Financial Connectedness and Risk Transmission among MENA Countries: Evidence from Connectedness Network and Clustering Analysis*

In Press: *Journal of International Financial Markets, Institutions and Money*.
https://doi.org/10.1016/j.intfin.2022.101656

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Abstract. This study examines the financial connectedness and risk transmission among MENA economies by accounting for financial connectedness in the short and long run as well dependency under extreme market conditions and network graph analysis. To this end, Composite Financial Stress Indices are constructed for 11 MENA countries. In addition, a battery of econometric models is applied including the standard spillover approach, the frequency domain method, the quantile connectedness technique, and connectedness networks analysis. Using daily data over the period from June 30, 2006 to June 30, 2021, the empirical results show a positive and strong association between financial stress co-movements and spillovers in those MENA countries, particularly during the long run and high extreme stress periods. Furthermore, the five Gulf countries are strongly financially connected among themselves than with the other countries. Contrary, to Tunisia, Saudi Arabia is the main financial stress and risk transmitter to other MENA economies whereas, the North African countries are relatively mild receivers of risk. Finally, the more open countries in terms of capital controls, particularly Kuwait, Oman, Qatar, and UAE seem to play a more central role in financial connectedness and risk spillovers.

JEL classification: C32, C38, F3, G1.

Keywords: Financial stress and openness, financial connectedness, risk transmission, QVAR, network analysis.

* Best Paper Award, Economic Research Forum, 28th Annual Conference, 26 - 30 March 2022, Cairo, Egypt.

1. Introduction

The MENA region has its share of global and regional financial stresses over the last several decades, beginning from the Global Financial Crisis in 2007, going through the Arab spring that began in 2011, and ending with the COVID-19 in 2021. This region also lived through different episodes of oil price slumps, particularly the collapse of oil prices during the years from June 2014 until February 2016. The experiences of other countries indicate that household and business often pull back on investment and consumption during uncertainty caused by stressful financial conditions, which may push the economy into recessions. Theoretically, a financial stress first works its way through the real options theory which incorporates waiting in the decision making until uncertainty is resolved. Second, when financial conditions are stressful, financial markets become impaired, and obtaining funds from savers to borrowers during those conditions becomes costly for households and businesses and the premium that borrowers should pay increases (Bernanke, Gertler and Gilchrist,1999).

There has been an ongoing discussion of topics such as globalization, synchronization, spillover, risk transmission, contagion, connection, decoupling, and recoupling in the wake of the global financial crisis and the European debt crisis. The network connectedness (cross-firm, cross-asset, cross-market, cross-country, etc.) of various assets, asset classes, portfolios, and other entities, however, was the focus of more recent studies. Returns or return volatility often make up the related objects in the connectedness studies.[1] Financial and economic connectedness is a relatively new concept in economic theory. The degree to which financial markets are interconnected is more closely correlated with the risk spillover or contagion, which has gained attention after the global financial crisis of 2008. (Billio et al., 2012).

Recently, connectedness has been used to quantitatively assess spillover because it is a key indicator of the relationship among factors relating to the market (Diebold and Yilmaz, 2012, 2015; Xiao et al., 2020). Although market or country connectedness represents a contagion risk, it may also be tied to systemic and systematic risk (Andries and Galasan, 2020). The importance of significant systemic risk may be highlighted by a high level of connectedness at the national level (Andries and Galasan, 2020). An oft-cited definition of the systemic is given by DeBandt and Hartmann (2000): "A systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system …

[1] See DeBandt and Hartmann (2000), Bech and Atalay (2010), Brunnermeier et al. (2012), Diebold and Yilmaz (2015), Adamic et al. (2017), and Maggi et al. (2020) for a survey of the relevant literature.

particularly strong propagation of failures from one institution, market or system to another." This definition clearly highlights the roles played by connectedness. Systemic risk is often understood to be the risk associated with the total failure of a company, financial institution, sector, or more broadly, an industry, or the entire economy (Bisias et al., 2012; Maggi et al., 2020; Torrente and Uberti, 2021). Connectivity gauges how closely connected and dependent a system's constituent parts are to one another (Maggi et al., 2020). According to Torrente and Uberti (2021), a portfolio's high connectedness between its assets indicates a high level of interdependence between them but is not directly correlated with the portfolio's size. One of the main causes of systemic risk being a pertinent topic is the financial crises of 2007–2009.

Connectedness and the spread of contagion are thus linked to systemic risk. Financial connectedness is a well-known potential cause of systemic risk, as Maggi et al. (2020) contend. In order to identify systemic risk, Maggi et al. (2020) describe several uses of connectedness. A broad notion called connectedness connects several aspects of financial risk. Various connectedness measures are used in empirical and theoretical literature to study market risk (return connectedness and market diversification; see, for example, Belsley et al., 2005; Maggi et al., 2020), credit risk (default connectedness; see, for instance, Merton, 2014), and systemic risk more broadly (system wide connectedness, see e.g., Acharya et al., 2012; Billio et al., 2012; Acemoglu et al., 2015; Figini et al., 2020). According to Diebold and Yilmaz (2015), ongoing discussion of topics like globalization, synchronization, decoupling, and recoupling is intricately related to the connectedness of real activity across sectors within a country or across countries. Since many people believe that a financial firm's systemic risk is related to the chance that its failure would have an impact on the real economy, several components of systemic risk thinking also entail actual activities.

Previous studies examined financial contagion and risk transmission in the context of MENA region focused solely on information transmit across one segment of the financial system that is stock markets (Lagoarde-Segot and Lucey, 2009; Graham et al., 2013; Chau et al., 2014; Yahchouchi, 2014; Maghyereh et al., 2015; Neaime, 2016). However, they lack information from other segments such as banks, and foreign exchange markets and therefore, not a good representative of the health conditions of the overall financial systems in these counties. Despite the importance of this topic, no previous attempt has been made to examine financial connectedness and risk transmission among MENA economies based on a more comprehensive and holistic approach that takes into account the aggregate effects of the banking sectors, stock markets, and foreign exchange markets on the stability of the financial systems in a more integrated framework that embraces those financial markets.

Contrary to previous literature, in this study we constructed Composite Financial Stress Indexes for individual MENA countries using data form stock markets, banking systems and foreign exchange markets. These constructs are more accurate than the single proxies in the literature (see for example, Kliesen et al., 2012; Apostolakis & Papadopoulos, 2015; MacDonald et al., 2018; Elsayed & Yarovaya, 2019, among many others). They also provide a comprehensive and complete view of the financial conditions in each of the MENA economies and hence accurately capture financial instabilities and turbulences events over the sample period. Furthermore, to the best of our knowledge, no previous study has addressed the impact of the COVID-19 pandemic on risk transmission among MENA countries.

The objectives of this paper are threefold: (i) To examine the dynamics of financial connectedness and risk transmission among MENA countries and determine which country is a net transmitter/receiver of financial shocks; (ii) to investigate the connectedness under extreme market conditions of the tail distribution using the quantile connectedness; and (iii) to explore the impact of economic and financial turbulences such as COVID-19 on the connectedness and transmission of shocks across MENA countries.

This study contributes to the MENA finance literature in the following ways. We first calculate the financial stress indices for 11 MENA countries to examine the financial connectedness and stress spillovers using the standard VAR model (Diebold and Yilmaz, 2012, 2014) and the frequency connectedness method developed by Barunik and Krehlik (2018).[2] This approach allows us to examine the magnitude and evolution of volatility spillovers in the frequency domains, and hence helps identify the frequency that most countries contribute to the total connectedness of the system. We also take into account the important linkages between the MENA economies under extreme market conditions by considering both the mean and tail financial stress distributions, using the quantile connectedness based on the Quantile VAR (QVAR) model. Finally, we investigate the connectedness structure of the MENA countries using the network statistics and various connectedness network layouts.

[2] Connectedness reflects a high degree of interdependence between components of the set under consideration. Common quantification of connectedness used in the literature includes principal components, correlation, Granger causality, and impulse response (forecast error variance decomposition) based on statistical measures. Billio et al. (2012) and Maggi et al. (2020) present a survey of the related literature. In this current study, we adopt the total connectedness index of Diebold and Yilmaz (2009, 2012) as a measure of connectedness (a measure based on the forecast error variance decomposition) because of its easy interpretation and flexibility to adopt various features of the data. However, we have added newer advanced techniques to achieve the objectives.

The overall empirical results demonstrate a positive connectedness between financial stress co-movements and spillovers in the 11 MENA countries under consideration. On average, 27.8% of the total forecast error variance can be attributed to the spillovers and interlinkages between the 11 MENA countries. More importantly, MENA financial systems are more connected during the long run and high extreme stress periods (26.3% and 90.6%, respectively), compared with the short run and the extreme low stress periods (4.1% and 80.6%, respectively). In addition, Tunisia has the weakest financial stress connection with the other MENA countries, whereas Saudi Arabia is the prevalent net financial stress risk transmitter, while Bahrain, Jordan, Qatar, and Oman are significant receivers. All North African countries are relatively mild receivers of risk. There is also an important role for openness (KOPEN). The more open countries, particularly Kuwait, Oman, Qatar, and UAE, seem to play a more central role in the financial connectedness and risk spillovers among those countries.

The remainder of the study is organized as follows. Section 2 provides a review of the literature. Second 3 presents the methodology, while Section 4 discusses the data. Section 5 analyzes the empirical results, and Section 6 concludes.

2. Literature review

The attention given to financial stress co-movements and risk transmission across financial markets has increased rapidly in the wake of the US subprime market in 2007. It becomes even more relevant during the Global Financial Crisis in 2008 where the collapse of the US housing market triggered a financial crisis that spread from the United States of America to the rest of the world through linkages in the global financial system. In particular, financial contagion and connectedness among international markets increase during periods of economic and financial stress as markets have become more integrated and interconnected (Cardarelli et al., 2011; Chau and Deesomsak, 2014; Apostolakis and Papadopoulos, 2015; Elsayed and Yarovaya, 2019).

The theoretical foundation of financial contagion and risk transmission across markets could be traced back to Engle et al. (1990) who present the ‘‘heat wave” and ‘‘meteor shower” hypotheses. According to Engle, the “*news follows a process like a heat wave so that a hot day in New York Is likely to be followed by another hot day in New York but not typically by a hot day in Tokyo … a meteor shower in New York will almost surely be followed by one in Tokyo … volatility appears to be a meteor shower rather than a heat wave*” (Engle et al., 1990, p.

526). Furthermore, previous studies have documented the key channels through which financial shocks transmit across countries such as trade and financial linkages (Illing and Liu, 2006; Cardarelli et al., 2011). On the one hand, Glick and Rose (1999), and Forbes (2002) stress the importance of trade and exchange linkages as the main channel through which financial shocks could spill over from one country to another. On the other hand, Kaminsky and Reinhart (2000), Caramazza et al. (2004), and Forbes and Chinn (2004) identify financial linkages as another impotent channel of financial transmission across countries. In this regard, Jacobson et. al. (2005) highlight the fact that credit is the most important channel through which financial shocks transmit across countries that could be strengthened further through the financial accelerator mechanism (Bernanke et. al., 1999; Goodhart et. al., 2006). In a similar vein, Cardarelli et. al. (2011) indicate that financial turmoil characterized by banking distress is much more important and is more likely to have a deeper impact and longer downturns, compared with stress periods that are mainly triggered by securities or foreign exchange markets.

In addition to the previous two main channels of transmission, other studies attributed cross country contagion and financial transmission to common factors that could affect many countries at the same point of time such as a global turmoil or crisis which could be aggravated further by investors' herding behaviour and high integration among financial markets especially during stress periods (Balakrishnan et al., 2009; Apostolakis and Papadopoulos, 2014).

Against this backdrop, a large body of the literature examines financial contagion and risk transmission between advanced and developing countries (e.g., Balakrishnan et al., 2011, Duca and Peltonen, 2013; Vardar et. al., 2018; Mohti et al., 2019, among others). In the context of the MENA region, the literature on financial contagion and volatility spillovers could be divided into two main categories. The first strand are the studies that examine financial contagion and co-movement among the MENA economies based on a single segment of the financial sectors. In this respect, several empirical papers focus on stock market co-movement and connectedness among MENA and international stock markets. For example, Bouri and Yahchouchi (2014) assess the returns and volatility dynamic across MENA stock markets based on a multivariate model with leptokurtic distribution, using data from June 2005 to January 2012. Their results confirm that MENA stock markets are strongly interconnected by their volatilities and not by their returns. On contrary, Graham et al., (2013) examine financial connectedness between selected MENA stock markets and the U.S. stock market, using the wavelet squared coherency with simulated confidence bounds over the period from June 2002 to June 2010. The results indicate a high degree of co-movement among MENA stock markets at the lower frequencies only. However, there is a modest degree of dependency between the US market and MENA stock markets at the higher frequencies. A similar insight is provided by Neaime (2016) who examines financial integration and contagion vulnerability between MENA and the rest of the world at both regional and international levels. The results from the Granger causality tests and impulse response functions indicate that stock markets of Egypt, Tunisia, Jordan, and Morocco are highly linked with the world financial markets, but less integrated at the regional level. However, the GCC stock markets are weakly integrated and separated from the rest of the world.

Bahloul and Abid (2014) study the regime-switching behavior in the conditional volatility of 11 MENA stock market returns, using a Markov-regime switching volatility model over the period from 30 October 2006 to 21 October 2011. Their results reveal that information transmitted from the world market to the MENA stock markets is stronger and only statistically significant during stress period. In line with the previous study, Maghyereh et al. (2015) investigate returns and volatility spillovers between the U.S. stock market and major 5 MENA stock markets between January 2, 1998 to February 15, 2013. In line with the previous literature, the results from a DCC-GARCH model and spillover approach developed show a weak correlation and volatility spillover before and after the 2008 global financial crisis, with an exceptional high record during the crisis period.

Another strand of the literature follows a more accurate and efficient approach by constructing Aggregated Financial Stress Indices using several indicators that take into account different types of risk and sources of financial instability across different dimensions of the country's financial sector such as the banking sector, stock market, and foreign exchange market (Illing & Liu, 2006; Hakkio and Keeton, 2009; Balakrishnan et al., 2011, Apostolakis & Papadopoulos, 2015; Elsayed & Yarovaya, 2019). To this end, different combination methods have been applied such as the average of standardized variables or the Principal Component Analysis (PCA) approach to combine several market indicators into a single composite index (Illing and Liu 2006; Kliesen et al., 2012; Apostolakis & Papadopoulos, 2015; MacDonald et al., 2018; Elsayed & Yarovaya, 2019).

In this regard, Aggregated Financial Stress Indices could be used to serve several purposes. For instance, Ishrakieh et al. (2020) construct a comprehensive Financial Stress Index for Lebanon in an attempt to quantify the level of systemic risk and an early working system that could provide valuable information to macroprudential regulators. Likewise, Matkovskyy et al. (2016) create a Financial Safety Index for Tunisia over the period 2000Q1–2014Q3 based on a wide range of financial and macroeconomic indicators to detect disturbances and financial stress periods with sufficient accuracy. Following the same approach, Ekinci (2013) establishes a Financial Stress Index for the Turkish economy over the period August 1, 2002 to January 31, 2013 to help financial institutions and policymakers identify stress periods in sub-markets and the financial sector, and hence effectively helps manage monetary policy.

Other studies developed Aggregated Financial Stress Indices to examine their impact on macroeconomic aggregates. El-Shal (2012) investigates the spillover impact of the global financial crisis of 2007 on the Egyptian economy and the channels through which financial stress could affect macroeconomic activities. To this end, an Egyptian Financial Stress Index has been created and included in the VAR model. The results confirm that increased financial stress would have an adverse impact on economic activity in Egypt. Along the same line, Cevik et al. (2013) develop a financial stress index for the Turkish economy to assess the impact of financial stress episodes on the economy over the period 1997–2010. Their findings indicate that the Financial Stress Index is a leading indicator of economic activities and has a negative impact on the real economy through several channels. Finally, Elsayed and Yarovaya (2019) construct Financial Stress Indices for eight MENA counties to examine the impact of political instability caused by Arab Spring on MENA financial markets. The findings show that stress transmission between markets is higher at the low frequencies than at the high frequencies. Furthermore, the adverse impact of the 2008 Global Financial Crisis has stronger spillover effects on MENA markets compared with the political turmoil created by the Arab Spring.

Although the increasing studies have enriched this strand of the literature, no previous attempt has been made to examine financial connectedness and risk transmission among MENA economies based on a more comprehensive and holistic approach that takes into account the aggregate effects of the banking sectors, stock markets, and foreign exchange markets on the stability of the financial systems. Furthermore, to the best of our knowledge, no previous study has addressed the impact of the COVID-19 pandemic on risk transmission among MENA countries. To this end, this study tends to fill this gap in the literature by constructing new financial stress indices and investigating the key forces driving financial co-movements and dynamics between 11 MENA economies. Besides, network clustering and connectedness are examined under extreme market conditions as well as in both the short-run and long-run horizons. Finally, we explore the impact of economic and financial turbulences such as COVID-19 on the connectedness and transmission of shocks across the 11 MENA countries.

3. Methodology

Firstly, by building on the works of Diebold and Yilmaz (2012, 2014), we examine the financial interconnectedness and stress spillovers, using the standard VAR model (of Diebold and Yilmaz, 2012, 2014) and the frequency connectedness method developed by Barunik and Krehlik, (2018). Furthermore, the important linkages between MENA economies have been taken into account by considering both the mean and tail financial stress, using the quantile connectedness based on the quantile VAR (QVAR) model (Cecchetti and Li, 2008; White et al. 2015; Chavleishvili and Manganelli 2016; Ando et al. 2018; Balcilar, et al. 2020). We also examine the connectedness structure of the MENA countries using network statistics, such as in-degree, out-degree, closeness, eigenvector centrality, betweenness, and page rank. These statistics reveal important information on the structure of the connectedness and the various roles the different countries or group of countries play in terms of transmitting and/or receiving risk. Additionally, we perform clustering based on the modularity of the links in order to discover groups of countries that are connected stronger than the average connections of all countries.

3.1. *The standard VAR model*

Consider a K-variable covariance stationary VAR(p) model defined as $X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t$, $X_t = (X_{1t}, X_{2t}, \dots, X_{Kt})'$ is a K-vector of variables with the time index $t = 1,2,..,T$, p being the lag order, Φ_i are $K \times K$ coefficient matrix, and ε_t is a normally distributed white noise error term with a 0 mean and variance Σ, $\varepsilon_t \sim N(0, \Sigma)$. Using the Wold decomposition theorem, the moving average (MA) representation of this model is given by $X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where A_i denote $K \times K$ coefficient matrices following the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with A_0 as a $K \times K$ identity matrix and $A_i = 0$ for $i < 0$. Due to the fact that the Cholesky factorization is dependent on the variable orderings, we follow Diebold and Yilmaz (2012) and employ the generalized approaches of Koop *et al*. (1996) and

Pesaran and Shin (1980), which account for correlated shocks and assist in computing the variance decomposition that is invariant to the variable ordering.

Following Diebold and Yilmaz (2012), we base our connectedness on the spillover table. Then each entry of the spillover connectedness table, $\theta_{ij}^{g}(H)$, estimates the country j's contribution to country i's obtained from the H-step-ahead generalized forecast error variance as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)^2} \tag{1}$$

where Σ denotes the covariance matrix of errors, σ_{jj} denotes the standard deviation of the disturbance term in the j-th equation, and e_i denotes the selection vector, which takes the value 1 if the i-th component is zero. Due to the fact that the total of the rows in the generalized variance decomposition matrix is not equal to one (i.e., $\sum_{j=1}^{K} \theta_{ij}^{g}(H) \neq 1$), the normalization of each entry in the relevant matrix is required as:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{2}$$

Thus, the sum of the variance decompositions in individual country, including own shocks, equals one, or $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, and the sum of the total variance decompositions in all markets equals $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = K$.

The connectedness table is obtained by transforming $\theta_{ij}^{g}(H)$ to a directional spillover from country j to country i from, denoted $C_{i \leftarrow j}^{H}$. Due to the fact that $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$ generally holds, we obtain the $(K^2 - K)$ different pairwise directional connectedness measurements. To calculate the amount of net volatility spillover from country i to country j, we must first compute the net pairwise directional connectedness, abbreviated $C_{ij}^{H} = C_{j \leftarrow i}^{H} - C_{i \leftarrow j}^{H}$. As a result, the $(K^2 - K)/2$ measures of net pairwise directional connectedness are obtained. Indeed, the table of the net pairwise directional connectedness constructed in this section is nothing more than the $K \times K$ adjacency matrix A, which comprises all network properties. As a result, we can use this adjacency matrix A to create a weighted directed network graph.

The magnitude of the volatility spillover between two countries is used to create weighted edges in the net pairwise connectedness table, while the countries examined in this study are denoted by nodes (vertices). The arrows denote the direction of volatility spillover from country j to country i.

3.2. *Frequency decompositions of connectedness measures*

The normalized pairwise connectedness measure $\tilde{\theta}_{ij}(H)$, presented in Subsection 3.1, gives a time-domain measure of pairwise connectedness between countries j and i. Inspired by comparable methods in the literature, several studies including Stiassny (1996), Dew-Becker and Giglio (2016), and, more recently, Barunk and Kehlk (2018), suggest a framework for estimating frequency connectedness using spectrum representations of the variance decompositions. This is essential because market actors have different investment horizons and their reactions to shocks vary with their horizons. The formation of their preferences is the primary reason that agents operate with varying investment horizons represented by different frequencies. In a financial system, asset prices driven by consumption growth with different cyclical components will generate shocks with heterogeneous frequency responses, thereby creating short-, medium-, and long-term systemic risks from diverse sources of connectedness. In turn, when studying connectedness, we should concentrate on the underlying linkages with varying degrees of persistence that contribute to systemic risk. The frequency decomposition employs the frequency response function rather than the time domain generalized impulse response function. The spectral density of X_t at frequency ω can be defined as follows:

$$S_X(\omega) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ih\omega} = \Psi(e^{-ih\omega})\Sigma\,\Psi(e^{ih\omega}) \tag{3}$$

where $\Psi\left(e^{-ih\omega}\right) = \sum_{h=0}^{\infty} \Psi_h\, e^{-ih\omega}$. Using this definition, we may define the generalized forecast error variance decomposition (GFEVD) on frequency ω as

$$(\theta(\omega))_{i,j} = \frac{\sum_{j,j}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-ih\omega})\Sigma)_{i,j}^2}{\sum_{h=0}^{\infty} (\Psi(e^{-ih\omega})\Sigma\Psi(e^{ih\omega}))_{i,i}} \tag{4}$$

The normalized version of $(\theta(\omega))_{i,j}$ is obtained as

$$(\tilde{\theta}(\omega))_{i,j} = \frac{(\theta(\omega))_{i,j}}{\sum_{j=1}^{k} (\theta(\omega))_{i,j}} \tag{5}$$

Because the connectedness table at a specific frequency ω is information for the spillover analysis, we combine connectedness measures with a frequency ω less than one week and a remainder into two distinct connectedness tables called the short- and long-run. To accomplish this, we define the connectedness table for a given frequency band $d = (a, b)$ as follows:

$$(\tilde{\theta}_d)_{i,j} = \int_a^b (\tilde{\theta}(\omega))_{i,j} d\omega. \tag{6}$$

As a result, for any frequency band d, we can apply the measures described in Eq (6) to obtain the total connectedness measure:

$$C^d = \frac{\sum_{i,j=1,i\neq j}^{K} (\tilde{\theta}_d)_{i,j}}{\sum_{i,j} (\tilde{\theta}_d)_{i,j}} \tag{7}$$

where d denotes the corresponding frequency band. Thus, C^d is a measure of total connectedness. Other metrics of connectedness defined in Diebold and Yilmaz (2009, 2012) can be defined similarly for the frequency band d. As with the time domain analysis, the pairwise connectedness can be calculated in the frequency domain as follows:

$$C_{i,j}^d = (\tilde{\theta}_d)_{i,j} - (\tilde{\theta}_d)_{j,i} \tag{8}$$

Indeed, this type of analysis is helpful for both short- and long-term investors, given that the countries' risk structures are highly varied.

3.3. *Quantile connectedness measures*

We investigate the volatility connectedness measures at various quantiles, using the quantile connectedness approach proposed by Ando et al. (2018) and Balcilar et al. (2020). At the quantiles $\tau \in (0,1)$, the reduced-form QVAR(p) model can be represented as:

$$X_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_i(\tau) X_{t-j} + \varepsilon_t(\tau) \tag{9}$$

where X_t is the $K \times 1$ vector of endogenous variables, p denotes the lag order, $\mu(\tau)$ denotes the $K \times 1$ dimensional mean vector, $\Phi_j(\tau)$ denotes the $K \times K$ dimensional coefficient matrix, and $\varepsilon_t(\tau)$ is the vector of error terms with a $K \times K$ dimensional variance-covariance matrix, $\Sigma(\tau)$. We can rewrite the QVAR(p) in its quantile moving-average representation using the Wold decomposition theorem as:

$$X_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_i(\tau)\, X_{t-j} + \varepsilon_t(\tau) = \mu(\tau) + \sum_{j=0}^{\infty} \Psi_j(\tau) \varepsilon_{t-j}(\tau)$$

As with earlier methods, we compute the quantile spillover and normalized quantile spillover indices, denoted $\psi_{ij}^{\tau}(H)$ *and* $\tilde{\psi}_{ij}^{\tau}(H)$, respectively, as follows from the H-step ahead FEVDs:

$$\begin{aligned}
\psi_{ij}^{\tau}(H) &= \frac{\Sigma(\tau)_{ii}^{-1}\sum_{h=0}^{H-1}(e_i'\Psi_h(\tau)\Sigma(\tau)e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Psi_h(\tau)\Sigma(\tau)\Psi_h(\tau)'e_i)} \\
\tilde{\psi}_{ij}^{\tau}(H) &= \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{N}\psi_{ij}^{g}(H)}
\end{aligned} \tag{10}$$

where e_i is a zero-vector having a value of unity at the i-th entry. We normalize each entry in the connectivity table to $\sum_{j=1}^{N}\tilde{\psi}_{ij}^{\tau}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\psi}_{ij}^{\tau}(H) = K$ prior to calculating the pairwise connectedness measures at various quantiles. Then, as indicated in Subsection 3.1, we obtain the net pairwise connectedness.

3.4. Network centrality measures

Although the connectedness based on the spillover metrics gives useful information about risk transmission between countries, the network statistics provide additional information about the strength of links between countries. These statistics shed light on countries' roles in risk transmission and enable us to perform useful clustering. Certain network centrality indicators are used in the graph theory and network analysis to identify the most critical vertices (nodes) inside a graph. This study examines six different network centrality measurements. To begin, degree centrality is a simple network analysis metric that simply counts the number of links that a node has. The degree centrality of a node i is defined as:

$$D_i = \frac{1}{n-1}\sum_{j=1}^{n} A_{ij}, \tag{12}$$

where A_{ij} is the ij-th element of the adjacency matrix A formed by the spillover table, and n is the number of nodes. In a directed network, we can define two centrality degree measurements (i.e., in- and out-degrees). While in-degree centrality is a count of links from other nodes, out-degree centrality is a measure of the degree scores of outgoing links from the target node.

Second, we calculate Freeman's (1977) betweenness centrality, which measures the number of times a node acts as a bridge along the shortest path between two other nodes. The betweenness centrality metric is a normalized measure of the fraction of geodesic pathways in graph that pass-through node i:

$$B_i = \frac{1}{(n-1)(n-2)} \sum\nolimits_{u,v=1, u \neq i \neq v}^{n} \frac{\sigma_{uv}^{i}}{\sigma_{uv}} \tag{13}$$

where u and v denote nodes and the geodesic path is defined as the path with the fewest potential edges connecting these two nodes. σ_{uv} specifies the number of geodesics, whereas σ_{uv}^{i} denotes the number of geodesic paths that pass through the nodes u and v and likewise via node i.

Another centrality metric that we employ is the closeness centrality, which is a centrality score that quantifies the average distance between the nodes. Closeness centrality is a type of centrality metric that quantifies the mean distance between two nodes. Assume d_{ij} is the shortest distance between nodes i and j. The mean shortest distance between i and each node in the network is thus $l_i = \sum_{i=1}^{n} d_{ij}/n$. Closeness centrality is the inverse of l_i given as

$$C_i = \frac{1}{l_i} = \frac{n}{\sum_{i=1}^{n} d_{ij}} \tag{14}$$

Finally, we compute the eigenvector centrality (E_i) and its version, page rank, in order to identify the most influential nodes in terms of the risk transmission role. A node's high eigenvector and page rank centrality values indicate that this node contains more volatility information than nodes with equal connections to low-scoring nodes. While useful, the degree is a rather crude measure of centrality. In effect, it assigns one "centrality point" to a node for each neighbor it has. However, not all neighbors are equivalent. In many cases, a node's value in a network is increased by its links to other significant nodes. Eigenvector centrality is a variant of degree centrality that incorporates this factor. The eigenvector centrality is defined as

$$x_i = \lambda_o^{-1} \sum_{j=1}^{n} A_{ij} x_j \tag{15}$$

where λ_o is the eigenvector corresponding to the largest (most positive) eigenvalue obtained by solving the eigenvalue problem $Ax = \lambda x$ and the centrality scores x_j are the elements of the eigenvector x. Instead of just awarding one point for every network neighbor a node has, eigenvector centrality awards a number of points proportional to the centrality scores of the neighbors.

The centrality gained through a link from an important node should be mitigated if the key vertex is extremely generous with endorsements. Page rank, which is employed by Google as a fundamental component of their site ranking technology for web search, takes this into account. Three distinct elements contribute to a node's page rank: (i) the number of links it receives, (ii) the linkers' link proclivity, and (iii) the linkers' centrality. The first component is self-explanatory: the more links a node receives, the more significant it is regarded to be. Reasonably, the endorsement's value depreciates according to the quantity of connections distributed by the endorsing node: links emanating from thrifty nodes are more valuable than those emanating from spendthrift nodes. Finally, not all nodes are equal: linkages to significant vertices are more useful than ties to obscure ones. The page rank for the node i is obtained as the i-the entry of the vector x defined as

$$x = (I - \alpha D^{-1})^{-1}\mathbf{1} \tag{14}$$

where $\mathbf{1}$ is a vector of ones (1, 1, 1, . . .)' and D is a diagonal matrix with elements $D_{ii} = \max(k_i^{\text{out}}, 1)$ with k_i^{out} being the out-degree of node i.

The ultimate purpose of the connectedness analysis is to have a deeper understanding of the behavior of the systems it represents. We investigate volatility spillover to gain a better understanding of the dynamics of the spillover and its consequences for a cross-border risk transmission. In this regard, identifying clusters (groups) of nodes in densely connected countries sheds light on the volatility transmission dynamics. Community detection is the process of identifying clusters of nodes in networks. In this study, we employ the optimum clustering to identify country clusters. Modularity is a property of networks or graphs that indicate the degree to which they can be divided into modules (also called groups, clusters or communities).

Brandes *et al*. (2007) determine the best clustering that optimizes Newman and Girvan's modularity measure (2004). The community structure (CS) of vertices V is a collection of distinct clusters of vertices $C = \{C_1, C_2, \ldots, C_l\}$ that the union yields back V. The Newman-and Girvan (2004)'s modularity of C is defined as

$$Q(C) = \frac{1}{2M}\sum_{i,j=1}^{n}\left(A_{ij} - \frac{k_i k_j}{2M}\right)\delta_{ij} \tag{15}$$

where k_i and k_j denote the degrees of nodes i and j, respectively, M denotes the total edge weights, and the membership matrix element δ_{ij} is specified as equal to 1 if i and j belong to the same community, and as 0 otherwise. Brandes *et al*. (2007) use an optimal clustering approach to identify a division that maximizes the modularity value in Eq. (15). Integer linear programming is used to solve the maximization problem.

3.5. Connectedness network

The network analysis provides additional information based on the visual layout. For instance, we can see which countries are closer to each other, which countries are in a hub position in terms of spreading the financial risk, and which countries are more isolated from the others, … etc. This is useful information that helps one to understand the structure of financial risk connectedness in the MENA region. The network representations are weighted networks based on either pairwise spillovers or net pairwise spillovers where the weights are the magnitudes of the spillovers and the thickness of the arrow indicates the magnitude of the spillover.

In order to understand the structure of the financial stress connectedness among the MENA countries in addition to geographic grouping, we also perform statistical grouping using clustering. Countries falling in the same cluster are linked closer among themselves compared to whole set of countries. Thus, clustering allows us to discover countries that co-move more closely, and financial stress in one of the countries affects the countries in the cluster more than the other countries. Clustering also allows us to determine the countries which are the most isolated and the least affected by the financial conditions in the MENA region. Clusters are defined using Brandes *et al.* (2007)'s optimal clustering algorithm. The color of the vertex (node) denotes the cluster group, whereas the color of the vertex labels denotes the geographic group. The graph layout is generated using the Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991). In each graph, the countries in the Middle East region (Bahrain, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Turkey, and UAE) are marked with a red country symbol face color, while countries in the North Africa group are likewise marked with a blue country symbol face color.

4. Data and preliminary analysis

This paper examines financial stress co-movements and volatility transmissions among the 11 MENA countries. The sample period runs from June 30, 2006 to June 30, 2021, with a sample size of 3916 observations. This sample period is determined by data availability, but it still covers several significant events such as the 2008 Global Financial Crisis; the Arab Spring that started in December 2010; the oil crises between 2014 and 2016; Qatar diplomatic crisis and the going COVID-19 pandemic that started in March 2020. Data has been collected from the Refinitiv Eikon database.

Contrary to other studies that used a single proxy to capture the aggregated financial soundness of an economy (see for example, Alves, 2005; Zicchino et al., 2006; Carlson et al., 2011, among others), our Composite Financial Stress Indices are far more accurate and provide informative measures of financial conditions and the soundness of country's financial system. They capture different types of risk and sources of financial instability across different dimensions of the country's financial sector, namely banking sector, equity market, and foreign exchange market (Illing & Liu, 2006; Balakrishnan et al., 2011, Apostolakis & Papadopoulos, 2015; Elsayed & Yarovaya, 2019). To this end, Composite Financial Stress Indices comprise six standardized variables that are grouped together using the variance-equal weighted approach and capture the financial conditions of banking sector, the stock market and the foreign exchange market as follows[3]:

i. The banking sector is comprised of three main variables including the banking sector systematic risk which is calculated from a standard Capital Asset Pricing Model (CAPM) with a 60-day rolling window using banking sector index,[4] the negative return of the banking index where a decline in bank returns indicates a higher financial instability in the banking sector, and the volatility of banking sector;
ii. Similarly, the stock market includes two proxies: the negative stock returns computed as equity returns multiplied by minus one so that a fall in the stock returns signals a higher stress in the stock market, and the stock market volatility; and
iii. Finally, the condition of the foreign exchange market is captured by the exchange rate volatility. Following the literature, the volatilities of the banking sector, stock market,

[3] The variance-equal weighting approach for constructing Composite Financial Indices has been extensively utilised in the literature because of the simplicity of calculation and precision in representing and signalling financial stress and turbulence periods (e.g., Balakrishnan et al., 2011; Cardarelli et al., 2011; Apostolakis & Papadopoulos, 2015; MacDonald et al., 2018; Elsayed & Yarovaya, 2019).
[4] The analysis period starts from September 21, 2006, due to the calculation of the beta banking, using a 60-day rolling window.

and foreign exchange market are estimated based on GARCH (1, 1) models (Apostolakis & Papadopoulos, 2015; Elsayed & Yarovaya, 2019).

Figure 1 displays the time series plots of the FSI series for the 11 MENA countries we study.

[Insert Figure 1 here]

Table 1 reports the summary statistics of the financial stress indices (FSI) of the 11 MENA countries and the cluster class of each corresponding country based on the optimal clustering algorithm of Brandes et al. (2007). We also indicate the cluster membership of each country for each model. Clusters names are randomly assigned and has no relevance to other groupings such as the geographic location.[5]

According to the Chinn-Ito index of a country's degree capital account openness (Chinn and Ito, 2006), Bahrain, Jordan, Kuwait, Oman, Qatar, and UAE are classified as countries with low controls, whereas Egypt and Saudi Arabia have medium levels of capital controls. Bahrain in particular has a large offshore banking that accounts for 330% of its GDP which is not connected with its domestic economy. Finally, Morocco, Tunisia, and Turkey have the highest capital barriers among those MENA countries.

Based on the standard deviation results, the variation of the financial stress indices across those MENA countries is very minimal and ranges between 0.429 to 0.585. Furthermore, the maximum value of financial stress is observed for Bahrain Morocco, and Saudi Arabia (7.084, 6.671, and 6.251, respectively). It is also worth noting that all the FSI series are positively skewed (most of the observations are clustered around the left tail of the distribution). The value of kurtosis is greater than 3 for all those FSI series, which implies that the distributions of all the series are leptokurtic (higher peaked around the mean with fatter tails). These results are in line with the Jarque–Bera test statistics, which confirm that none of the variables under consideration is normally distributed at the 1% significance level. In addition, the Ljung–Box test statistics for the standard residuals reject the null hypothesis of no serial correlation in all series at 1 and 5 lags. Engle's ARCH-LM tests confirm the significance of the ARCH effects in all FSI series under consideration. Finally, the results from

[5] Please, refer to Section 5.5 “connectedness network analysis” for further discussion on clustering of MENA countries.

the Augmented Dickey-Fuller unit root test (ADF) indicate that all the series are stationary at their levels, which motivates the use of different specifications of the VAR models.

[Insert Table 1 here]

5. Empirical results

In this section, we analyze the empirical results of the approaches illustrated in the methodology subsections as follows.

5.1. Time-Domain Spillovers Analysis

We start the analysis by examining the static connectedness among the 11 MENA economies based on the time-domain spillovers approach of Diebold and Yilmaz (2012, 2014). Table 2 provides a summary of the average spillovers as well as the intra-country and inter-country spillovers over the full sample period. As can be seen from the table, the total spillover index accounts for 27.8% of the total forecast-error variance, thus indicating that those countries are highly interconnected where more than one-quarter of the total forecast error variance can be attributed to the spillovers across the 11 MENA countries. Furthermore, the intra-country spillovers (diagonal elements) account for a large proportion of forecast error variance in the case of Turkey and Tunisia, reaching 85.3% and 96.4%, respectively. On contrary, UAE, Oman, and Qatar have the lowest intra-country spillovers in the system (56.4%, 58.1%, and 61.8%, respectively), therefore indicating that these countries are fully integrated within the MENA region.

[Insert Table 2 here]

Now turning into the inter-country spillovers, the pairwise directional connectedness shows that the five Gulf countries (Kuwait, Oman, Qatar, Saudi Arabia, and UAE) are strongly financially connected among themselves than with the other countries. This result is in line with previous literature (Ahmed, 2011; Elsayed and Helmi, 2021). There is also a strong financial connection between Jordan and those Gulf countries. On the other hand, Tunisia has the weakest financial stress connection with the other MENA countries in this model. The Tunisian economy is very disconnected from other MENA markets, given the weak trade relations with the rest of MENA countries (Bouri & Yahchouchi, 2014). These findings confirm our previous discussion on the intra-country connectedness spillovers.

The “To” row highlights that, among MENA countries, the largest gross directional spillovers to others come from Saudi Arabia (70.27%) whereas Kuwait is the second largest transmitter of risk spillovers (51.74%). By contrast, Tunisia (1.5%) and Egypt (10.6%) are responsible for the lowest gross direction spillovers to MENA markets. Likewise, the “From” column shows that the gross directional spillovers from others are the largest for the UAE (43.54%) and Oman (41.84%) and the lowest for Tunisia (3.60%) and Turkey (14.68%).

According to the net directional spillovers, Saudi Arabia is the prevalent net financial stress risk transmitter. This finding is consistent with Maghyereh et al. (2015) who indicate that Saudi Arabia is a key driving force in the MENA region, and its influence is even more pronounced after the 2008 global financial crisis. On the other hand, Bahrain, Jordan, Qatar, and Oman are significant receivers, while all North African countries are relatively mild receivers of risk.

5.2. Frequency-Domain Spillovers Analysis

Results from the time-domain spillover approach are very useful. However, financial systems are very dynamic and respond differently to economic and financial shocks across different time horizons or frequencies (Ferrer et al., 2018). In particular, economic and financial stress periods may provoke different responses from different financial systems in different time scales. To comprehend the sources of risk connectedness across the MENA economies, we examine the frequency dynamics of the connectedness, as shocks to the economies of these countries impact the underlying variables in the FSI at varying frequencies and magnitudes. To examine the short- and long-run frequency responses to shocks, we use the approach proposed by Barunik and Krehlik (2018) to estimate financial risk connectedness at a desired frequency band. Therefore, the magnitude and direction of spillovers among countries may vary across different investment horizons (Elsayed and Yarovaya, 2019). In contrast to the time-domain spillover technique of Diebold and Yilmaz, the frequency spillover approach developed by Baruník-Křehlík (2018) uses spectral representations of variance decomposition locally to calculate time-frequency spillovers. It, therefore, allows an examination of the magnitude and evolution of spillovers in the frequency domains, and hence the frequency that most contributes to the total connectedness of the system.

[Insert Table 3 here]

Table 3 reports the total frequency-domain spillover indices constructed using the methodology proposed by Barunik and Krehlik (2018). When distinguishing between the short and long run, the financial stress connectedness among those MENA countries is weak in the short run (one week), compared with the long run (over a week to infinity). The total spillover index shows that around 4.1% of the forecast error variance decomposition can be attributed to the spillovers between the MENA countries in the short run. Whereas the majority of the forecast-error variance (26.3%) is explained by the spillovers between the MENA economies in the long run. Similar results are reported by Elsayed and Yarovaya (2019). Their results show a higher degree of connectedness at the lower investment horizon (over 4 days) which indicates that the MENA countries are too slow in adjusting to the information they receive, and hence respond very slowly to shocks originated within the region.

As for the net directional spillovers, albeit small in the short run, UAE and Saudi Arabia are the main net transmitters of financial shocks to other MENA countries, while Qatar and Jordan are net receivers. Finally, the net directional spillovers pattern in the long run (greater than 5 days) are similar to what is observed in the linear VAR case where Saudi Arabia is the largest transmitter of volatility to other MENA countries (48.5%), followed by Kuwait and Qatar (20.6% and 12.3%, respectively).

5.3. Quantile Connectedness Analysis

We extended the analysis of the MENA spillover connectedness by considering the volatility spillover under extreme market conditions, using the quantile connectedness approach introduced by Ando et al. (2018) and Balcilar et al. (2020). The results of the extreme quantile connectedness are presented in Table 4. There are significant differences in the spillover patterns among the MENA countries at different quantiles. The total spillover index is 80.6% and 90.6% at the lower and upper quantiles 0.05th and 0.95^{th}, respectively, which is higher than the average total spillover index of the VAR model (27.8%). The MENA financial systems are highly interlinked and connected under extreme market conditions. Put it differently, the extreme tail behavior in one country is sensitive to the extreme risk shocks in other MENA countries.

[Insert Table 4 here]

As for the net directional spillovers during the low financial stress periods (the 0.05th quantile), UAE is the largest net transmitters of financial shocks to other MENA countries, with the net spillover amounts at 8.1%, followed by Saudi Arabia and Oman (5.1% and 3.8%, respectively), while Tunisia is dominantly the main net financial risk receiver in the tranquil periods (-18.3%). For the upper regime, the volatility transmission pattern doesn't change much compared to what has been observed under the lower tail. However, we notice much higher magnitudes of spillovers in every direction. In other words, all MENA countries in the upper tail distribution have significant connectedness links, with Saudi Arabia being the major risk transmitter under the high financial risk conditions, followed by UAE and Oman (15.9%, 8.6%, and 8.2% respectively). While Tunisia remains the primary net receiver of financial shocks however with a magnitude of -24.2%.

5.4. Dynamic spillover analysis

The static spillover analysis provides interesting and useful insights on the average financial spillovers among the MENA countries over the entire sample period. However, it masks important information on the dynamic evolution of the spillover pattern over time and the impact of economic and financial crises on intensity and the direction of spillover transmission across the MENA economies. To this end, the time-varying spillover indices for the time-domain and frequency-domain connectedness models are estimated using a 250-day rolling window and a 10-day forecast horizon. The dynamic spillover indices are presented in Figure 2. As noted, the spillover index is very sensitive to financial, political, and economic turmoil events over the sample period. For instance, the spikes in the total spillover index are associated with the global financial crisis in 2008, the Arab Spring during the period 2010-2011, the collapse of oil prices during 2014-2016 followed by the Qatar diplomatic crisis, and finally the COVID-19 pandemic period with the onset of 2020. However, the 2008 global financial crisis is found to have a greater impact on financial connectedness in the MENA region, compared with the Arab Spring. This is consistent with the findings of Elsayed and Yarovaya (2019), who report that the global financial crisis generated a stronger spillover effect in the MENA region compared with the political turbulence caused by the Arab Spring. Another striking feature is that the COVID-19 pandemic has created a massive and unprecedented jump in the total spillover among the MENA countries at the beginning of 2020; however, it reverts to its mean level by 2021.

[Insert Figure 2 here]

Similar patterns have been identified in Figure 2 which also depicts the dynamic total return spillover indices from a frequency-domain spillovers analysis at both the short run and long run. However, the magnetite of the spillovers and the degree of connectedness in the long run is much higher, compared to spillovers transmitted in the short run which is consistent with our previous discussion and indicates that MENA countries are too slow transmitting shocks and in adjusting to information they receive.

In order to check the robustness of the time-varying spillover index estimates shown in Figure 2 to window size, we estimate the time-varying time-domain connectedness model also for window sizes 125 and 500. The time-varying time-domain spillover index estimates for window sizes 125 and 500, along with the estimates for the window size of 250, are shown in Figure 3. The results in Figure 3 show that the estimates for window sizes 125 and 500, although they have numerical differences, have the same time pattern and are quite analogous to the results with the window size of 250. Thus, our time-varying results are robust to window size and not driven by an inadequate window size choice.

[Insert Figure 3 here]

Figure 4 shows the dynamic net directional spillover estimates for each of the MENA countries over the sample period. The overall rolling spillover indices are calculated using a normal VAR model, whilst the short- and long-run rolling spillover indices are estimated using a frequency domain VAR model with periods of five days, less than five days, and greater than five days, respectively. A 250-day rolling window size is used. While the orange color represents the total spillover from a standard VAR model, the green and light blue indicate total spillover indices at both short run and long run, respectively. The net spillover estimates show whether a country is a net receiver or a transmitter of financial risk. First and foremost, we observe that the net spillovers deviate significantly from their levels during the 2008-2010 subprime financial crisis period and the 2020-2021 COVID-19 pandemic period. As with the total spillover case, the short-run net spillover values are usually small with some spikes during crisis periods. For the average and long-run net spillover estimates, we observe a significant time-varying behavior. There is also an asymmetry across countries in terms of how the net spillover changes over time. Bahrain and Egypt are net risk receivers during the sub-prime crisis period, while they became net transmitters during the pandemic period. Jordan, Morocco, Oman, Qatar, and Tunisia are significant financial stress receivers during both the sub-prime and pandemic crisis period. Saudi Arabia and the UAE are usually either transmitters or receivers rather than being neutral over the whole sample period. However, they both have the net transmitter roles during both the sub-prime and pandemic crises. Turkey was a significant risk transmitter during the sub-prime crisis but has the reverse role during the pandemic crisis.

[Insert Figure 4 here]

5. 5. Network Centrality Measures

Table 5 presents the various network statistics which are discussed in Subsection 3.4. These statistics, which are computed from the spillover measures in Tables 2-4 without thresholding, allow us to have a bird's eye view of the structure of connectedness. We first present the discussion of the connectedness based on the mean-based linear VAR model. Then, we will compare the short- and long-run connectedness, as well as the tail connectedness structure.

[Insert Table 5 here]

Panel A of Table 5 gives the network statistics from the linear VAR model. Since the in- and out-degrees measures are weighted, they correspond to the Diebold-Yilmaz spillover tables. The in-degree links show that Oman, Qatar, and UAE are the top three financial risk receivers, while Kuwait, Saudi Arabia, and the UAE are the most important risk transmitters. As indicated earlier, Saudi Arabia is the largest economy in the MENA region and has experienced major changes in asset quality, while the UAE is the second largest economy in that region. Egypt, Tunisia, and Turkey have quite weak links both for the in- and out-degrees, implying they are the least prone to the MENA region financial condition risks. We gave a probable reason for Tunisia. However, Turkey has connection with Europe as well as the Middle East, while Egypt has connection with Africa as well as the Middle East. We should, however, note this is true on average and does generalize to the tail risks. The closeness estimates show that Kuwait, Qatar, and Tunisia have the closest risk transmission and receiving connections, while the eigenvalue centrality estimates indicate that Kuwait, Oman, Qatar, and UAE have high risk connectedness that are also connected to countries with higher risk connectedness, and they play a central role in the spread of financial stress risk in the MENA region. In our context, the betweenness centrality measure a country's influence on the spread of financial stress to other countries. According to betweenness score estimates in Panel A of Table 5, Tunisia and Qatar are the only two countries with a non-zero estimate. However, the betweenness score of Qatar is 8, while for Tunisia it is 82. Thus, Tunisia and Qatar, but more importantly, Tunisia acts as a financial stress transmission link between two (or two other groups) countries. As it is explained in Subsection 3.4, the page rank scores of a country in the connectedness network measure a country's importance according to the incoming risk to it and the importance of the corresponding transmitter country. For the linear model connectedness in Table 5, Kuwait, Qatar, Oman, and the UAE have relatively high page rank scores, with the UAE having the highest score. Thus, these countries have stronger connections to the countries that have stronger risk connections with other countries, making them critical in controlling the transmission of financial risk. These statistics are computed from the spillover measures in Tables 2-4 without thresholding. Turkey and Tunisia have relatively smaller weighted in-degree and/or out-degree. Thus, removing an edge from these economies causes a large reduction in the total spillover, because the nodes they fall between large spillover flows. This explains their high betweenness scores.

Panels B and C of Table 5 display the network statistics for the short- and long-run connectedness, respectively. The long-run network statistics are quite analogous to the average connectedness network statistics implied by the linear VAR model. Thus, we only comment on the short-run statistics. As the spillover tables in Table 3 indicate, all short-run in- and out-degree scores are low. In terms of the in-degree measure, Qatar and the UAE have considerable higher scores, indicating that these two countries respond quickly to the financial stress changes in the MENA region. Both countries have ambitions in the MENA region. Out-degree scores show that the UAE is the most important risk transmitter in the short-run, followed by Saudi Arabia, Qatar and Oman. In terms of closeness, we have quite different structure in the short-run compared to the long-run. Bahrain, Kuwait, Qatar, and Tunisia are located as close risk transmission nodes to all other nodes in the short run. On the other hand, the eigenvector centrality scores indicate that Oman, Qatar, Saudi Arabia, and the UAE have large importance weights in the short-run financial stress spread, as they are also connected to the countries with high in- and out-degrees. Similar to the average connectedness results, Tunisia plays an important role as a mediator of financial risk in the short run as indicated by the betweenness scores. Morocco and Turkey also play some small role of mediating financial risk. With a notable page rank score estimate, Oman, Qatar, and the UAE are important nodes as risk spread points, which are also connected to other important nodes in the network.

The network statistics for the tail financial risk connectedness at the quantiles 0.05 (low) and 0.95 (high) are given in Panels D and E of Table 5. A notable structure of the tail connectedness is the observation that no country significantly dominates others in the tail connectedness networks, because all countries are almost equally connected in the tails. This result is also reflected in the higher score values for all countries for all network statistics except the betweenness scores. Both the lower and upper tail connectedness is much stronger than the normal times as indicated by the in- and out-degree scores. In the lower tail, Tunisia is closer to all other countries with the in- and out connectedness, while Bahrain, Egypt, Qatar, and the UAE are in the upper tail. Although all countries play an important role for spreading financial risk, the UAE has a higher role in the lower tail, while Saudi Arabia does that in the upper tail. No country plays a significant role of risk spread intermediation in the extreme risk periods since all of them have strong connections in the tails. The page rank scores also verify that all countries have an important risk spread role in the tails. Overall, we observe significant asymmetric risk connectedness in the short-run and tails compared to the normal times with the average connectedness.

5.6. Connectedness network analysis

Figures 5-7 present the connectedness network graph of the pairwise volatility spillover and net pairwise volatility spillover. The net spillover is calculated as the difference between volatility transmitted and volatility received. The pairwise connectedness is based on the spillover tables reported in Tables 2-4. Net connectedness is based on the net pairwise spillovers obtained from the spillover results in Tables 2-4. The direction of the arrows shows the volatility received (inward) and volatility transmitted (outward). The network representation is a weighted network where the weights are the magnitudes of the spillovers. The thickness of the arrow lines indicates the magnitude of the spillover. Since there are 11 countries in the network graph, there will be a total of 110 links connecting these countries. As we see from Tables 2-4, some of these spillovers are negligible, and thereby eliminating these small links helps us better understand the spillover dynamics among the MENA countries. To achieve this goal, we present the network graphs with a thresholding in each of Figures 5-7. Thresholding sets the values below the 75-th percentile of the spillover to zero.

Figure 5 presents the financial stress connectedness graph based on the benchmark linear VAR model. Figure 5(a) give the pairwise total directional and net directional connectedness, respectively. Panel (a) shows that Gulf countries are connected more closely among themselves than the others. Kuwait, Oman, Qatar, Saudi Arabia and UAE have a notably stronger financial stress connectedness. There is also a strong connection to Jordan from Saudi Arabia. Tunisia seems to have the weakest financial stress connections with all of the other MENA countries probably due to the ongoing Arab spring crisis in that country. The net spillover connections in Figure 5(b) indicate that Bahrain, Jordan, Oman, Qatar, and Saudi Arabia have the largest net financial stress connectedness. Amon these, Saudi Arabia is a prevalent net risk transmitter, while Bahrain, Jordan, Qatar, and Oman are significant receiver figures. Saudi Arabia has the largest economy in the MENA region. All North African countries are net risk receivers, but their risk receiving magnitude is much lower than the net receivers in the Middle East group. Pairwise total connectedness splits into three clusters, while net pairwise risk connectedness splits four clusters. The pairwise connectedness Cluster 1 is formed by Bahrain, Egypt, Kuwait, Morocco, Oman, Qatar, UAE, Cluster 2 is formed by Jordan, Saudi Arabia, Turkey while Cluster 3 is formed by Tunisia.

[Insert Figure 5 here]

Figure 5(b) reveals more clearly the financial risk connectedness of the Gulf countries, Bahrain, Oman, Qatar, and Saudi Arabia, and UAE. Tunisia does not belong to any cluster, because it has the weakest financial links with the other MENA countries as explained above. Net connectedness network graph in Figure 5(b) gives a better picture of the important risk transmitters: Kuwait and Saudi Arabia. On the other hand, Bahrain, Jordan, Oman, and Qatar are significant net receivers of financial stress. Three important clusters are formed by (1) Bahrain, Egypt, and UAE, (2) Jordan, Oman, Saudi Arabia, and Turkey, and (3) Kuwait, Morocco, and Qatar.

Connectedness analysis based on the linear VAR model does not make a distinction between the short- and long-run connectedness. Both short- and long-run financial conditions connectedness affects the mean based linear VAR estimates. In order to have better idea about the relative effects of the short- and long-run financial risk transmission, we decompose the effects into short- (less than 5 days) and long-run (greater than 5 days) components. Figures 5(a) and 5(b) display the connectedness network graphs for the pairwise spillovers and net spillovers with thresholding. Overall, we observe that the financial stress connectedness among the MENA countries is weak in the short run (one week). The clustering of the countries is also more scattered with 5 clusters. Moreover, the net spillover is much weaker with all net connectedness link that can be reasonably ignored.

[Insert Figure 6 here]

Considering the short-run pairwise connectedness, the structure of the clusters is analogous to the results of the linear VAR model, where the Gulf countries have much stronger connectedness among themselves. However, we do observe a significant difference in terms of transmitters and receivers compared to the linear case. For instance, Saudi Arabia is no longer a widespread net risk transmitter. The Gulf countries are both net transmitters and net receivers depending on the country they are paired with. On the other hand, the North African countries and Turkey are more of a net receiver than net transmitters. Among the Middle East countries Bahrain, Jordan, and Qatar have more receiving links than transmitting links. Considering the important clustering groups, we note that five clusters are formed for short-run pairwise connectedness: (i) Bahrain, Egypt, Jordan, Oman, Saudi Arabia, and UAE in Cluster 1, (ii) Qatar and Kuwait in Cluster 2, (iii) Turkey in Cluster 3, (iv) Morocco in Cluster 4, and (v) Tunisia in Cluster 5. When thresholding with net connectedness is considered, Morocco, Tunisia, and Turkey become disconnected. Saudi Arabia is major net transmitter of financial stress while Qatar is the major receiver of financial stress. In this case Morocco, Tunisia, and Turkey do not belong to any cluster. Two other clusters are formed by (1) Bahrain, Egypt, Kuwait, Qatar, and UAE and (2) Jordan, Oman, and Saudi Arabia.

Figures 6(c) and 6(d) display the long-run connectedness networks, corresponding to frequencies greeter than 5 days. The most important aspect of the connectedness graphs in Figure 6 is their similarity to Figure 5, the linear VAR case. This indicates that linear VAR results are mostly driven by the long-run financial stress connectedness, while the short-run risk spillover does not play a significant role. Both Figures 6(c) and 6(d) show that much of the risk transmission occurs within the Middle East group and particularly within the Gulf countries. Compared to the linear model, we observe that Kuwait, Saudi Arabia, and UAE are major transmitters of financial stress they both also receive. On the other hand, major receivers of risk are Bahrain, Oman, and Qatar. Tunisia once again separated from all others when thresholding is performed.

Net connectedness in Panels (c) and (d) of Figure 6 show a similar structure in terms of the risk transmitters and receivers. Majority of the risk connectedness occur among Bahrain, Kuwait, Oman, Qatar, and Saudi Arabia. When thresholding is considered, Saudi Arabia is a sole risk transmitter and Kuwait is the second major source of risk transmission. Bahrain, Jordon, Oman, Morocco, Qatar, and UAE are major net risk receivers. Turkey transmits risks to Qatar and Jordan, as it has closer economic integration with these two countries. When pairwise connectedness without thresholding is considered two clusters are formed. The first cluster is formed by Bahrain, Egypt, Kuwait, Morocco, Oman, Qatar, Tunisia, and UAE while the second by Jordan, Saudi Arabia, and Turkey. Considering the long-run net connectedness with thresholding, Tunisia is separate from all others, while remaining countries form three clusters: (1) Bahrain, Kuwait, Morocco, and Qatar, (2) Egypt and UAE, and (3) Jordan, Oman, Saudi Arabia, and Turkey.

Both the linear VAR and frequency connectedness networks are based on estimates from a mean-based VAR model. This VAR model fits to the mean of the conditional distribution, and hence the spillover measures from such a model represent mean spillovers. However, financial stress and risk are more important in the tails of the distribution. It is well known that the financial variables are more correlated in the extremes such as in the crises periods than the normal times. Indeed, the financial risk connectedness might be much stronger when the level of financial stress is high. On the other hand, connectedness might be quite different when financial stress is at the low levels. In order to see whether connectedness varies in the tails of the distribution, we obtain connectedness graphs based on the QVAR model. For the high financial stress case, we consider the 0.95th quantile estimates and 0.05th quantile estimates for the low financial stress case. We do not estimate a QVAR around the mid quantile such as the 0.50th quantile since the linear VAR estimates represent the same case.

Figures 7(a) and 7(b) present the connectedness graphs for the 0.05th quantile, which corresponds to the low financial stress or tranquil financial conditions case. Considering the pairwise connectedness, Figure 7(a) indicates two-way links across the country pairs, some structure is observed. First, Bahrain, Morocco, and Tunisia fall outside any clusters and with no significant links to other countries. The Gulf countries Oman, Kuwait, Qatar, and UAE belong to the largest cluster, also including Jordan, with almost equal inward and outward pairwise links, indicating their widespread co-movement. Egypt, Saudi Arabia, and Turkey form another cluster. When we consider net pairwise connectedness some notable structure occurs. Tunisia is dominantly a net financial risk receiver in tranquil periods, followed by Bahrain, Egypt, Jordon, Morocco, Qatar. We observe that Tunisia is almost the sole receiver of financial stress spillover. Bahrain is also an important risk receiver. There are four connectedness clusters that form more homogenous and closer groups among themselves: (1) Bahrain, Qatar, and Saudi Arabia, (2) Egypt and UAE, (3) Jordan, Kuwait, Tunisia, and Turkey, and (4) Morocco and Oman.

[Insert Figure 7 here]

Financial conditions connectedness network graphs for the high financial stress case, which are based on the estimates from a QVAR model at the 0.95th quantile are given in Figures 7(c) and 7(d). Figure 8(c) displays the total network connectedness graph with thresholding. Compared to the same type of network graphs in Figures 5-6, this graph has a unique feature: All countries have significant connectedness links even when small spillover links are eliminated. This finding is consistent with the well-known feature of financial markets: all financial markets get significantly interlinked under crises or high financial stress case. Even under this case, we note that the Gulf countries Oman, Kuwait, Saudi Arabia, and UAE are more closely connected than the others in group and the fall near each other in the network layout. Another important difference in Figure 7(c) is that the Saudi Arabia is not the major risk transmitter under high financial risk conditions. In this case, Kuwait and UAE also become strong risk transmitters. Bahrain, Egypt, Jordan, Oman, Morocco, Qatar, Tunisia, and Turkey are all risk receivers than transmitters. When the net risk connectedness is considered, Figures 7(c) and 7(d) indicate a similar asymmetric structure when they are compared to the cases in Figures 5-6. Note that Figure 7(c) shows significant two-way net spillovers across most countries. Tunisia is the major net risk receiver and Saudi Arabia as more of a net risk transmitter than receiver. We also note that no country is separated from the clusters even when thresholding is performed. When considering the net pairwise connectedness, three clusters are formed: (1) Bahrain, Kuwait, Morocco, Oman, and UAE, (2) Egypt, Qatar, and Saudi Arabia, and (3) Jordan, Tunisia, and Turkey. The different structures observed in network graphs in Figures 7(c) and 7(d) point out to the asymmetry in the connectedness structures. The MENA countries' connectedness is much stronger, the clusters contain different members, and the net risk transmitting and receiving countries do also vary under extreme financial stress conditions.

5.7. Effect of global macroeconomic conditions on the MENA financial risk connectedness

In the light of the economic theory of financial and economic connectedness of countries (Bech and Atalay, 2010; Billio et al., 2012; Brunnermeier et al., 2012; Acemoglu et al., 2015; Diebold and Yılmaz, 2015; Bisias et al., 2018; Andries and Galasan, 2020; Maggi et al., 2020; Torrente and Uberti, 2021) explained in Section 1 and recent empirical works showing risk exposure of the MENA economies to various global factors (see, among others, Dewandaru et al. 2014; Aloui, et al., 2015; Balcilar et al., 2015; Nazlioglu, et al., 2015), we examine the role of global macroeconomic conditions in driving the risk connectedness of the

MENA economies. Global macroeconomic factors may have a direct spillover to MENA economies, or they may rather affect the internal connectedness of these economies. The first case may be considered as a direct contagion effect. In this case, global factors may affect the connectedness with a spillover effect to MENA economies in the same direction, which will change the financial risk in these economies, similarly, increasing their connectedness. On the other hand, the repose of economic agents to global economic conditions may change the financial conditions in the MEAN economies together in the same way, increasing their connectedness. In this latter case, global macroeconomic factors paly a driving force role behind the financial risk transmission across the MENA economics. In any case, global factors may be a leading source of changes in the systemic risk across the MENA economies as they are integrated or exposed to the financial risk of the broader global system.

We consider a number of macroeconomic conditions variables and financial stress indices capturing the state of the global economy, which are available at the daily frequency and cover the period of our study. The global macroeconomic conditions variables include the news sentiment index (NWS) of the Federal Reserve Bank of San Francisco, the US economic policy uncertainty index (UNC) of Baker et al. (2016), the infectious disease equity market volatility (IDV) of Baker et al. (2019), and the Chicago Board Options Exchange (CBOE) volatility index (VIX). We also consider direct measures of the global financial stress. These global financial stress variables are constructed by the Office of Financial Research (OFR) of the US Department of the Treasury and include the world financial stress index (FSIWRD), the advanced economies financial stress index (FSIADV), the US financial stress index (FSIUS), the emerging markets financial stress index (FSIEMR), and the world volatility index (VOLWRD). Sources of these variables are given in the note of Table 6. We note that these variables are highly correlated with each other. Moreover, the variables of the world and emerging market financial stress indices and the world volatility index includes the MEAN countries and, thus, may correlate with our estimates because of this reason.

We first re-estimate the DY spillover indices based on the standard VAR model by including one of the global variables in the model. We avoid including more variables as this will distort the result due to a high dynamic interaction among the additional global macroeconomic variables. The results of the estimates are summarized in Table 6.[6] First of all, none of these global factors has a significant effect on the total connectedness index. The estimate of the basic model spillover index in Table 2 is 27.76, and only the model with the

[6] We do not report full spillover tables to preserve space, but they are available from the authors upon request.

VIX variable has a slightly higher spillover index estimate, being at a value of 28.08, which is really not significantly higher than the basic model value. This is because the spillover that the global macroeconomic variable adds to the MENA risk network, when included as an additional variable, is less than the average spillover per variable in the basic model.

We observe that the news sentiment, the US economic policy uncertainty, and the infectious disease volatility indices have less than a 5% spillover to the MENA countries' FSIs. The highest spillover to these countries' FSIs is found for the VIX, which is 57.66. Other global financial stress variables also have considerable high spillovers to MENA countries' FSIs. Considering the net spillovers for the global macroeconomic variables, we only find a considerable positive net spillover from the VIX, with a net spillover index value of 26.85, followed by the global volatility index of the OFR with a value of 14.94. The news sentiment index, that news sentiment, the US economic policy uncertainty, and the infectious disease volatility indices, as well as the emerging market financial stress index, have negative net spillovers to MENA countries' FSIs.

[Insert Table 6 here]

The results in Table 6 indicate that the role of global factors on the financial risk connectedness of the MENA economies is likely to as an underlying implicit factor rather than a direct spillover role. To illustrate this point, we regress the global macroeconomic variables on the time-varying total connectedness index estimated with the rolling window size of 250 days. Both univariate and multivariate regression estimates are reported in Table 7. A univariate regression is not estimated for the advanced economies financial stress index, the US financial stress index, and the emerging markets financial stress index variables as these indices are jointly included in a separate regression (i.e., Model 7). The univariate regression estimates indicate that all macroeconomic factors are significant determinants of the MENA financial stress connectedness. Estimates for Model 7 also indicate that the US, emerging, and advanced market financial stress variables are also jointly significant. The US economic policy uncertainty, infectious disease equity market volatility, VIX, global FSI, advanced market FSI, emerging market FSI, and global volatility have a positive effect on the MENA financial risk connectedness, while the news sentiment index and the US FSI have a negative effect. The unexpected signs on the news sentiment index and the US FSI may be due to time-varying effects. The multivariate regressions in Models 8-10 confirm the univariate regression results except for the US economic policy uncertainty, which has an insignificant coefficient estimate.

The coefficient determination coefficients indicate that the VIX has the highest explanatory power.

[Insert Table 7 here]

The effect of global factors on the connectedness of the MENA economies is likely to be time-varying. Over time, pandemics like COVID-19 can change investor behavior. Prices reflect asymmetric and time-dependent investor behavior because markets do not operate in a vacuum. The Adaptive Markets Hypothesis (AMH) of Lo (2004) as well as the Heterogeneous Markets Hypothesis (HMH) of Müller et al. (1993) explain this phenomenon. By analyzing historical and contemporary news, the HMH proposes that diverse economic agents make investment decisions across a wide range of time horizons based on their risk and return preferences. Spillovers and information flows between assets and/or asset classes intensify during crisis periods, due in part to the unrelenting search by rational and irrational market participants for competitive risks and returns to satisfy portfolio objectives, i.e., by minimizing risk while maximizing returns. Naturally, market participants' expectations of the financial markets' responsiveness to intensified spillovers and information in uncertain periods, such as those caused by the COVID-19 pandemic, would lead to frantic trading of assets, resulting in unexpected non-fundamental connections between assets and/or asset classes. Therefore, the global macroeconomic variables might have time-varying impact on the connectedness of the MENA economies.

To investigate the time-varying effect, we estimate the time-varying regression coefficient of the VIX using a rolling regression. The rolling egression slope estimates from a regression of the VIX on the time-varying connectedness index estimate with a 250-day window size (reported in Figure 3) are presented in Figure 8. The results in this figure indicate a strong time-varying effect of the VIX on the risk connectedness of the MENA economies. Although most of the estimates are positive, there are periods when the estimates are negative, although small in magnitude. We observe that the highest positive impact of the VIX on the connectedness corresponds to the periods of higher volatility, i.e., 2011-2012, 2013, 2017-2018, and 2020-2021.

[Insert Figure 8 here]

6. Conclusion

This study constructs Financial Stress Indices for 11 countries in the MENA region and examines financial connectedness for those countries, using the linear VAR, frequency domain VAR approach, QVAR and network graph analyses. We examine pairwise connectedness and net pairwise connectedness with thresholding and without thresholding for clusters of those countries.

The pairwise directional and net directional connectedness show that the five Gulf countries are strongly financially connected among themselves than with the other countries. Kuwait, Oman, Qatar, Saudi Arabia and UAE have a notably stronger financial connectedness. There is also a strong financial connection between Jordan and those Gulf countries. On the other hand, Tunisia has the weakest financial stress connection with the other MENA countries in this model. Saudi Arabia is the prevalent net financial stress risk transmitter, while Bahrain, Jordan, Qatar, and Oman are significant receivers. All North African countries are relatively mild receivers of risk. In terms of pairwise financial clustering, Bahrain, Kuwait, Morocco, and Qatar form Cluster 1, while the remaining seven MENA countries form Cluster 2. Net pairwise connectedness has three clusters where Egypt and UAE form their own cluster. In terms of thresholding for this model, Tunisia does not belong to any clustering.

When distinguishing between the short and long run using the frequency connectedness network graphs, the financial stress connectedness among all the countries under consideration is weak in the short run (one week) and the clustering of the countries is also more scattered than the linear case, with three clusters with no thresholding and five clusters with thresholding. The Gulf countries are also both net receivers and net transmitters. The long-run (greater than 5 days) connectedness networks are similar to the linear VAR case as explained earlier.

When considering the connectedness for the extreme (0.05^{th} and 0.95^{th}) tails of the distribution in the QVAR model, we have distinct results. The pairwise connectedness without thresholding in the 0.05^{th} quantile indicates that the low financial stress periods are rather unique, with all countries transmitting and receiving low financial risk and forming a unique whole cluster. When applying thresholding, we show that Bahrain, Morocco, and Tunisia fall outside any clusters, while the other Gulf countries Oman, Kuwait, Qatar, and UAE belong to the largest cluster which also includes Jordan. When we consider the net pairwise connectedness, for the no-thresholding case, Tunisia is dominantly a net financial risk receiver in tranquil periods, followed by Bahrain, Egypt, Jordon, Morocco, Qatar. With a QVAR thresholding, Tunisia is almost the sole receiver of financial stress spillover. and there are three connectedness clusters that form more homogenous groups among themselves. For the estimates in the 0.95th quantile, we notice a much higher magnitudes of spillovers in every direction. For the pairwise connectedness, all countries are in the same cluster with a two-way significant link. With thresholding, all countries in this tail distribution have significant connectedness links.

Our overall empirical results suggest a positive association between financial stress co-movements and spillovers in the MENA countries under consideration, particularly during the long run and high extreme stress periods. This is not the case for the short run and the extreme low stress periods. Moreover, financial openness plays an important role in the financial network. The more open countries, particularly Kuwait, Oman, Qatar, and the UAE, seem to play a more central role in the financial connectedness and transmission of risk in the MENA region. This implies that investors and policy makers may ride out stresses during the short run and low risk periods, but they have to be very prudent during the long run and crises. Hedges are recommended during those difficult periods. The hedges can be done within the local markets using hedging tools such as futures and options or diversification with international stock markets in developed countries.

Saudi Arabia is the main risk transmitter which squares well with the reality that this country has the largest economy in the MENA region. Therefore, investors in this region should be cognizant of the risks emanating from KSA. Moreover, since the results show that the countries in the GCC region are strongly connected in certain circumstance, then diversification within this region does not produce the desired goal of reducing risk in those circumstances. Diversification should come from outside this GCC region. Tunisia is not connected with many MENA countries, and thus can be a diversifier for the GCC region. Further, understanding of the nature of financial connectedness and dynamics among MENA economies allows policymakers and regulators to implement the right measures to safeguard and maintain sound and stable financial systems.

Table 1. Descriptive statistics and definitions

	Bahrain	Egypt	Jordan	Kuwait	Morocco	Oman	Qatar	Saudi Arabia	Tunisia	Turkey	United Arab Emirates
Code	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE
KAOPEN	0.99	0.58	1.00	0.70	0.16	1.00	1.00	0.70	0.16	0.37	1.00
KAOPEN class	High	Medium	High	High	Low	High	High	Medium	Low	Low	High
Region	Middle East	North Africa	Middle East	Middle East	North Africa	Middle East	Middle East	North Africa	North Africa	Middle East	Middle East
Membership: Standard VAR	Cluster 1	Cluster 1	Cluster 2	Cluster 3	Cluster 3	Cluster 2	Cluster 3	Cluster 2	Cluster 4	Cluster 2	Cluster 1
Membership: Short-run VAR	Cluster 1	Cluster 1	Cluster 2	Cluster 1	Cluster 3	Cluster 2	Cluster 1	Cluster 2	Cluster 4	Cluster 5	Cluster 1
Membership: Long-run VAR	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 1	Cluster 3	Cluster 1	Cluster 3	Cluster 4	Cluster 3	Cluster 2
Membership: Quantile VAR ($q = 0.05$)	Cluster 1	Cluster 2	Cluster 3	Cluster 3	Cluster 4	Cluster 4	Cluster 1	Cluster 1	Cluster 3	Cluster 3	Cluster 2
Membership: Quantile VAR ($q = 0.95$)	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 1	Cluster 1	Cluster 2	Cluster 2	Cluster 3	Cluster 3	Cluster 1
N	3855	3855	3855	3855	3855	3855	3855	3855	3855	3855	3855
Mean	0.002	0.009	-0.006	0.007	0.004	0.005	0.001	-0.007	0.003	0.007	0.003
S.D.	0.482	0.527	0.489	0.493	0.585	0.543	0.429	0.534	0.475	0.563	0.535
Min	-4.470	-1.556	-1.333	-2.761	-1.455	-1.531	-3.743	-1.561	-8.254	-1.438	-1.353
Max	7.084	4.661	3.338	4.489	6.671	4.547	4.961	6.251	5.588	3.767	4.214
Skewness	2.226	1.989	1.463	2.668	2.398	2.498	1.859	2.787	1.413	1.783	2.527
Kurtosis	22.986	9.610	4.389	13.296	14.286	11.401	15.792	16.861	41.443	5.889	11.091
JB	88154.919***	17396.682***	4475.118***	33011.603***	36520.536***	24917.930***	42328.843***	50717.002***	277468.096***	7622.931***	23889.544***
Q(1)	1521.058***	1711.978***	1398.288***	1686.642***	2070.958***	1745.266***	824.688***	1717.498***	1593.162***	1728.955***	1689.286***
Q(5)	5743.404***	6098.251***	4435.850***	7288.012***	8103.921***	6708.709***	3576.516***	7431.914***	5365.773***	7628.624***	6451.033***
ARCH(1)	1520.987***	1758.954***	1174.586***	1618.186***	1977.027***	1302.301***	775.446***	2006.636***	1322.404***	1707.202***	1567.736***
ARCH(5)	1548.754***	1820.250***	1261.812***	1795.707***	2115.189***	1457.048***	1010.701***	2183.610***	1401.679***	2054.546***	1704.664***
ADF	-11.385***	-12.021***	-10.369***	-7.394***	-8.118***	-6.540***	-8.696***	-8.852***	-10.273***	-10.011***	-8.443***

Note: Table reports the definitions and statistics of the financial stress index (FSI) for Bahrain, Egypt, Jordan, Kuwait, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey, and United Arab Emirates. KAOPEN is the Chinn-Ito index of capital account openness (Chinn and Ito, 2006). In addition to the mean, standard deviation (S.D.), minimum maximum, skewness and excess kurtosis, the table reports the Jarque-Bera test of normality (JB), the Ljung-Box test of first- [Q(1)] and fifth-order [Q(5)] autocorrelation, and the first- [ARCH(1)] and the fifth-order [ARCH(5)] test of the autoregressive conditional heteroskedasticity test. ADF is the Augmented Dickey-Fuller unit root test with a constant term for testing the null hypothesis of the presence of a unit root against the alternative hypothesis of stationarity. *N* denotes number of observations. Membership reports the cluster class of the corresponding country which is obtained from the optimal clustering algorithm of Brandes *et al*. (2007). The clusters are obtained from the connectedness network illustrated in the version of the spillover of the table defined in Deibold and Yilmaz (2012). The cluster membership reported here corresponds to the net spillover networks with thresholding. The short- and long-run VAR models are the frequency VAR model models of Baruník and Křehlík (2018). The short-run VAR is defined for a period of up to five days, while the long-run VAR is defined for a period greater than five days. The quantile VAR models are estimated using the approach of White *et al*. (2015) at the quantiles (q) 0.05 and 0.95. The lag order of the VAR models is 3 which is selected using the Bayesian information criterion (BIC).

Table 2. Overall connectedness based on a standard VAR model

	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	From
BH	70.59	0.42	0.57	7.52	1.16	2.29	3.82	7.12	0.12	1.35	5.06	29.41
EG	0.57	80.79	0.38	3.74	0.93	1.66	0.70	3.10	0.19	2.49	5.44	19.21
JO	1.01	0.65	68.75	3.13	1.77	5.02	1.44	10.81	0.35	3.41	3.66	31.25
KW	3.34	1.82	1.25	66.61	3.41	5.28	5.36	4.62	0.08	2.26	5.96	33.39
MA	2.15	1.32	1.85	6.83	76.00	2.84	0.65	4.41	0.16	0.97	2.82	24.00
OM	1.30	0.75	4.08	7.94	3.90	58.16	3.42	11.74	0.31	2.43	5.98	41.84
QA	2.19	0.59	1.33	10.75	0.76	4.69	61.81	9.62	0.05	2.54	5.67	38.19
SA	2.16	1.05	1.20	1.90	1.00	3.22	2.52	73.74	0.03	5.67	7.49	26.26
TN	0.62	0.53	0.37	0.01	0.78	0.61	0.01	0.13	96.40	0.29	0.25	3.60
TR	0.69	0.94	0.73	1.11	1.02	1.08	0.41	6.43	0.08	85.32	2.19	14.68
AE	2.87	2.53	2.15	8.81	1.77	5.20	4.49	12.29	0.12	3.32	56.46	43.54
To	16.91	10.60	13.90	51.74	16.50	31.91	22.82	70.27	1.50	24.72	44.52	**27.76**
Net	-12.50	-8.61	-17.35	18.35	-7.50	-9.94	-15.37	44.01	-2.10	10.04	0.98	

Note: The table reports the generalized spillover measures estimated using the approach of Diebold and Yilmaz (2012). The lag order of the VAR models is 3 which is selected using the Bayesian information criterion (BIC). Bold denotes the overall spillover index.

Table 3. Frequency connectedness

	Short run (up to 5 days)											
	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	From
BH	24.18	0.09	0.20	0.45	0.30	0.48	0.19	0.20	0.02	0.04	0.68	2.66
EG	0.09	23.97	0.24	0.30	0.11	0.34	0.31	0.38	0.03	0.23	0.86	2.89
JO	0.20	0.32	28.08	0.21	0.12	0.93	0.47	0.71	0.20	0.12	1.01	4.29
KW	0.40	0.34	0.16	19.91	0.08	0.46	1.63	0.38	0.01	0.08	0.90	4.43
MA	0.20	0.09	0.13	0.09	18.64	0.08	0.05	0.11	0.02	0.03	0.18	0.97
OM	0.37	0.30	0.56	0.38	0.07	19.01	0.98	1.30	0.04	0.31	1.50	5.81
QA	0.23	0.42	0.46	2.16	0.12	1.44	29.86	1.05	0.03	0.15	2.66	8.70
SA	0.16	0.36	0.23	0.20	0.21	0.80	0.51	20.10	0.03	0.59	1.78	4.87
TN	0.00	0.03	0.15	0.01	0.06	0.06	0.01	0.06	30.53	0.04	0.06	0.48
TR	0.03	0.24	0.07	0.09	0.03	0.25	0.14	0.65	0.04	22.38	0.51	2.05
AE	0.43	0.69	0.63	0.70	0.19	1.32	1.63	1.75	0.03	0.40	17.46	7.77
To	2.12	2.87	2.83	4.61	1.29	6.14	5.91	6.59	0.45	1.99	10.12	**4.08**
Net	-0.54	-0.03	-1.46	0.17	0.32	0.33	-2.79	1.72	-0.03	-0.05	2.35	
	Long run (from 5 days onward)											
	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	From
BH	43.43	0.43	0.38	7.56	1.03	1.91	3.74	8.06	0.11	1.95	4.57	29.74
EG	0.58	55.60	0.13	3.80	0.92	1.37	0.39	2.89	0.16	2.50	4.79	17.54
JO	0.98	0.31	37.40	3.41	2.11	4.33	1.06	11.26	0.15	3.97	2.65	30.23
KW	3.13	1.66	1.20	43.59	4.03	5.14	3.56	5.28	0.07	2.82	5.19	32.07
MA	2.24	1.38	1.87	8.26	51.74	3.48	0.81	5.81	0.12	1.61	3.09	28.66
OM	1.05	0.47	3.56	8.41	4.70	36.05	2.39	11.33	0.30	2.55	4.37	39.13
QA	2.16	0.17	0.92	8.73	0.92	3.35	29.84	9.44	0.02	2.95	2.93	31.60
SA	2.35	0.71	1.02	2.19	1.06	2.57	2.12	51.53	0.00	5.87	5.62	23.51
TN	0.72	0.58	0.22	0.01	0.73	0.62	0.01	0.07	65.52	0.30	0.21	3.47
TR	0.92	0.79	0.76	1.55	1.38	1.03	0.36	6.92	0.04	60.02	1.82	15.55
AE	2.62	1.96	1.50	8.77	1.88	4.00	2.78	11.03	0.10	3.37	36.76	38.00
To	16.74	8.46	11.56	52.68	18.75	27.79	17.22	72.09	1.06	27.88	35.24	**26.32**
Net	-13.00	-9.07	-18.66	20.61	-9.90	-11.34	-14.37	48.58	-2.41	12.33	-2.76	

Note: The table reports the frequency domain spillover measures estimated using the approach of Baruník and Křehlík (2018). The lag order of the VAR models is 3 which is selected using the Bayesian information criterion (BIC). Bold denotes the overall spillover index.

Table 4. Extreme Quantile connectedness

	The 0.05-th quantile											
	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	From
BH	20.49	7.60	8.03	8.62	8.14	7.98	8.30	8.42	5.56	8.11	8.76	79.51
EG	7.56	19.66	8.03	8.18	8.06	8.04	7.80	8.30	6.22	8.93	9.22	80.34
JO	7.69	7.68	18.22	8.30	8.11	9.20	8.29	8.76	6.06	8.61	9.09	81.78
KW	7.89	7.73	8.13	19.10	7.79	9.01	9.82	8.20	4.97	7.83	9.54	80.90
MA	8.22	8.10	8.82	8.39	18.63	8.51	7.95	8.23	6.12	8.56	8.47	81.37
OM	7.38	7.58	9.02	8.45	7.51	17.65	9.11	9.63	5.37	8.50	9.80	82.35
QA	7.21	7.33	8.44	9.59	7.43	9.30	18.83	8.77	5.40	7.87	9.83	81.17
SA	7.27	7.67	8.50	7.83	7.96	9.22	8.42	18.60	5.27	9.25	10.03	81.40
TN	7.35	7.77	7.99	6.81	8.02	6.86	7.32	7.19	25.22	8.31	7.18	74.78
TR	7.51	8.21	8.50	7.72	8.20	8.59	7.74	9.35	6.34	19.06	8.78	80.94
AE	7.59	8.03	8.49	8.84	7.85	9.49	9.12	9.64	5.19	8.38	17.38	82.62
To	75.66	77.70	83.97	82.72	79.06	86.19	83.87	86.50	56.50	84.34	90.67	**80.65**
Net	-3.84	-2.64	2.19	1.82	-2.31	3.83	2.70	5.09	-18.28	3.40	8.05	

	The 0.95-th quantile											
	BH	EG	JO	KW	MA	OM	QA	SA	TN	TR	AE	From
BH	7.98	8.58	9.29	9.88	9.58	9.73	8.60	10.28	7.10	9.18	9.81	92.02
EG	7.87	8.94	9.27	9.94	9.55	9.82	8.42	10.27	6.81	9.08	10.02	91.06
JO	7.75	8.07	9.56	9.69	9.41	10.06	8.68	11.01	6.53	9.45	9.78	90.44
KW	7.87	8.49	9.35	9.91	9.58	9.82	8.61	10.44	6.94	9.18	9.82	90.09
MA	7.89	8.59	9.34	9.89	9.74	9.78	8.52	10.29	7.10	9.07	9.78	90.26
OM	7.78	8.30	9.43	9.84	9.47	9.97	8.65	10.75	6.69	9.27	9.85	90.03
QA	7.84	8.23	9.39	9.75	9.47	9.86	8.74	10.69	6.96	9.33	9.72	91.26
SA	7.78	8.29	9.40	9.62	9.29	9.97	8.64	11.01	6.63	9.42	9.95	88.99
TN	8.05	8.86	9.18	9.62	9.79	9.57	8.35	9.96	7.57	9.13	9.91	92.43
TR	7.92	8.33	9.38	9.62	9.49	9.78	8.56	10.57	6.72	9.77	9.86	90.23
AE	7.87	8.54	9.30	9.82	9.46	9.84	8.55	10.61	6.78	9.18	10.06	89.94
To	78.62	84.29	93.33	97.68	95.07	98.23	85.59	104.87	68.25	92.29	98.50	**90.61**
Net	-13.40	-6.77	2.89	7.59	4.81	8.20	-5.66	15.88	-24.17	2.07	8.56	

Note: The table reports the frequency domain spillover measures estimated using the approach of White *et al.* (2015). The lag order of the VAR models is 3 which is selected by the Bayesian information criterion (BIC). Bold denotes the overall spillover index.

Table 5. Statistics for network characteristics

	In-degree	Out-degree	Closeness	Eigenvector centrality	Betweenness	Page rank	In-degree	Out-degree	Closeness	Eigenvector centrality	Betweenness	Page rank
	Panel A: Overall connectedness based on a standard VAR model						*Panel B: Short-run frequency connectedness (up to 5 days)*					
BH	0.29	0.17	13.62	0.56	0	0.09	0.03	0.02	242.82	0.28	0	0.06
EG	0.19	0.11	16.57	0.35	0	0.06	0.03	0.03	153.99	0.36	0	0.07
JO	0.31	0.14	21.66	0.53	0	0.09	0.04	0.03	84.44	0.43	0	0.09
KW	0.33	0.52	65.24	0.89	0	0.13	0.04	0.05	211.27	0.60	0	0.10
MA	0.24	0.17	11.15	0.46	0	0.08	0.01	0.01	128.63	0.11	8	0.03
OM	0.42	0.32	13.78	0.83	0	0.13	0.06	0.06	109.30	0.73	0	0.12
QA	0.38	0.23	63.57	0.75	8	0.11	0.09	0.06	237.52	0.91	0	0.17
SA	0.26	0.70	35.80	1.00	0	0.09	0.05	0.07	103.32	0.71	0	0.10
TN	0.04	0.02	66.66	0.05	82	0.03	0.00	0.00	254.61	0.04	77	0.02
TR	0.15	0.25	23.38	0.46	0	0.05	0.02	0.02	159.18	0.25	10	0.05
AE	0.44	0.45	25.47	0.96	0	0.14	0.08	0.10	99.66	1.00	0	0.17
	Panel C: Long-run frequency connectedness (from 5 days onward)						*Panel D: Quantile connectedness at the 0.05-th quantile*					
BH	0.30	0.17	12.72	0.58	0	0.09	0.80	0.76	1.32	0.90	0	0.09
EG	0.18	0.08	37.29	0.32	0	0.06	0.80	0.78	1.29	0.92	0	0.09
JO	0.30	0.12	34.70	0.52	0	0.09	0.82	0.84	1.19	0.96	0	0.09
KW	0.32	0.53	95.35	0.91	0	0.13	0.81	0.83	1.21	0.95	0	0.09
MA	0.29	0.19	12.09	0.57	0	0.10	0.81	0.79	1.26	0.93	0	0.09
OM	0.39	0.28	14.29	0.79	0	0.13	0.82	0.86	1.16	0.98	0	0.09
QA	0.32	0.17	88.00	0.62	7	0.09	0.81	0.84	1.19	0.96	0	0.09
SA	0.24	0.72	56.30	1.00	0	0.09	0.81	0.87	1.16	0.97	0	0.09
TN	0.03	0.01	94.10	0.04	85	0.03	0.75	0.57	1.77	0.77	0	0.08
TR	0.16	0.28	25.10	0.52	0	0.06	0.81	0.84	1.19	0.95	0	0.09
AE	0.38	0.35	32.19	0.85	0	0.12	0.83	0.91	1.10	1.00	0	0.09

Table 5. Statistics for network characteristics (*continued*)

	In-degree	Out-degree	Closeness	Eigenvector centrality	Betweenness	Page rank
	Panel E: Quantile connectedness at the 0.95-th quantile					
BH	0.92	0.79	1.27	0.89	0	0.09
EG	0.91	0.84	1.19	0.91	0	0.09
JO	0.90	0.93	1.07	0.95	0	0.09
KW	0.90	0.98	1.02	0.97	0	0.09
MA	0.90	0.95	1.05	0.96	0	0.09
OM	0.90	0.98	1.02	0.97	0	0.09
QA	0.91	0.86	1.17	0.92	0	0.09
SA	0.89	1.05	0.95	1.00	0	0.09
TN	0.92	0.68	1.47	0.84	0	0.09
TR	0.90	0.92	1.08	0.95	0	0.09
AE	0.90	0.99	1.02	0.97	0	0.09

Note: The network statistics are based on the connectedness networks defined using the spillover tables reported in Tables 2-4. See notes to Tables 2-4.

Table 6. Overall connectedness effect of global variables based on a standard VAR model

Variable	**DY spillover index with a global variable**	**Spillover from a global variable to MENA FSIs**	**Net spillover from a global variable to MENA FSIs**
News sentiment index (NWS)	25.83	2.21	-8.48
US economic policy uncertainty (UNC)	26.98	3.04	-12.65
Infectious disease equity market volatility (IDV)	26.33	4.62	-0.93
CBOE volatility index (VIX)	28.03	57.66	26.85
OFR world financial stress index (FSIWRD)	26.74	45.29	7.55
OFR advanced economies financial stress index (FSIADV)	27.65	42.75	1.18
OFR US financial stress index (FSIUS)	24.89	36.98	8.86
OFR emerging markets financial stress index (FSIEMR)	26.98	33.14	-12.16
OFR world volatility index (VOLWRD)	27.76	54.28	14.94

Note: The table reports the generalized spillover measures estimated using the approach of Diebold and Yilmaz (2012). The lag order of the VAR models is selected using the Bayesian information criterion (BIC). The global macroeconomic conditions variables include: News sentiment index (NWS) of the Federal Reserve Bank of San Francisco (sourced from https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/), US economic policy uncertainty index (UNC) of Baker et al. (2016) (sourced from fhttp://policyuncertainty.com/us_monthly.html), infectious disease equity market volatility (IDV) of Baker et al. (2019) (sourced from http://policyuncertainty.com/infectious_EMV.html), Chicago Board Options Exchange (CBOE) volatility index (VIX) (sourced from https://www.cboe.com/tradable_products/vix/vix_historical_data/). Global financial stress variables of the Office of Financial Research (OFR) of the US Department of the Treasury include: OFR world financial stress index (FSIWRD), OFR advanced economies financial stress index (FSIADV), OFR US financial stress index (FSIUS), OFR emerging markets financial stress index (FSIEMR), and OFR world volatility index (VOLWRD) (all sourced from https://www.financialresearch.gov/financial-stress-index/).

Table 7: Regression estimates of the time-varying total connectedness on global macroeconomic factors

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	33.177***	26.253***	33.327***	17.606***	35.489***	37.513***	34.200***	26.029***	27.683***	39.494***
	(0.155)	(0.301)	(0.175)	(0.351)	(0.194)	(0.182)	(0.178)	(0.821)	(0.826)	(0.924)
NWS	-43.808***							-16.760***	-14.475***	-21.134***
	(1.015)							(1.241)	(1.290)	(1.314)
UNC		0.079***						-0.002	-0.005	-0.005
		(0.003)						(0.003)	(0.002)	(0.002)
IDV			1.121***					0.808***	0.882***	0.804***
			(0.045)					(0.058)	(0.064)	(0.063)
VIX				0.909***				0.353***	0.236***	-0.200***
				(0.020)				(0.044)	(0.043)	(0.046)
FSIWRD					1.293***			0.343***		
					(0.031)			(0.084)		
VOLWRD						4.693***				6.981***
						(0.092)				(0.303)
FSIUS							-4.645***		-4.236***	-2.821***
							(0.271)		(0.212)	(0.234)
FSIADV							3.784***		3.285***	-1.043**
							(0.233)		(0.289)	(0.369)
FSIEMR							18.297***		10.160***	8.078***
							(1.062)		(0.675)	(0.600)
R^2	0.3850	0.2730	0.3360	0.4450	0.2340	0.3640	0.3120	0.6170	0.6520	0.6890

Note: The table reports regression estimates from a regression of the time-varying total connectedness estimates with a rolling window size of 250 reported in Figure 2 on the global macroeconomic variables. Standard errors are heteroskedasticity and autocorrelation robust. R^2 denotes coefficient of determination. *** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05. See the note to Table 6 for the variable definitions.

Figure 1. Financial stress index for the MENA countries

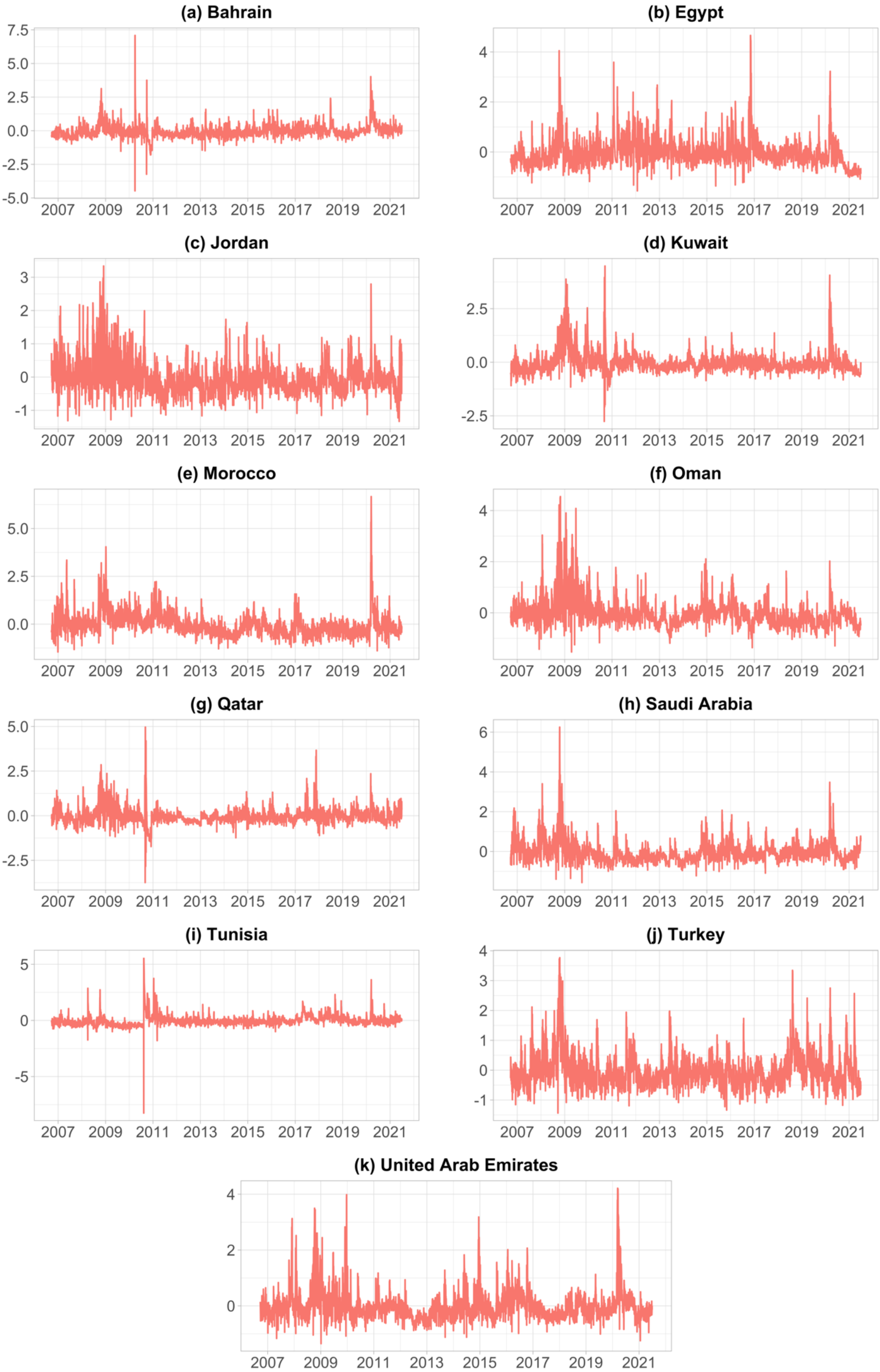
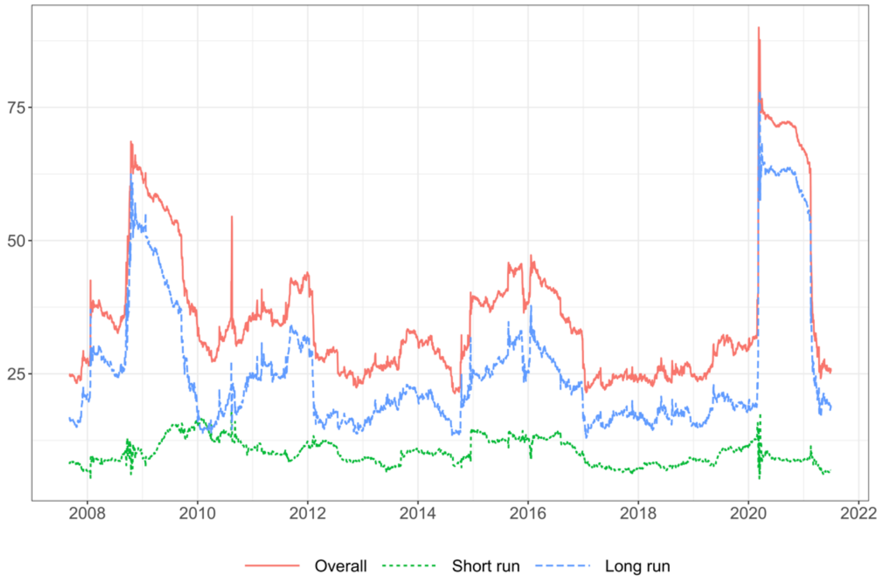
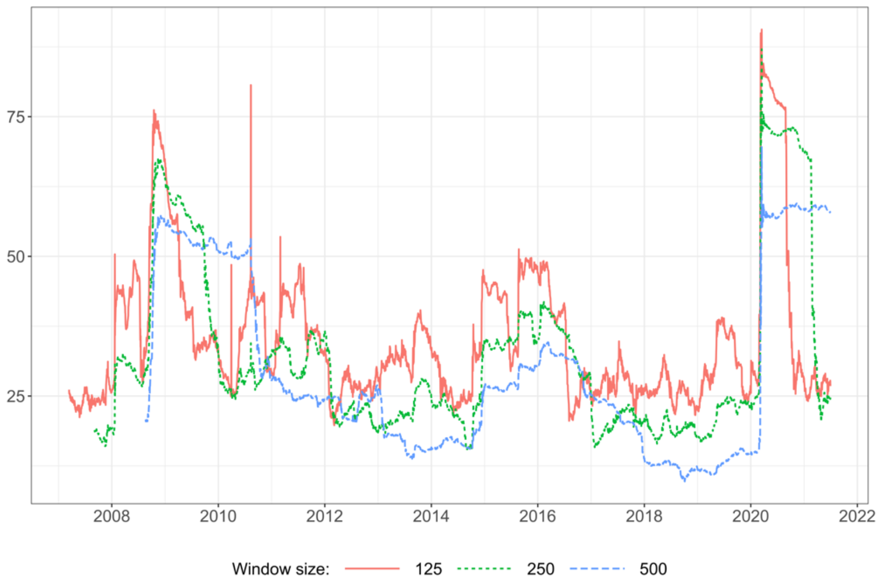


Figure 2. Rolling spillover index estimates



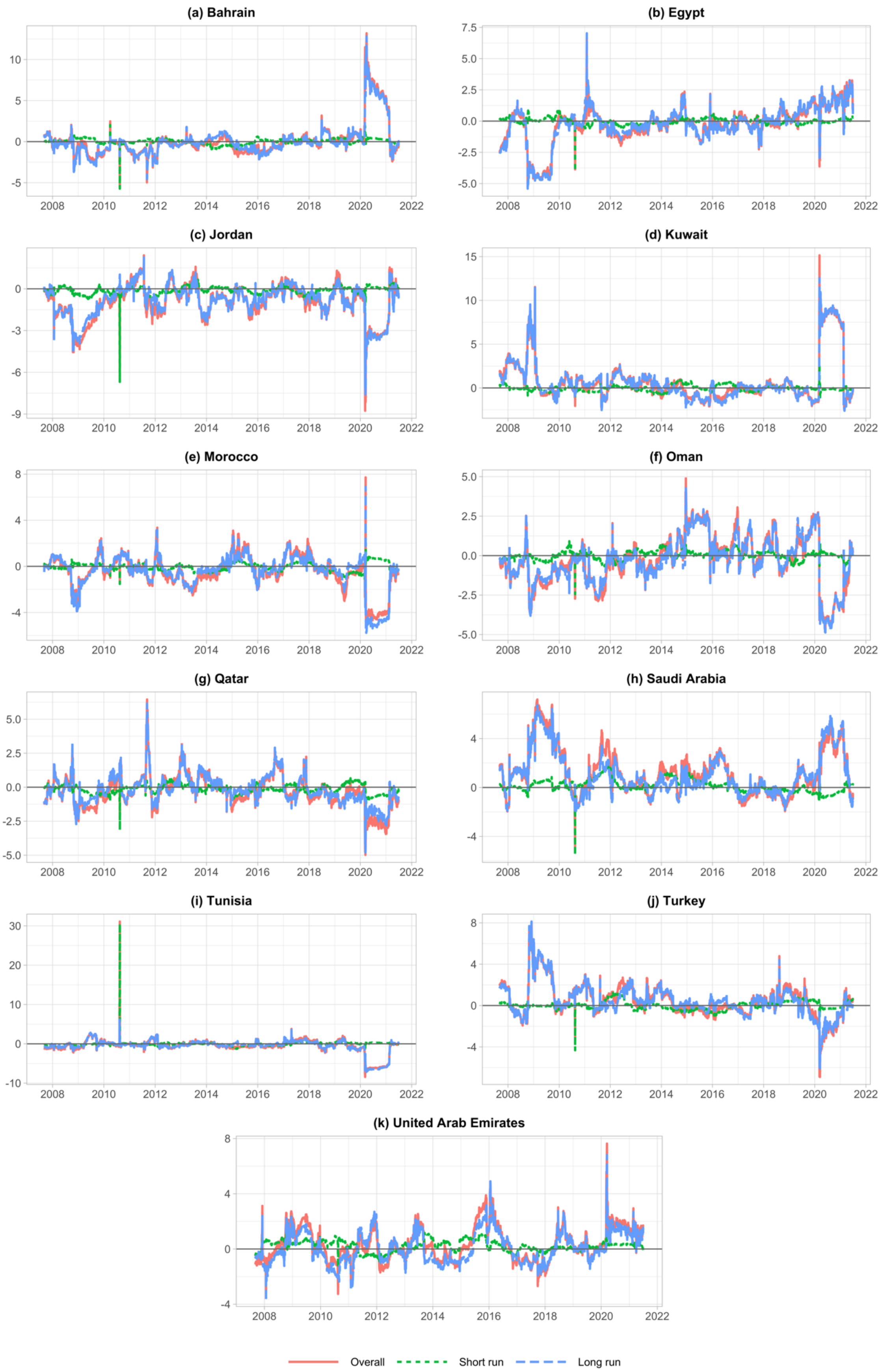
Note: Overall rolling spillover index is obtained with a standard VAR model while short- and long-run rolling spillover indexes are obtained from a frequency domain VAR model with 5-day and less and greater than 5-day periods, respectively. The rolling window sizes are 250 days. See the notes to Tables 2-3.

Figure 3. Rolling spillover index estimates at different window sizes



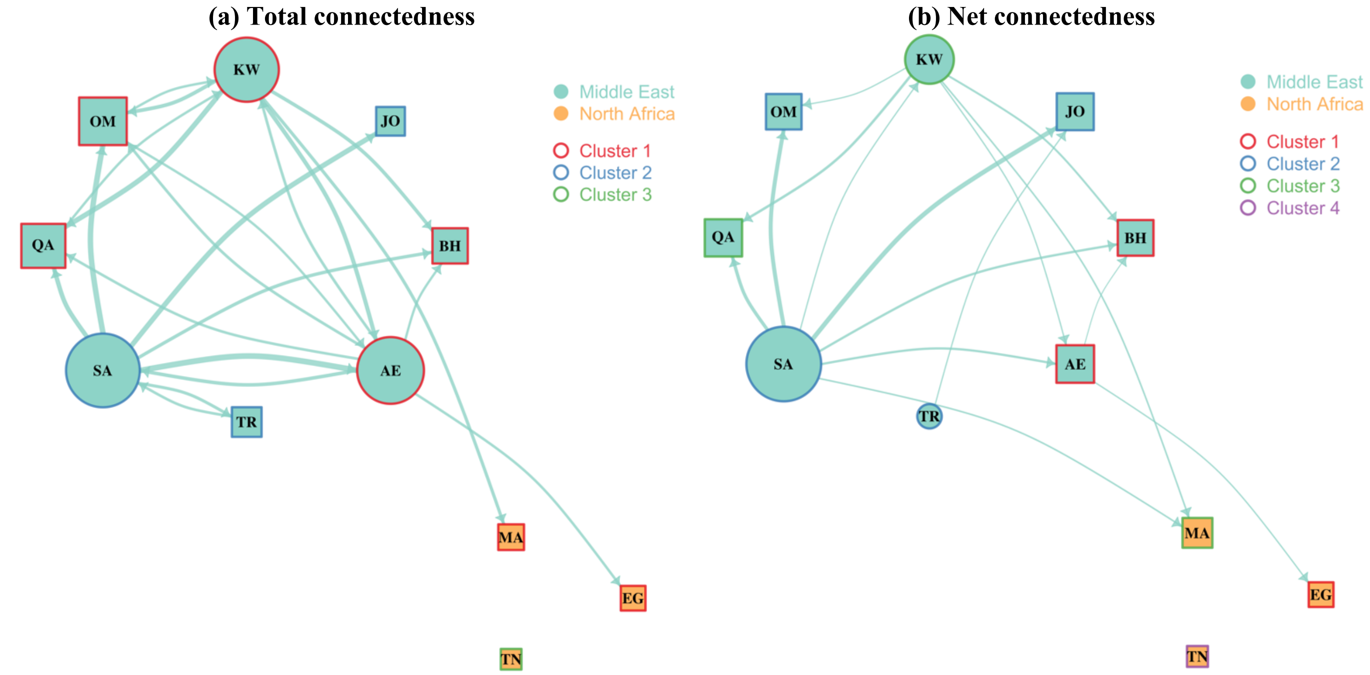
Note: The figure plots the overall rolling spillover indices obtained from a standard VAR model with rolling window sizes of 125, 250, and 500 days. See the notes to Tables 2-3.

Figure 4. Rolling net spillover estimates



Note: See the note to Figure 2.

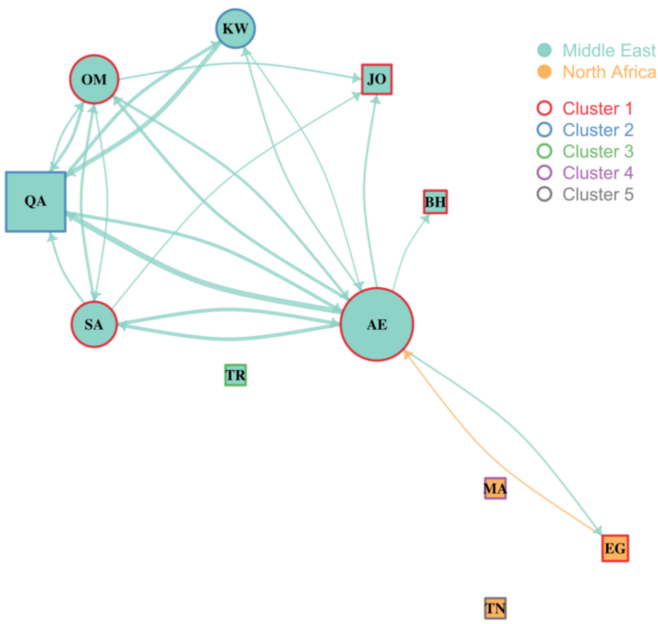
Figure 5. Connectedness from the standard VAR model



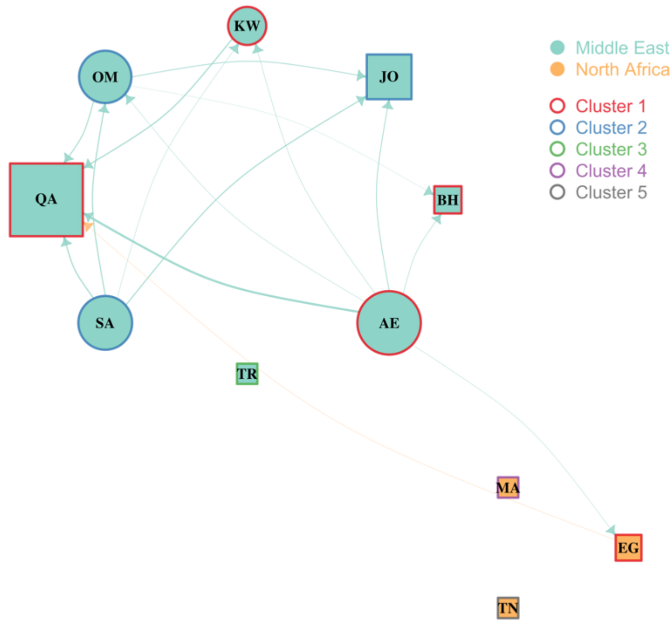
Note: The figure presents the connectedness network with a 25% thresholding. Bothe the total and net connectedness's are based on the spillover table reported in Table 2. Thresholding sets values below the 75-th percentile of the spillover to zero. Clusters are defined using the optimal clustering algorithm of Brandes *et al*. (2008). Vertex (node) colors indicate the four geographic groups, with the circle shapes indicating net volatility transmitters while the square shapes indicating net volatility receivers. The sizes of the node shapes are proportional to the degree (sum of in-degree and out-degree for total connectedness and out-degree for net connectedness). The color of the vertex frame indicates the cluster group.

Figure 6. The short- and long-run connectedness's from the frequency VAR model

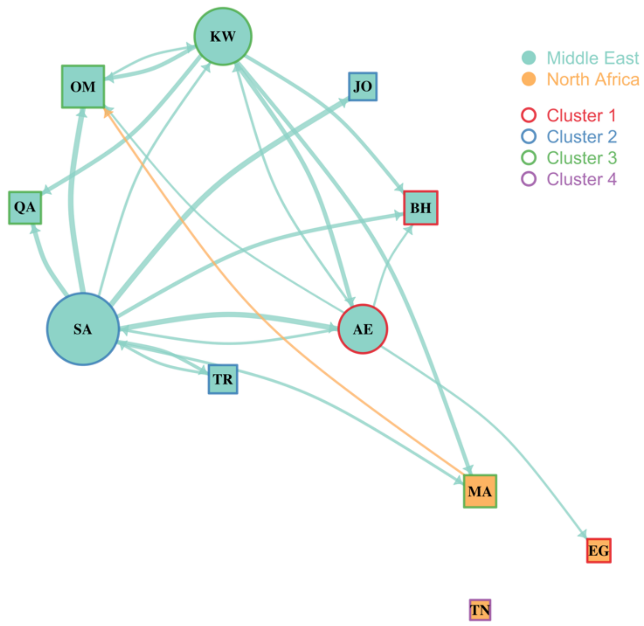
(a) Short-run total connectedness



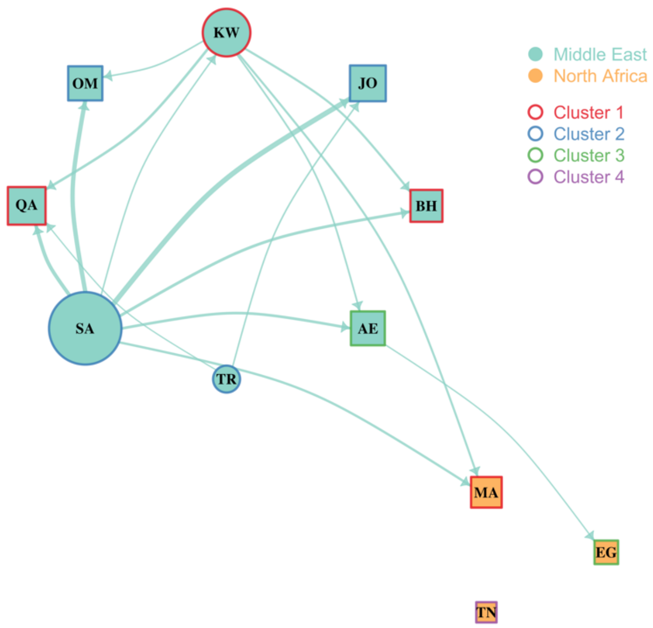
(b) Short-run net connectedness



(c) Long-run total connectedness

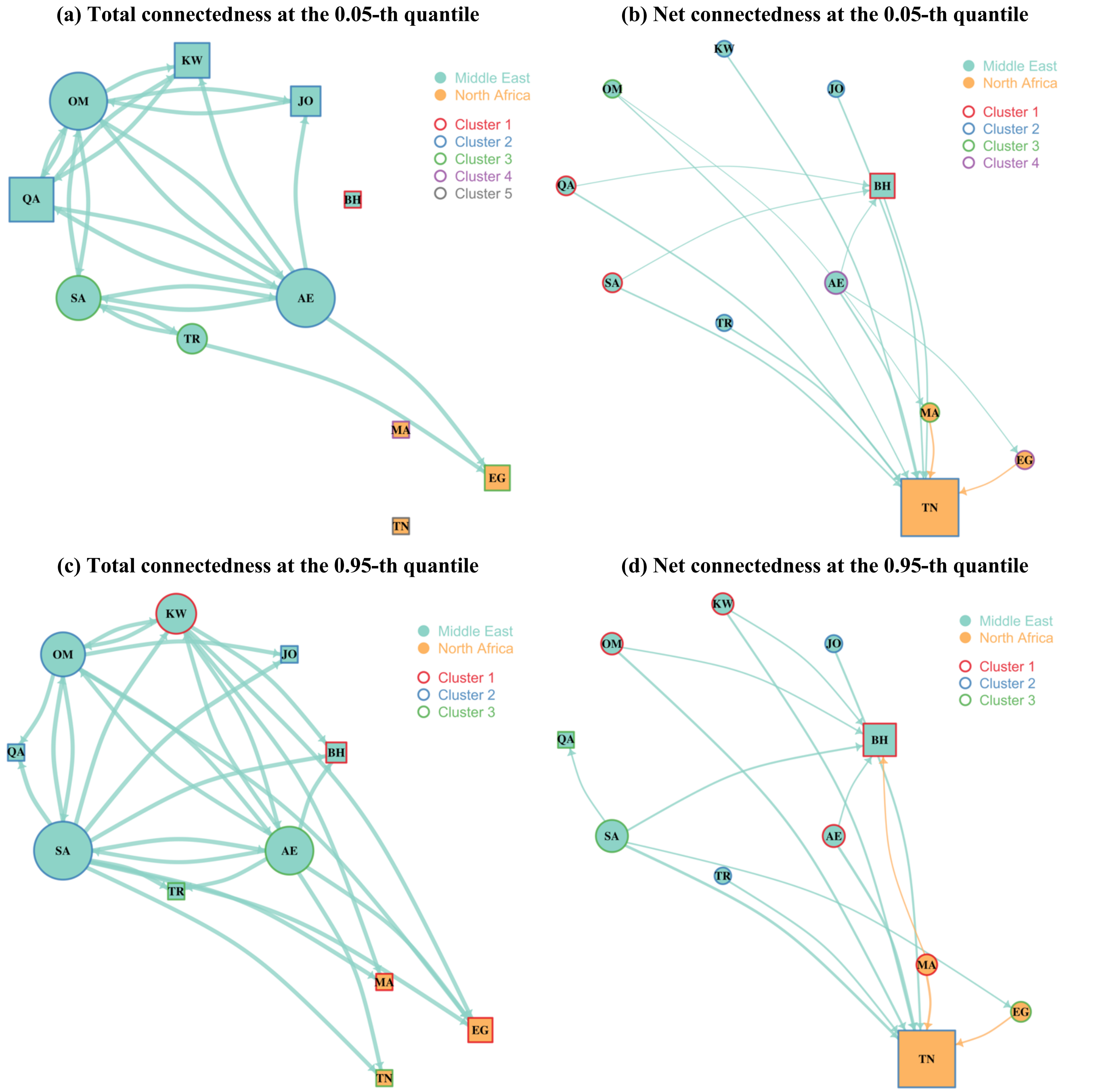


(d) Long-run net connectedness



Note: The figure presents the connectedness network with a 25% thresholding. Both the total and net short- and long-run total connectedness's are, respectively, based on the spillover table reported in the first and second panels of Table 3. The short run is defined as a period of 5 days, while the long run is defined as a period longer than 5 days. Thresholding sets values below the 75-th percentile of the spillover to zero. Clusters are defined using the optimal clustering algorithm of Brandes *et al*. (2008). Vertex (node) colors indicate the four geographic groups, with the circle shapes indicating net volatility transmitters while the square shapes indicating net volatility receivers. The sizes of the node shapes are proportional to the degree (sum of in-degree and out-degree for total connectedness and out-degree for net connectedness). The color of the vertex frame indicates the cluster group.

Figure 7. The tail connectedness from the quantile VAR model



Note: The figure presents the tail connectedness network with 25% thresholding. The estimates are based on a quantile VAR model estimated for the 0.05-th and 0.95-th quantiles. Both the total and net 0.05-th and 0.95-th total connectedness are, respectively, based on the spillover table reported in the first and second panels of Table 4. Thresholding sets values below the 75-th percentile of the spillover to zero. Clusters are defined using the optimal clustering algorithm of Brandes *et al.* (2008). Vertex (node) colors indicate the four geographic groups, with the circle shapes indicating net volatility transmitters while the square shapes indicating net volatility receivers. The sizes of the node shapes are proportional to the degree (sum of in-degree and out-degree for total connectedness and out-degree for net connectedness). The color of the vertex frame indicates the cluster group.

Figure 8. Time-varying regression analysis of total connectedness and VIX index

Note: The figure presents the rolling regression slope estimates $\hat{\beta}_1$ from a regression of the CBOE VIX index VIX_t on the total time-varying connectendness measures TC_t obtained from a rolling linear VAR model of the 11 FSI series with a rolling window size of 250 dayse. The bivariate model $TC_t = \beta_0 + \beta_1 VIX_t + \varepsilon_t$ is estimated using ordinary least squares (OLS) for each window and the slope estimates $\hat{\beta}_1$ are plooted in the figure. The window size for the rolling bivariate regression is 250 days. A point-wise 95% confidence interval is indicated (the gray shaded regions) around the regression slope parameter estimates $\hat{\beta}_1$. Superimposed on the graphs are the OLS parameter estimates (the solid horizontal red line) and their 95% confidence intervals (the light red color). A horizontal line is drawn at zero (the thin light line) to indicate $\beta_1 = 0$, the null effect.

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