfolio managers who want to diversify their portfolios at MENA stock markets. However, this market is connected to the Brent market to some extent, especially in the short term, thus hedgers need to be careful about investing in these markets in a short period. Overall, among MENA stock markets, QE general contributes more to the other markets in the short and medium terms, and ADX general has more influence on the other markets in the long term.

Table 3. Short-term Connectedness of MENA Stock Markets and Commodities[1]

Column1	ADX General	BIST100	Tadawul	EGX 100	QE general	TEPIX	Brent	Gold	FROM-ABS	FROM-WTH
ADX General	42.55	1.93	8.33	3.43	13.9	0.16	4.46	3.06	4.41	6.33
BIST100	3.13	55.54	3.84	2.47	4.29	1.22	3.54	1.83	2.54	3.64
Tadawul	7.97	2.87	39.64	5.19	10.85	0.34	3.2	2.48	4.11	5.9
EGX 100	1.99	1.35	3.76	33.24	2.18	0.47	1.83	1.46	1.63	2.34
QE General	13.79	2.99	12.4	3.38	36.77	0.75	3.87	1.87	4.88	7.01
TEPIX	0.43	0.63	0.92	0.59	1.58	50.7	1.98	0.7	0.85	1.22
Brent	3.12	3.62	3.56	1.89	4.45	0.88	52.59	3.96	2.69	3.85
Gold	1.07	3.6	1.5	0.82	1.44	1.2	5.87	61.98	1.94	2.78
TO-ABS	3.94	2.12	4.29	2.22	4.84	0.63	3.09	1.92	23.04	
TO-WTH	5.65	3.05	6.16	3.19	6.94	0.9	4.44	2.76		33.08

Source: Authors

[1] abs" implies "absolute" and "wth" implies "within"

Table 4. Medium-term Connectedness of MENA Stock Markets and Commodities

	ADX	BIST1	Tadaw	EGX	QE	TEPI	Bre	Gold	FROM-	FROM-
ADX	5.36	0.56	1.08	0.34	2.37	0.39	0.54	0.14	0.68	4.33
BIST100	0.43	11.51	0.49	0.46	0.96	0.11	0.69	0.28	0.43	2.72
Tadawul	1.01	1.01	7.57	0.77	2.9	0.07	1.04	0.24	0.88	5.62
EGX 100	1.15	1.1	2.71	17.46	2.74	0.38	0.34	0.02	1.05	6.72
QE	1.18	1.23	1.34	0.42	7.48	0.3	0.69	0.3	0.68	4.36
TEPIX	0.04	0.42	0.24	0.04	0.29	16.48	0.42	0.15	0.2	1.28
Brent	0.36	0.57	0.91	0.07	0.77	0.25	8.56	0.28	0.4	2.57
Gold	0.03	0.1	0.12	0.09	0.01	0.14	0.82	14.97	0.16	1.05
TO-ABS	0.53	0.62	0.86	0.27	1.26	0.2	0.57	0.17	4.49	
TO-WTH	3.35	3.97	5.5	1.75	8.03	1.31	3.63	1.11		28.65

Source: Authors

Table 5. Long-term Connectedness of MENA Stock Markets and Commodities

	ADX General	BIST10 0	Tadaw ul	EGX 100	QE general	TEPI X	Bren t	Gold	FROM-ABS	FROM-WTH
ADX General	4.78	0.56	1.72	0.71	1.72	0.74	1.06	0.11	0.83	5.64
BIST100	0.39	6.73	0.08	0.19	0.52	0.07	0.74	0.5	0.31	2.13
Tadawul	1.73	1.46	4.42	0.8	2.17	0.07	1.84	0.37	1.05	7.19
EGX 100	2.04	1.88	1.57	20.45	1.28	0.15	0.35	0.1	0.92	6.29
QE General	2.43	0.88	1.47	0.55	4.51	0.45	0.87	0.08	0.84	5.73
TEPIX	0.79	0.24	0.67	0.03	1.07	18.38	3.17	0.05	0.75	5.14
Brent	1.16	1.25	1.58	0.12	1.39	0.21	7.44	0.98	0.84	5.71
Gold	0.04	0.1	0.08	0.05	0.04	0.05	0.37	5.52	0.09	0.61
TO-ABS	1.07	0.8	0.9	0.31	1.03	0.22	1.05	0.27	5.64	
TO-WTH	7.31	5.42	6.12	2.08	6.99	1.48	7.15	1.87		38.44

Source: Authors

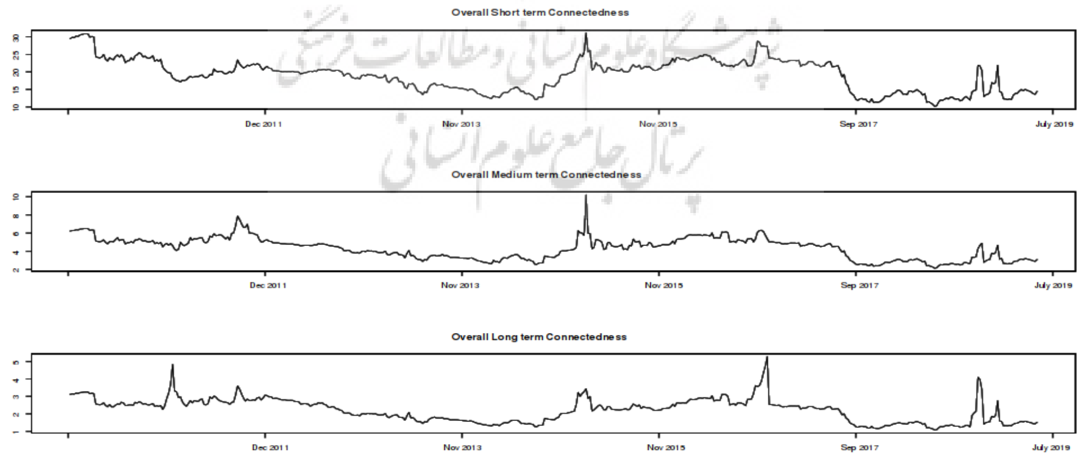

Fig 1. Overall Frequency Connectedness of MENA Stock Markets and Commodities

Source: Authors

Here, we use a rolling window to analyze the time-varying of the overall frequency connectedness to investigate the behavior of this system over time with a window size of 100 weeks. The results in Figure 1 indicate that the overall short-term return connectedness increased dramatically in the financial crisis of 2008 and the oil price crash during 2014 while it rose in the long term with a delay, suggesting that the considerable shocks are maintained in this system for a long time. Moreover, the return connectedness of MENA stock markets, and the Brent crude oil and gold market grow significantly during a crisis. It is also necessary for investors to be careful about taking advantage of the portfolio diversification in the period of inconsiderable connectedness because the connectedness between the two markets may be strengthened strongly, particularly during a crisis.

5. Conclusion and Suggestions

In this study, we consider the time-frequency dynamics of the return connectedness among MENA stock markets, Brent crude oil, and Gold market from 2008 to 2019 using an empirical approach developed by Barunik and Krehlik (2018) and a causality test to solve the main drawback of this model. The following are the main contributions of this study:

1- The variance of forecast error in most markets is due to the shocks themselves, thus it is necessary to analyze the structures of the markets.

2- Markets are highly speculative in the short term; hence, there is less chance of portfolio diversification among these markets in the short term.

3- Among MENA stock markets, QE General contributes more to the Brent crude oil market in the short term and Tadawul has more return connectedness with this market in other timeframes.

4- TEPIX and EGX 100 contribute less to other markets.

5- The gold market is a suitable choice for portfolio managers who want to diversify their portfolios at MENA stock markets as it has an insignificant return connectedness to these markets.

6- The rolling analysis suggests that considerable shocks are maintained in this system for a long period and connectedness increases during a crisis. Therefore, there is less chance for long-term investors to be satisfied with diversification in these markets.

7- The Granger casualty test suggests that Brent crude oil, Gold, and ADX general contribute to the prediction of TEPIX.

8- QE general contributes more to other markets in the short and medium terms, and ADX general has more influence on other markets in the long term.

The results suggest that TEPIX, EGX 100, and Gold are appropriate choices for investors who want to hedge their risks and investors in MENA stock markets; in particular, Tadawul and QE General should track crude oil markets carefully. Moreover, investors need to be careful about taking advantage of portfolio diversification in a period of inconsiderable connectedness because the connectedness between the two markets may be strengthened strongly, particularly during a crisis. Besides, authorities in each stock market need to track the Crude oil movement as it has a considerable potential to increase volatility in MENA stock markets.

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