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Financial Stress Dynamics in the MENA Region: Evidence from the Arab Spring

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Abstract

In this paper we analyse the impact of instability caused by the Arab Spring on the co-movements and volatility spillovers of aggregated Financial Stress Indices for eight MENA countries. Using a dynamic frequency connectedness framework, we conclude that stress transmission between markets is higher at low frequencies than at high frequencies, which implies that MENA markets are slow in adjusting to the information they receive. The Global Financial Crisis generated stronger spillover effects between MENA markets than the political turmoil of the Arab Spring. These results are useful for investors with different investment horizons, and have policy implications for the maintenance of financial stability in this region.

Keywords: financial stress indexes; dynamic frequency connectedness; spillover effect; MENA economies; impact of Arab Spring.

JEL Classification: G1, F3

1. Introduction

There is no doubt that the study of financial contagion and volatility spillover effects within markets and across countries has gained increased attention from academic researchers and policymakers in the MENA region, and worldwide, following the Global Financial Crisis and collapse of world financial markets in 2007/2008. In the context of the MENA region, empirical literature has focused mainly on financial contagion and volatility transmission among stock markets in either MENA countries themselves or MENA and advanced economies. This is due to the central role played by stock markets in advancing economic development processes in those countries, such as facilitating risk diversification, encouraging capital allocations and savings mobilisation, as well as easing the trade in goods, services, and financial contracts (Levine, 1997). Recent studies that investigated interdependence between stock markets in the MENA region include Chau, Deesomsak, and Wang (2014), Lagoarde-Segot and Lucey (2009) and Neaime (2005, 2016). Other papers have focused on volatility spillover and interconnectedness between MENA stock markets and advanced equity markets (see e. g., Darrat, Elkhal, & Hakim, 2000; Graham, Kiviaho, Nikkinen, & Omran, 2013; Maghyereh, Awartani, & Hilu, 2015; Neaime, 2012.).

More recently, the MENA region has witnessed the political turmoil known as the 'Arab Spring', which refers to a series of anti-government protests, pro-democracy uprisings, and armed rebellions against existing political regimes in a number of MENA countries. Such protests began in Tunisia in late 2010 and rapidly spread to other Arab countries by early 2011, including Morocco, Libya, Egypt, Bahrain, Yemen, and Syria. This revolutionary wave has led to a number of political changes, ranging from governmental overthrow and political reforms in some countries, to the establishment of new legal frameworks and the introduction of new policies and regulations in others. As political uncertainty and risks intensified in the region, investor confidence deteriorated and CDS spread expanded (Ghosh, 2016). Consequently, Standard and Poor cut the rating of five MENA countries in March 2011.

Major political events such as the Arab Spring are more likely to have a profound impact on financial markets volatilities and interconnectedness due to their social and economic implications (Chau et al., 2014). Despite the importance of this event, prior studies have, in the main, examined the impact of political uncertainty that emerged due to political events such as elections and terrorist attacks. Very little attention has been paid to the effects of political instability caused by civil revolutions, such as those of the Arab Spring, on stability and the interconnectedness of financial markets (Chau et al., 2014). In addition, these studies focused only on one dimension of the financial markets in MENA countries; either the stock market or the banking sector.

Current literature examining financial interconnectedness and volatility spillovers in MENA countries is limited to volatility transmission among stock markets. No previous attempt has been made to study the volatility spillover among MENA economies based on a more comprehensive approach that takes into account the aggregate effects of banking sectors, stock markets, and foreign exchange markets in an integrated framework. Furthermore, to the best of our knowledge, no previous study has addressed the impact of political uncertainty caused by the Arab Spring on aggregated Financial Stress Indices for MENA countries.

In particular, this study seeks answers to the following questions:

- What are the key driving force(s) behind the dynamic co-movement of financial distress between MENA economies?
- Which country is the net transmitter/receiver of financial stress?
- What is the impact of global financial crises and political instability caused by the Arab Spring on co-movements and stress spillovers among the MENA countries?

In answering these questions, this article adds to the existing literature in several important ways. First, this paper examines financial stress co-movements and volatility transmission in MENA countries. In contrast to previous research, this study does not limit the analysis to volatility transmission and interconnectedness in MENA stock market indices (Chau, Deesomsak and Wang, 2014). Instead, it adopts a more comprehensive approach that takes into account the potential risk and volatility spillover from banking sectors and foreign exchange markets, as well as stock markets. Second, to the best of our knowledge, while earlier studies have focused mainly on the effect of the Arab Spring on either stock markets or banks in MENA countries, we analyse the impact of political instability caused by the Arab Spring on co-movements and volatility spillovers of aggregated Financial Stress Indices for eight MENA countries. Following the paper by Apostolakis and Papadopoulos (2014), which used the Financial Stress Index as a proxy variable and to account for financial instability in its analysis of stress co-movements across G7 countries, we employ a similar approach for MENA economies. Third, we have extended the analysis by splitting the full sample into three sub-samples in order to compare the impact of the Global Financial Crisis in 2007/2008 and the Arab Spring in 2011/2012 on the stability and dynamic interconnectedness of the financial systems in the selected MENA countries.

Finally, yet significantly, this study employs an innovative econometric technique, recently developed by Barunik and Krehlik (2015, 2018), namely the frequency connectedness method, to examine the volatility spillovers and dynamic interdependence of financial stress in MENA countries. This approach enables the identification of the dynamics and level of intensity of cross-national volatility spillovers between FSIs of the selected MENA countries in time-frequency domain. In contrast to Diebold and Yilmaz (2012), this framework uses spectral representations of variance decomposition locally to retrieve time-frequency. Furthermore, dynamic interactions between FSIs of MENA countries have been taken into account by considering both the average and time-variations of total and net directional financial stress that indicate financial innovations and spillover dynamics over time.

Our findings provide a clear view of the transmission of financial stress during key episodes, particularly, the dynamics and intensity of spillovers in different frequency domains. The results are useful for investors with different investment horizons since in this paper we show how quickly MENA markets can adjust to the information transmitted from other markets. The impact of both the Global Financial Crisis and the Arab Spring on the dynamics of stress transmission is explored and explained. These results are robust to model specification and are consistent with the notion that political uncertainty contributes to financial instability and volatility spillovers. Overall, they are of great importance to investors, policy-makers, and market regulators for understanding the impact of financial and political uncertainty on financial markets. Understanding financial volatility transmission and dynamics helps policy-makers and regulators adopt appropriate policy measures to safeguard and maintain sound and stable financial systems.

This paper is organised as follows. Relevant literature is critically analysed and presented in the next section. Section 3 outlines the empirical methodology, data sources, and the construction of Financial Stress Indices for the selected MENA countries. Empirical results from the full sample and three sub-samples, as well as tests to ensure their soundness, are presented in Section 4. Finally, Section 5 provides conclusions.

2. Literature Review

This paper contributes to two strands of literature on financial transmission and volatility spillovers. First, we consider the literature on financial contagion and interconnectedness and the main theoretical hypotheses developed in this area. Second, we extend the literature review by exploring the effect of political uncertainty on the volatility of financial markets, in particular, the impact of political instability caused by the Arab Spring in the MENA region.

Literature on financial contagion and financial transmission can be traced back to Engle, Ito, and Lin (1990) who developed "heat wave" and "meteor shower" hypotheses. According to the heat wave hypothesis, financial volatility is a country-specific phenomenon and, hence, depends on market fundamentals, whereas the meteor shower hypothesis examines the transmission of financial volatility from one country to another. Both the heat wave and meteor shower hypotheses have important implications for portfolio management and trading strategies. The meteor shower hypothesis also has implications for policy makers and financial regulators, since the crisis shock originated in one market can spillover to other markets via a variety of channels. Nowadays, none of the financial markets are immune to external shocks. The literature stressed the importance of trade and financial linkages as two fundamental channels through which financial distress transmits across countries.

Glick and Rose (1999) and Forbes (2002) both emphasised the significance of trade connections in volatility transmission, while Kaminsky and Reinhart (2000) and Caramazza, Ricci, and Salgado (2004) identified financial linkages as a second channel for financial spillovers across countries. In addition to these factors, Balakrishnan, Danninger, Elekdag, and Tytell (2011) argued that financial stress could be transmitted due to common factors affecting several countries such as a global turmoil or crisis. Since then, several attempts have been made to study financial contagion and volatility spillovers among financial markets and across countries (see, e.g., Apostolakis & Papadopoulos, 2015; Balakrishnan et al., 2011; Beirne, Caporale, Schulze-Ghattas, & Spagnolo, 2013; Caramazza et al., 2004; Cardarelli, Elekdag, & Lall, 2011; Chau & Deesomsak, 2014; Francis X. Diebold & Yilmaz, 2009; Francis X Diebold & Yilmaz, 2012; Yarovaya, Brzeszczyński, & Lau, 2016, among others).

There is an abundance of literature on MENA economies dealing with financial interconnectedness and volatility spillovers. Nevertheless, most of this literature has focused on co-movement and contagion between stock markets. For instance, Lagoarde-Segot and Lucey (2009) studied the impact of major financial crises (in Asia, Russia, Turkey, and Argentina), as well as the 2007/2008 Global Financial Crisis, on the vulnerability of seven stock markets in the MENA region using panel data analysis over the period September 1, 1997 to March 23, 2009. Empirical findings indicated heterogeneous levels of financial volatility and vulnerability over this sample period. Furthermore, the study shows that MENA countries are highly connected with developed economies rather than between themselves. Neaime (2012, 2016) analysed global contagion and regional financial spillovers in MENA and advanced stock markets. Results revealed a weak regional integration between MENA stock markets. In addition, the impact of the global financial crises on MENA stock markets is heterogeneous and depends on the degree of international financial integration.

In a similar vein, Maghyereh et al. (2015) used the DCC-GARCH model and spillover approach developed by Diebold and Yilmaz (2012) to explore the dynamic correlation of both return and volatility transmissions between the U.S. and the five biggest MENA stock markets using a dataset for January 2, 1998 to February 15, 2013. Their empirical results of dynamic association pre- and post- the Global Financial Crisis conforms well with previous literature. They reported an unprecedented jump in dynamic correlations and volatility spillovers during the crisis that reverted to normal patterns thereafter. Other studies examined contagion vulnerability and financial integration among major stock markets in the MENA region that highlighted low levels of correlation and less integration among MENA stock markets, particularly in the long run compared with the short run (Lagoarde-Segot & Lucey, 2007; Neaime, 2005, 2016).

Another parallel strand of literature documented the adverse impact of political uncertainty on returns and the volatility of financial markets (Gemmill, 1992; Li & Born, 2006; Nippani & Medlin, 2002; Sy & Al Zaman, 2011). Factors engendering political instability could be attributed to a number of events such as elections, armed conflict, and terrorist attacks. Nevertheless, the majority of the literature on political instability has focused more on the reaction of financial markets to political elections. While several studies investigated the effects of elections on stock markets (Białkowski, Gottschalk, & Wisniewski, 2008; Li & Born, 2006; Nippani & Arize, 2005; Nippani & Medlin, 2002; Pástor & Veronesi, 2013), others focused on the banking sector (Chen & Liu, 2013; Francis, Hasan, & Zhu, 2014; Önder & Özyıldırım, 2013). In general, the literature has highlighted the importance of political uncertainty and its role in generating uncertainty and reinforcing vulnerability in financial markets (Batten et al., 2019; Guo et al., 2018; Mei et al., 2018).

In the context of MENA countries, only a handful of papers have scrutinised the effect of political uncertainty caused by the Arab Spring on returns and the stability of financial systems. These studies focused on one single dimension of financial markets in MENA countries; either the stock market or the banking sector. Chau et al. (2014) examine the impact of political uncertainty caused by the Arab Uprising on stock market volatility in MENA countries from the perspective that political instability and uncertainty generates higher volatility in financial markets. To this end, three different specifications of the GARCH model have been applied to conventional and Islamic stock indices in major MENA stock markets (Bahrain, Kuwait, Oman, Egypt, Jordon, and Lebanon) over the period June 1, 2009 to June 29, 2012: standard symmetric GARCH, asymmetric GARCH (GJR-GARCH) and exponential GARCH (E-GARCH). Results show that the Arab Spring had little or insignificant impact on the volatility of conventional stock markets, whereas Islamic stock indices witness increased volatility during this period of political unrest. Moreover, findings highlighted that MENA stock markets are less integrated with international financial markets.

Others examined the impact of the Arab Spring on the stability of the banking system in the MENA region. For example, Alraheb and Tarazi (2018) investigate the impact of national and international shocks on the stability of the banking sector in the MENA region using annual bank-level data for 21 MENA countries over the period 2004-2012. Results indicate that the Global Financial Crisis of 2007/2008 had a negative impact on the stability of the banking sector in the MENA region, whereas the regional crisis, that is political uncertainty caused by the Arab Spring, had no impact. Another interesting paper by Ghosh (2016) examined the impact of the Arab Spring on return and volatility in 112 banks in 12 MENA economies during 2000-2012. Findings show that political uncertainty caused by the Arab Spring had an asymmetric impact on return and volatility in banks across the MENA region. In other words, political instability lowered profitability and increased risk for banks in countries directly hit by the Arab Spring compared with other countries.

While research in this general area has burgeoned, no previous attempt has been made to study the volatility spillover among MENA economies based on a more comprehensive approach that takes into account the aggregate effects on the banking sector, stock markets, and foreign exchange markets in an integrated framework.

Very few attempts have been made to explore the dynamic impact of the Arab Spring on either stock markets or the banking sectors in the MENA region. To the best of our knowledge, no previous study has examined the impact of political uncertainty caused by the Arab Spring on the aggregated Financial Stress Indices of MENA countries. However, developing such a broader and inclusive perspective is vital as there are serious implications for a number of market players. In addition, understanding how financial shocks are transmitted across markets and countries offers invaluable insights for both policymakers and investors seeking portfolio diversification. Such analysis informs the debate on government regulation of financial markets, in particular macroprudential policy, with the aim of preventing future financial crises.

3. Methodology

3.1 Data and Descriptive Statistics

The dataset used to construct Financial Stress Indices (FSIs) is based on daily observations retrieved from the DataStream database over the period December 12, 2005 to July 31, 2018, with a total number of 3360 observations covering the Global Financial Crisis and most recent events in the region such as the Arab Spring. The sample includes eight MENA countries: Bahrain, Egypt, Kuwait, Morocco, Oman, Qatar, Turkey and the United Arab Emirates, all chosen based on data availability.

We further divide our sample into pre-, during, and after- Arab Spring periods to examine the changes in connectedness. While the beginning of the Arab Spring is easy to define since the protests in Tunisia (Jasmine Revolution) arose following Mohamed Bouazizi’s self-immolation on December 17, 2010, the end of the Arab Awakening movement is not as precise. In this paper, we consider the period from December 17, 2010 to December 31, 2012 as the Arab Spring as these dates include the protests that erupted in Egypt on November 22, 2012, and which we identify as the final events that can be attributed to the Arab Spring and its immediate aftermath. The period from 2013 to 2015 is also often considered as part of the Arab Spring aftermath. However, events in that period are also related to the escalation of the conflict in Syria and the growth of the Islamic State, which cannot be attributed to the Arab Spring. Consequently, we conclude that these events belong more properly to the post-Arab Spring period.

Following examples in financial stress literature, a set of variables are used in constructing the aggregated (country-level) financial stress index for each country that covers a broad array of financial indicators and provides valuable information on financial market conditions. Compared with individual indicators, aggregated Financial Stress Indices provide more accurate and informative measures of financial health and the soundness of a country's financial system due to the ability to capture different types of risk and sources of financial instability. Using the approach of Apostolakis and Papadopoulos (2015), the Financial Stress Indices are calculated based on variance-equal weighting of three sub-indices; the bank sector, stock market, and foreign exchange market (for example, the Bahrain Bank Index

(BHBI), Bahrain Stock market Index (BHSI), and Bahrain foreign Exchange market Index (BHEI)), where an equal weight is assigned to all variables used in the construction process (see Eq. 1).

$$FSI_t^{country_i} = (FSI_t^{Bank} + FSI_t^{Stock} + FSI_t^{Exchnage\ rate})/3 \qquad (1)$$

Where; $FSI_t^{market_i} = \frac{1}{n}\sum_{j=1}^{n} x_{jt}^{standardized}$ (2)

Similarly, Market Stress Indices have been computed based on a variance-equal aggregation approach (Eq. (2)) where x_{jt} stands for standardised financial variables on time t and n represents the number of standardised variables used in constructing Financial Stress Index for market i. In more detail, the Banking Stress Index comprises three variables; beta for the banking sector calculated as a 60-day rolling window of standard beta of capital asset pricing model[1], negative bank equities returns, and bank equities volatility calculated using GRACH (1, 1) model. As for the stock market, two measures have been utilised; negative stock returns, computed as equities returns multiplied by minus one so a fall in the stock returns indicates higher tension in the stock market, along with stock market volatility estimated based on a GRACH (1,1) process. Finally, the volatility of the foreign exchange market is calculated similarly to the stock market volatility. Following the literature, all variables have been standardised before aggregation in order to avoid the problem of different units of measurement.

The variance-equal weighting approach is widely used in the literature and is proven to be a very efficient method in constructing financial indices due to the simplicity of calculations and its accuracy in representing and signalling financial stress and episodes of turbulence (e.g., Cardarelli et al., 2011; Kliesen, Owyang, & Vermann, 2012; MacDonald, Sogiakas, & Tsopanakis, 2018).

[Table 1 here]

Table 1 provides descriptive statistics of aggregated FSIs at market-level (panel A-C) as well as country-level (Panel D) for the selected MENA economies. In particular, Table 1

[1] Due to an estimation of beta banking sectors using 60-days rolling window Financial Stress indices, starting from March 23, 2006.

shows the first four statistical moments of the underlying series along with normality, autocorrelation, heteroscedasticity and stationarity tests. The mean of the Financial Stress Indices are very close to zero in all cases and rather small compared to their respective standard deviations, with the exception of the Banking Stress Index and Country Stress Index for Morocco. The kurtosis statistic is greater than 3 for all the series, suggesting that distributions of all series are leptokurtic (higher peaked around the mean with fatter tails compared to the normal distribution). It is also worth noting that all the series are skewed positively. The departure of the normality assumption has been statistically confirmed by the Jarque–Bera test, which rejects the null hypotheses of normality for all series; therefore, none of the series are normally distributed. In addition, the Ljung–Box test statistics (Q, Q^2) up to the 12th order and provides evidence of serial correlation and non-linear dependencies for all series.

The Engle's LM test for the presence of conditional heteroscedasticity computed using 12 lags exhibits significant ARCH effects in all the variables, which confirms some stylized facts of financial data such as asymmetry, fat tails and volatility clustering; hence, the support for the use of GARCH processes for modelling the financial volatilities of the underlying series. Finally, Augmented Dickey-Fuller unit root tests have been employed to check the time series property of all variables. Results indicate that almost all series are level stationary, i.e. I(0), at the 1% significance level, which justifies the use of VAR models in our analysis.

3.2 Empirical Method

We start our empirical analysis with an application of the Diebold and Yilmaz (2009; 2012) method, which has been widely used in analyses of spillovers across financial markets, for example, equities and futures (Yarovaya et al. 2016 a, b) and commodities markets (Batten et al. 2010; Batten et al. 2019). We use the Diebold and Yilmaz (2012) framework that employs a generalized VAR framework from Koop et al. (1996) and Pesaran and Shin (1998), in which variance decompositions are invariant to variables order. The Diebold and Yilmaz (2012) framework allows for the estimation of the total, directional, net, and pairwise spillover indices and can be applied to a large number of variables. The rolling window analysis is also a helpful tool enabling visualisation dynamics of the spillovers during the observation period. The output presented in the spillovers tables and plots make the results accessible for a non-academic audience because they can be easily interpreted by investors and practitioners. These factors have contributed to the popularity of this framework in contemporary finance literature. This method is already well-known, and for that reason we do not provide the details of this methodology here. Relevant econometric specifications for this framework are available in the Diebold and Yilmaz (2012) paper.

We further extend our spillover analysis by applying the Barunik and Krehlik (2015; 2018) frequency connectedness method to identify the dynamics and intensity of spillovers between the FSIs of selected MENA countries in time-frequency domain. In contrast to that of Diebold and Yilmaz (2012), this framework uses spectral representations of variance decomposition locally to retrieve time-frequency (Stiassny, 1996; Dew-becker and Giglio, 2016). For example, a shock with a strong long-term effect will have high power at low frequencies and in the cases where it transmits to other variables, it points to long-term connectedness (Barunik and Krehlik, 2018). Barunik and Krehlik (2015) distinguish spillovers at high and low frequencies, which is important for investors with different investment horizons and trading strategies. This framework has been employed in analysis of return spillovers between white precious metal ETFs (Lau et al., 2017), cryptocurrencies (Corbet et al. 2018), and other financial assets.

Consider the spectral behaviour of series X_t at frequency:

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

where ω is the frequency component, ∞ implies infinite horizon relations in the setting and $\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} \Psi_h e^{-ih\omega}$ (Barunik & Krehlik, 2015). The unconditional generalised forecast error variance decomposition on a particular frequency ω can be specified as:

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

where Eq. 4 can be standardised as:

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

The accumulative connectedness table (i.e. specified over an informative frequency band) proposed by Barunik and Krehlik (2015) allows an arbitrary frequency band $d = (a; b)$ to be expressed as:

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

Therefore, the overall connectedness within the frequency band d can be defined as:

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

$$C_{i\rightarrow\cdot}^{d} = \sum_{j=1,i\neq j}^{k}(\tilde{\Theta}_d)_{j,i} \tag{8}$$

$$C_{i\leftarrow\cdot}^{d} = \sum_{j=1,i\neq j}^{k}(\tilde{\Theta}_d)_{i,j} \tag{9}$$

We also measure the pairwise connectedness between markets using Eq. 10:

$$C_{i,j}^{d} = (\tilde{\Theta}_d)_{j,i} - (\tilde{\Theta}_d)_{i,j} \tag{10}$$

The contribution of a particular frequency band d to the aggregate measure has to be weighted, as:

$$\tilde{C}^d = C^d \cdot \Gamma(d) \tag{11}$$

where the spectral weight $\Gamma(d) = \frac{\sum_{i,j=1}^{k}(\tilde{\Theta}_d)_{i,j}}{\sum_{i,j}(\Theta)_{i,j}} = \frac{\sum_{i,j=1}^{k}(\tilde{\Theta}_d)_{i,j}}{k}$ is the contribution of frequency band d to the whole VAR system and C^d is the total connectedness measure on the connectedness tables $(\tilde{\Theta}_d)$ corresponding to an arbitrary frequency of band d.

4. Empirical Results

4.1 Full Sample Analysis

The results are presented in the spillover tables, where entries in columns show the spillover from this market to each other, while entries in rows show the received information transmitted from each other market to the market selected. Thus, the final column reports direction spillovers from other markets to this market, and the final row reports the contribution of this index to all other stress indices.

First, we perform our analysis for the full sample, March 23, 2006 to July 31, 2018. Table 2 tabulates the results of a generalised vector autoregressive framework using Diebold and Yilmaz (2012), while Tables 3 and 4 display the results of dynamic frequency connectedness tests based on Barunik and Krehlik (2015, 2018) at high and low frequencies, respectively.

[Table 2 here]

[Table 3 here]

[Table 4 here]

Findings show that the intensity of spillovers between the FSI indices of MENA countries from the period March 23, 2006 to July 31, 2018 was relatively low. The total spillover index as per Diebold and Yilmaz (2014) equals 19.76%, and at higher frequencies, 1- 4 days, as by Barunik and Krehlik (2015), equals 11.15%. We report a higher degree of connectedness at lower frequencies (22.02%), which corresponds to 4 days and higher. This implies absence of stress spillovers between selected MENA countries in the short term, but existence of stress transmission in the long term.

On part of pairwise connectedness between selected stress indices, the highest spillovers are found from Kuwait to Qatar (9.56% as by Diebold and Yilmaz, 2.33% at high frequencies, 7.23% at low frequencies) and from Qatar to Kuwait (6.00%, 2.11%, 3.88%), from Morocco to Turkey (8.67% as by Diebold and Yilmaz, 8.64% at low frequencies), and from Turkey to Morocco (11.26%, 11.24% at low frequencies). All cases support our previous arguments that in the long term (at low frequencies) the intensity of spillovers between markets is higher, which provides important implications for investors and portfolio managers keen to diversify their portfolios in MENA countries and who have relatively long investment horizons. According to the results reported in Tables 2, 3, and 4, the most influential stress-transmitters in this correlated system are Turkey, Kuwait and Morocco, since they contribute more than they receive. The main stress-recipient is Oman as it receives more than it transmits from or to the stress indices of other countries.

Adhering to Barunik and Krehlik (2018), we also preform analysis with and without cross-sectional correlation between markets to account for "pure" spillovers between markets. The results of variance decomposition might be biased due to strong contemporaneous relationships. Therefore, to identify the causal effect of stress transmission from one market to another we adjust the correlation matrix of VAR residuals by cross-sectional correlations (Barunik and Krehlik, 2018). Thus, the results reported in Panel A do not account for cross-sectional correlations, while the results reported in Panel B show the values of spillovers with nullified correlations. We note a significant decrease in connectedness adjusted for the correlation effect in all Tables 2, 3, and 4. However, it is the most pronounced at high frequencies. This means that the short-term connectedness between markets is mainly driven by cross-sectional correlations, while for the long-term connectedness we can still identify the causal linkages between markets and observe spillover effects.

4.2 Impact of the Arab Spring

In order to analyse the impact of the Arab Spring on the patterns of stress transmission between MENA economies, we divided our sample into pre-, during, and after-Arab Spring periods, and performed the same combination of tests. Table 5 presents the results of our application of the Diebold and Yilmaz (2012) framework to each sub-sample. The most interesting observation that can be made here is that the value of the total spillover index for the period before the Arab Spring was higher than that during and after this political turbulence; 34.20%, 19.77 %, and 8.66% respectively.

[Table 5 here]

More detailed analysis of the values of pairwise spillovers in each observation period allows the identification of a few additional strong channels of information transmission between selected pairs of FSIs. Thus, a very strong level of intensity of spillovers has been found in the pre-Arab Spring period in Turkey to Bahrain (10.51%), Egypt (28.10%), and Morocco (14.82%), with Turkey remaining as one of the main transmitters of shocks to other MENA countries. Prior to the Arab Spring, the strong spillovers from Egypt to Turkey (13.54%), from Kuwait to Qatar (10.31%), and from Morocco to Turkey (7.86%) have been reported elsewhere. However, these channels of stress transmission seem to disappear during the Arab Spring, since the intensity of spillovers between same markets pairs are very low in comparison to the previous period. According to Panel B, Table 5, the most influential market in the sample during the Arab Spring is the United Arab Emirates, an assessment that also holds good after the Arab Spring (see Panel C, Table 5). This can be explained by the fact that the UAE is one of a few Middle Eastern economies that was relatively less affected by the Arab Spring turmoil and managed to maintain its economic growth and development, consequently increasing its role in the region.

We further decomposed the connectedness using the Barunik and Krehlik method (2015; 2018) to identify the dynamics in the short and long term. Tables 6, 7, and 8 report the results for the pre-, during, and post-Arab Spring periods, respectively. For the periods before and after the Arab Spring, the connectedness at low frequencies is much higher than at short frequencies, which is similar to the whole sample results, and implies stronger stress transmission in the long term, as well as a relatively low pace of reaction to the transmitting shocks demonstrated by MENA economies. After the Arab Spring, the connectedness between markets is relatively low at both high and low frequencies (i.e., 9.15% and 8.46%), which indicates that after the political turbulence MENA countries became more isolated from external shocks.

[Table 6 here]

[Table 7 here]

[Table 8 here]

The analysis of dynamic connectedness between FSI indices displays a particularly high degree of total spillovers at low frequencies before the Arab Spring (39.21%), which remains relatively high even when correlation is nullified (22.69%). This clearly indicates the presence of causal linkages between MENA economies in this period. These results are very revealing because the period before the Arab Spring analysed is from March 23, 2006 to December 16, 2010, and includes the Global Financial Crisis. Therefore, further tests of robustness are necessary to identify the impact of the Global Financial Crisis on the intensity and dynamics of stress spillovers between MENA economies.

4.3 Robustness Test

4.3.1 Impact of the Global Financial Crisis

The results reported in the previous section suggest a decrease in spillovers between the FSI of MENA countries during and after the Arab Spring. We hypothesize that the high intensity of stress transmission between indices in pre-Arab Spring periods could be due to the impact of the Global Financial Crisis. We follow BIS (2012) guidance to identify the beginning and end of the Global Financial Crisis. Thus, we consider that the Global Financial Period was from July 2007, which refers to the Credit Crunch, to July 2009, which can be related to the fourth phase of the Global Financial Crisis. Therefore, we re-estimate our models in an additional sample from July 2, 2007 to July 2, 2009, giving 524 observations in order to compare the results with those found for pre- and during the Arab Spring period. The results are presented in Table 9 below.

[Table 9 here]

These tests confirm that the intensity of spillovers was the highest during the time of the Global Financial Crisis. The total spillover index during the crisis equals 48.83%, which is higher than the value of the total spillover found for the period before the Arab Spring (34.20%), and much higher than during the Arab Spring period (19.77%). This indicates that the higher intensity of the spillovers before the Arab Spring was due mainly to the contagion effect that occurred during the Global Financial Crisis. This result is in line with Maghyereh et al. (2015) who reported a significant increase in dynamic correlations and volatility spillovers among MENA countries during the global financial meltdown in 2008, and a subsequent reversion to lower levels. In addition, the results of dynamic frequency decompositions (see above) show that, as with other periods, during the Global Financial Crisis the connectedness was driven mainly by the information transmission at lower frequencies, suggesting that MENA markets participants are relatively slow in adjusting their expectations.

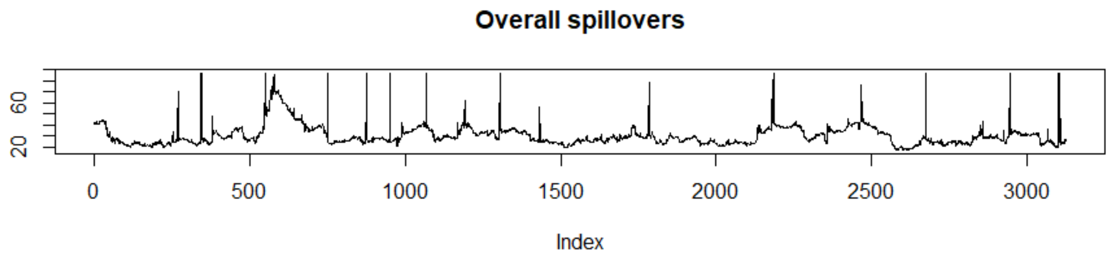
4.3.2 Short-, medium-, and long-term connectedness

To further support our results on dynamic spillovers between FSIs of MENA countries, we use the Barunik and Krehlik (2018) framework based on spectral representation of variance decompositions to analyse connectedness in three different frequency bands; 1 to 4 days; 4 to 10 days; and 10 days to infinity. We estimate short-, medium-, and long-term connectedness for all periods analysed in this paper. The results are presented in Table 10.

[Table 10 here]

With the exception of the post-Arab Spring period, where connectedness between markets at all frequencies is very low, for all periods analysed in this paper findings show that the connectedness between markets is higher at lower frequencies. The medium-term financial connectedness between FSI is higher than short-term-connectedness in all five observation periods considered. Table 10 also clearly illustrates how the degree of spillovers varies from period to period. Furthermore, we plot the overall spillovers using a 100-day rolling window (Figure 1), which also helps in the visualisation of the dynamics of total spillovers across the full sample.

Figure 1



5. Conclusion

This paper analyses the stress transmission across eight MENA economies using the Financial Stress Index as a proxy for financial stability based on the Diebold and Yilmaz (2014) and Barunik and Krehlik (2018) frameworks. Specifically, the paper addresses the following questions: (i) What are the key driving force(s) behind the dynamic co-movement of financial distress?; (ii) Which country is the net transmitter/receiver of financial stress?; and (iii) What is the impact of financial and political disturbances caused by global financial crises and the Arab Spring on co-movements and stress spillovers among the MENA countries?

The results reveal that stress transmission in MENA economies occurred due to a high spillover effect at lower frequencies, while the short-term connectedness between markets is driven primarily by cross-sectorial correlations. This implies the absence of stress spillovers in the short term but the existence of spillover effect and causal linkages between markets in the long term. Specifically, the decomposition shows a rich time-variation in the dynamics of connectedness, changing from an almost total absence of spillovers in the short term (at high frequencies) to significant connectedness in the long term (at low frequencies) in all of the observation periods analysed. These dynamics imply that MENA markets are too slow in adjusting to the information they receive, and in the short term the shocks originating in one of the countries will not significantly affect the other MENA markets. The fact that connectedness has been driven, in the main, by information transmission at lower frequencies, from 4 days to infinity, indicates that in the long term market participants would be able to adjust their understanding and expectations, thus, influencing market behaviour.

The paper reports the net-transmitters and net-receivers of information in full, from pre-, during- and post-Arab Spring observation periods. The analysis performed for the full sample, March 23, 2006 to July 31, 2018, demonstrates that the main stress-transmitters are Turkey, Kuwait and Morocco, since they contribute more than they receive, while the main stress-recipient is Oman, since it receives more than it transmits from or to other countries' Stress Indices. However, during the Arab Spring the United Arab Emirates becomes the most influential market, and this remains the case after the Arab Spring. These results are of great importance for managers who determine policy as the information included in this study enables the patterns of stress transmission in MENA economies to be revealed. In consequence, the findings can be used for the development of a better regulatory framework for the maintenance of financial stability in the region. Furthermore, the net-pairwise spillover indices reported in this paper can help investors to diversify their portfolios and estimate the risk of contagion caused by increased financial and political instability in MENA economies more accurately.

Finally, the value of total spillover index for the period before the Arab Spring was higher than that during and after this period of political turbulence. This indicates that after the Arab Spring, MENA countries became more isolated from external shocks. However, the robustness tests show that the high intensity of stress transmission between indices in pre-Arab Spring periods was due primarily to the impact of the Global Financial Crisis. This paper concludes that the Global Financial Crisis generated a much stronger spillover effect in MENA economies than the political turbulence created by the Arab Spring. This conclusion has important policy implications, and should be taken into account by financial regulators and policy-makers.

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Table 1 Descriptive Statistics

Countries	Bahrain	Egypt	Kuwait	Morocco	Oman	Qatar	Turkey	UAE
Panel A: Banking Sector								
Mean	-0.00004	-0.0001	-0.0005	1.2038	-0.0003	-0.0003	0.0005	0.0003
Std. Deviation	0.6231	0.5979	0.5787	0.6501	0.5864	0.5885	0.5371	0.5895
Kurtosis	344.2	3.689	5.790	3.218	8.868	7.742	3.562	5.470
Skewness	10.37	1.090	1.124	1.352	1.697	0.591	1.108	1.637
J-B Test	1593**	2459**	5165**	2368**	12074**	8212**	2357**	5445**
Q(12)	2702**	12303**	15510**	16100**	16478**	15866**	12240**	12691**
$Q^2(12)$	862.7**	4956**	10352**	12401**	8943**	13122**	9851**	4401**
ARCH (12)	119.2**	193.3**	299.3**	445.7**	284.6**	410.9**	301.9**	219.4**
ADF	-8.69**	-8.08**	-5.15**	-5.96**	-5.57**	-5.81**	-5.92**	-8.82**
Panel B: Stock Market								
Mean	-0.0002	-0.0001	0.0001	0.0003	-0.0002	0.0001	-0.0006	0.00004
Std. Deviation	0.7187	0.7081	0.6910	0.7104	0.7042	0.6972	0.7137	0.7161
Kurtosis	14.74	13.23	183.4	20.13	31.13	269.7	11.02	19.14
Skewness	2.445	2.512	10.57	3.147	4.452	12.48	2.493	3.309
J-B Test	32321**	26849**	45692**	59594**	14049**	98273**	19603**	54938**
Q(12)	5456**	8439**	4622**	3855**	8387**	2323**	7102**	8111**
$Q^2(12)$	8681**	8519**	6112**	3644**	7095**	3943**	8181**	6633**
ARCH (12)	369**	307**	319**	319**	277**	196**	299**	271**
ADF	-11.8**	-7.50**	-9.97**	-14.8**	-8.13**	-10.8**	-11.2**	-8.95**
Panel C: Foreign Exchange Market								
Mean	-0.0001	0.0006	0.0000	-0.0002	-0.0001	0.0000	0.0002	0.0001
Std. Deviation	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Kurtosis	308.1	961.5	183.1	7.784	954.5	245.8	35.62	206.6
Skewness	15.90	29.23	11.82	2.476	25.98	14.20	5.123	13.00
J-B Test	1.2E+07**	1.2E+08**	4.5E+06**	11404**	1.2E+08**	8.2E+06**	1.8E+05**	5.8E+06**
Q(12)	12384**	3777**	14428**	36258**	1577**	17627**	26836**	17700**
$Q^2(12)$	6018**	1252**	5049**	32126**	148.7**	7174**	19720**	8211**
ARCH (12)	1256**	99.44**	787.3**	11096**	11.15**	1086**	2074**	1332**
ADF	-12.20**	-22.50**	-13.46**	-2.92*	-24.31**	-8.448**	-7.139**	-10.45**
Panel D: Country FSIs								
Mean	-0.0001	0.0002	-0.0002	0.4005	-0.0002	-0.0001	0.0000	0.0001
Std. Deviation	0.4788	0.5147	0.4934	0.5980	0.5257	0.4488	0.6176	0.5163
Kurtosis	81.40	157.6	51.06	7.867	178.5	78.94	19.83	34.69
Skewness	6.404	8.611	5.612	2.126	8.718	6.323	3.607	4.422
J-B Test	9.0E+05**	3.3E+06**	3.6E+05**	10712**	4.3E+06**	8.5E+05**	59657**	1.7E+05**
Q(12)	7913**	6955**	11789**	20435**	5199**	8278**	18989**	12367**
$Q^2(12)$	5028**	1713**	6041**	15863**	192.3**	6042**	20058**	7908**
ARCH (12)	773.4**	131.5**	585.1**	820.4**	13.46**	578.9**	1020**	871.6**
ADF	-12.80**	-12.90**	-8.264**	-4.964**	-10.91**	-10.19**	-7.208**	-9.599**

Note: This table reports descriptive statistics for financial stress indices data used in the empirical analysis over the full sample starting from 23 March 2006 to 31 July 2018. J-B is the Jarque–Bera test for the null hypothesis of normality. Q (12) and $Q^2(12)$ is the Ljung–Box test for serial correlation in raw series and squared residuals up to 12 lag. Similarly, ARCH (12) testing Engle's ARCH effects up to 12 lags. ADF is the Augmented Dickey-Fuller unit root test with a constant term where the lag length is determined by the Schwartz Information Criteria (SIC). **, * indicate significant at 1% and 5% level.

Table 2 Generalised VAR results

Panel A Connectedness as by DY (2012)									
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM**
FSI_BH	87.97	0.25	1.35	0.58	2.02	1.64	3.75	2.43	1.50
FSI_EG	0.38	87.41	0.52	1.38	0.93	0.51	6.37	2.49	1.57
FSI_KW	0.48	0.24	80.62	6.27	2.13	**6.00**	1.48	2.79	2.42
FSI_MA	0.60	0.64	3.98	78.07	3.13	0.34	**11.26**	1.97	2.74
FSI_OM	1.45	0.53	4.59	6.48	71.86	2.92	5.26	6.91	**3.52**
FSI_QA	1.58	0.40	**9.56**	0.45	2.27	79.49	2.24	4.01	2.56
FSI_TR	1.62	1.85	0.53	**8.67**	2.65	0.82	78.72	5.15	2.66
FSI_AE	0.91	1.18	5.68	2.37	3.26	3.29	5.54	77.77	2.78
TO	0.88	0.64	**3.28**	**3.27**	2.05	1.94	**4.49**	3.22	**19.76**
Panel B Connectedness as by DY (2012), nullified correlation									
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM**
FSI_BH	96.12	0.00	0.13	0.15	0.11	0.29	3.16	0.03	0.49
FSI_EG	0.20	95.01	0.06	0.72	0.04	0.20	3.61	0.17	0.62
FSI_KW	0.03	0.19	89.98	5.90	0.70	2.02	1.06	0.11	1.25
FSI_MA	0.03	0.01	3.85	84.25	1.68	0.59	9.52	0.06	1.97
FSI_OM	0.08	0.36	3.41	6.37	85.32	0.36	3.77	0.32	1.83
FSI_QA	0.96	0.23	0.63	0.21	0.11	94.54	1.82	1.49	0.68
FSI_TR	0.70	0.04	0.36	7.39	0.54	0.06	90.50	0.41	1.19
FSI_AE	0.07	0.60	3.15	1.13	0.34	2.38	1.89	90.43	1.20
TO	0.26	0.18	**1.45**	2.73	0.44	0.74	**3.11**	0.32	**9.23**
Net Spillovers	-0.23	-0.45	0.19	0.76	-1.39	0.06	1.91	-0.87	

Note: This table reports the results estimated for the full sample starting from 23 March 2006 to 31 July 2018. **FROM**—directional spillover indices measure spillovers from all markets *j* to market *i*. **TO**—directional spillover indices measure spillovers from market *i* to all markets *j*. **Net Spillovers** is the difference between TO and FROM directional spillovers indices for each market.

Table 3 Dynamic connectedness at high frequencies (3.14 to 0.79 corresponds to 1 to 4 days).

Panel A Connectedness as by BK (2015)										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM_ABS**	**FROM_WITH**
FSI_BH	20.36	0.02	0.12	0.10	0.22	0.09	0.03	0.30	0.11	0.53
FSI_EG	0.06	22.89	0.11	0.06	0.20	0.21	0.27	0.63	0.19	0.93
FSI_KW	0.10	0.10	17.38	0.02	0.18	**2.11**	0.03	0.56	0.39	1.87
FSI_MA	0.06	0.03	0.02	11.58	0.03	0.01	0.02	0.08	0.03	0.15
FSI_OM	0.25	0.25	0.22	0.05	26.68	0.89	0.25	1.42	0.41	**1.97**
FSI_QA	0.10	0.21	**2.33**	0.05	0.80	21.44	0.09	1.51	0.64	3.07
FSI_TR	0.03	0.015	0.02	0.03	0.12	0.05	12.13	0.27	0.08	0.40
FSI_AE	0.25	0.42	0.46	0.13	1.01	1.09	0.35	15.03	0.46	2.24
TO_ABS	0.11	0.15	0.41	0.05	0.32	0.55	0.13	0.60	2.31	
TO_WTH	0.51	0.71	**1.98**	0.26	**1.54**	2.64	0.63	**2.88**		**11.15**
Panel B Connectedness as by BK (2015), nullified correlation										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	22.77	0.00	0.02	0.00	0.02	0.00	0.03	0.02	0.01	0.05
FSI_EG	0.04	25.41	0.00	0.02	0.00	0.00	0.09	0.07	0.03	0.14
FSI_KW	0.00	0.00	18.30	0.02	0.01	0.04	0.02	0.06	0.02	0.09
FSI_MA	0.01	0.00	0.03	12.96	0.03	0.01	0.02	0.00	0.01	0.06
FSI_OM	0.00	0.01	0.04	0.07	33.34	0.00	0.13	0.01	0.03	0.16
FSI_QA	0.02	0.01	0.31	0.04	0.05	25.27	0.05	0.01	0.06	0.28
FSI_TR	0.02	0.00	0.00	0.03	0.03	0.00	14.81	0.02	0.01	0.06
FSI_AE	0.01	0.01	0.03	0.05	0.02	0.01	0.06	17.10	0.02	0.11
TO-ABS	0.01	0.00	0.05	0.03	0.02	0.01	0.05	0.02	0.20	
TO_WTH	0.06	0.02	0.26	0.14	0.09	0.04	0.24	0.11		0.95

Note: The results are based on 100 simulations of VAR with the specified parameters of length 1000 with a burnout period of 100. The estimate is computed as mean of the 100 observations and the standard error is simple sample standard deviation.

Table 4 Dynamic connectedness at low frequencies (0.79 to 0.00 Corresponds to 4 days to Inf. days)

Panel A Connectedness as by BK (2015)										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	67.61	0.23	1.23	0.48	1.80	1.56	3.72	2.13	1.39	1.76
FSI_EG	0.32	64.51	0.41	1.32	0.73	0.31	6.10	1.86	1.38	1.74
FSI_KW	0.38	0.14	63.24	625	1.95	**3.88**	1.45	2.23	2.03	2.57
FSI_MA	0.55	0.62	3.96	66.49	3.10	0.33	**11.24**	1.89	2.71	3.42
FSI_OM	1.20	0.28	4.36	6.43	45.18	2.10	5.01	5.49	3.11	**3.92**
FSI_QA	1.48	0.19	**7.23**	0.40	1.47	58.05	2.15	2.50	1.93	2.43
FSI_TR	1.59	1.70	0.51	**8.64**	2.53	0.77	66.58	4.88	2.58	3.25
FSI_AE	0.67	0.76	5.22	2.24	2.25	2.21	5.18	62.73	2.32	2.92
TO-ABS	0.77	0.49	2.87	3.22	1.73	1.39	4.36	2.62	17.45	
TO_WTH	0.97	0.62	**3.62**	**4.06**	2.18	1.76	**5.50**	3.31		22.02
Panel B Connectedness as by BK (2015), nullified correlation										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	73.35	0.00	0.11	0.15	0.09	0.29	34	001	0.47	0.60
FSI_EG	0.15	69.60	0.06	0.70	0.04	0.19	3.52	0.09	0.59	0.76
FSI_KW	0.02	0.19	71.68	5.88	0.70	1.98	1.04	0.05	1.23	1.57
FSI_MA	0.03	0.01	3.82	71.29	1.65	0.58	9.50	0.06	1.96	2.49
FSI_OM	0.07	0.34	3.38	6.30	51.98	0.36	3.64	0.31	1.80	2.29
FSI_QA	0.94	0.22	0.32	0.17	0.06	69.28	1.77	1.49	0.62	0.79
FSI_TR	0.68	0.04	0.36	7.36	0.52	0.05	75.69	0.39	1.18	1.50
FSI_AE	0.06	0.59	3.12	1.08	0.32	2.38	1.83	73.33	1.17	1.49
TO-ABS	0.24	0.17	1.40	2.70	0.42	0.73	3.05	0.30	9.03	
TO_WTH	0.31	0.22	1.78	3.44	0.54	0.93	3.89	0.38		11.49

Note: The results are based on 100 simulations of VAR with the specified parameters of length 1000 with a burnout period of 100. The estimate is computed as mean of the 100 observations and the standard error is simple sample standard deviation.

Table 5 Generalised VAR results before, during, and after Arab Spring.

Panel A Connectedness as by DY (2012) before Arab Spring, 23/03/2006 - 16/12/2010									
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM**
FSI_BH	62.94	3.87	3.20	3.93	4.87	4.54	**<u>10.51</u>**	6.15	4.63
FSI_EG	2.35	48.13	1.30	6.78	4.06	2.67	**<u>28.10</u>**	6.60	6.48
FSI_KW	1.18	0.91	79.69	7.08	1.75	**5.65**	1.39	2.35	2.54
FSI_MA	2.68	5.17	4.51	65.71	3.21	1.50	**<u>14.82</u>**	2.41	4.29
FSI_OM	3.16	3.65	4.43	5.92	65.42	3.86	7.10	6.55	4.32
FSI_QA	3.19	3.21	**<u>13.54</u>**	2.50	4.03	62.78	5.34	5.40	4.65
FSI_TR	2.54	**<u>10.31</u>**	0.46	**<u>7.86</u>**	2.92	1.76	67.83	6.32	4.02
FSI_AE	1.80	3.48	5.80	2.70	2.36	2.89	7.09	73.88	3.26
TO	2.11	3.82	4.14	**<u>4.60</u>**	2.90	2.86	**<u>9.30</u>**	4.47	**34.20**
Panel B Connectedness as by DY (2012), during Arab Spring, 17/12/2010-31/12/2012									
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM**
FSI_BH	92.77	0.48	2.46	1.47	0.68	0.95	0.93	0.26	0.90
FSI_EG	2.34	92.49	1.23	0.55	0.89	0.60	0.94	0.96	0.94
FSI_KW	0.45	0.74	77.67	0.80	1.22	5.36	9.54	4.22	2.79
FSI_MA	0.32	1.22	1.44	77.98	0.27	4.78	2.77	11.23	2.75
FSI_OM	1.01	1.10	3.223	0.26	83.15	5.13	0.13	6.00	2.11
FSI_QA	0.83	0.24	4.28	4.02	2.65	70.27	0.25	17.46	3.72
FSI_TR	0.54	0.18	5.99	3.24	0.56	0.73	83.76	5.00	2.03
FSI_AE	0.34	0.74	3.56	7.54	3.96	16.87	3.29	63.71	4.54
TO	0.73	0.59	2.77	2.23	1.28	4.30	2.23	**<u>5.64</u>**	**19.77**
Panel B Connectedness as by DY (2012), post- Arab Spring, 01/01/2013- 31/07/2018									
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM**
FSI_BH	98.32	0.12	0.41	0.34	0.16	0.03	0.16	0.45	0.21
FSI_EG	0.04	95.95	0.24	0.13	0.41	0.52	0.49	2.22	0.51
FSI_KW	1.00	0.37	82.70	0.07	5.30	2.65	0.13	7.77	2.16
FSI_MA	0.35	0.07	0.11	96.71	0.87	0.70	1.13	0.06	0.41
FSI_OM	0.27	0.56	3.37	1.33	85.13	1.67	0.44	7.24	1.86
FSI_QA	1.01	0.17	1.01	0.31	0.79	94.17	0.17	2.37	0.73
FSI_TR	0.53	0.38	0.45	0.54	0.74	0.54	96.04	0.76	0.49
FSI_AE	0.41	1.22	5.95	0.06	5.55	4.45	0.71	81.65	2.29
TO	0.45	0.36	1.44	0.35	1.73	1.32	0.40	**<u>2.61</u>**	**8.66**

Note: For space consideration the results of DY (2012) with no correlation are not reported here. The values of total spillover indices when correlation nullified are 17.42 , 8.33, and 3.60 in pre-, during, and post Arab Spring periods respectively.

Table 6 Dynamic connectedness between FSI before Arab Spring.

Panel A Connectedness as by BK (2015), high frequency, 1-4 days										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	27.38	0.16	0.20	0.30	0.52	0.43	0.10	0.66	0.30	1.34
FSI_EG	0.13	15.56	0.15	0.17	0.42	0.50	0.73	1.36	0.43	1.96
FSI_KW	0.13	0.19	15.70	0.02	0.12	2.79	0.03	0.48	0.47	2.13
FSI_MA	0.12	0.12	0.03	10.39	0.03	0.03	0.04	0.18	0.07	0.30
FSI_OM	0.50	0.67	0.16	0.10	25.04	1.02	0.35	1.26	0.51	2.29
FSI_QA	0.50	1.10	4.44	0.17	1.37	34.66	0.23	2.36	1.27	5.75
FSI_TR	0.05	0.40	0.02	0.04	0.12	0.06	7.82	0.26	0.12	0.53
FSI_AE	0.38	1.08	0.30	0.25	0.74	0.96	0.40	11.14	0.51	2.32
TO-ABS	0.23	0.46	0.66	0.13	0.41	0.72	0.23	0.82	3.68	
TO_WTH	1.03	2.10	3.00	0.59	1.86	3.27	1.06	3.70		**16.61**
Panel B Connectedness as by BK (2015), low frequency, 4 days to Inf days.										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	35.56	3.71	3.00	3.62	4.35	4.11	10.41	5.50	4.34	5.57
FSI_EG	2.22	32.57	1.15	6.61	3.64	2.17	27.37	5.24	6.05	7.77
FSI_KW	1.05	0.71	63.99	7.06	1.63	2.85	1.36	1.87	2.07	2.66
FSI_MA	2.57	5.05	4.48	55.32	3.18	1.47	14.78	2.23	4.22	5.42
FSI_OM	2.66	2.98	4.18	5.83	40.38	2.84	6.75	5.29	3.82	4.90
FSI_QA	2.68	2.11	9.10	2.33	2.67	28.12	5.11	3.04	3.38	4.34
FSI_TR	2.49	9.91	0.44	7.83	2.80	1.70	60.01	6.07	3.90	5.01
FSI_AE	1.42	2.40	5.49	2.46	1.62	1.93	6.69	62.75	2.75	3.53
TO-ABS	1.88	3.36	3.48	4.47	2.49	2.13	9.06	3.65	30.53	
TO_WTH	2.42	4.31	4.47	5.74	3.19	2.74	11.64	4.69		**39.21**

Note: For space consideration the results of BK with no correlation are not reported here. The values of total spillover indices when correlation nullified are 2.57 and 22.69 at high and low frequency bands respectively.

Table 7 Dynamic connectedness between FSI during Arab Spring.

Panel A Connectedness as by BK (2015), high frequency, 1-4 days										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	56.09	0.21	1.12	0.27	0.31	0.08	0.24	0.21	0.31	0.78
FSI_EG	0.23	37.69	0.46	0.06	0.53	0.29	0.29	0.77	0.33	0.84
FSI_KW	0.13	0.49	42.31	0.03	0.63	0.85	1.63	1.26	0.63	1.60
FSI_MA	0.17	0.07	0.02	19.52	0.07	0.24	0.43	0.47	0.18	0.47
FSI_OM	0.25	0.67	0.69	0.18	37.55	1.42	0.08	3.14	0.80	2.06
FSI_QA	0.18	0.14	0.55	0.22	2.12	30.03	0.18	5.95	1.17	2.99
FSI_TR	0.12	0.14	0.85	0.06	0.04	0.18	30.03	0.22	0.20	0.52
FSI_AE	0.27	0.44	0.66	0.52	2.10	4.26	0.42	22.00	1.08	2.77
TO-ABS	0.17	0.27	0.54	0.17	0.73	0.92	0.41	1.50	4.70	
TO_WTH	0.43	0.69	1.39	0.43	1.85	2.34	1.04	3.84		**12.02**
Panel B Connectedness as by BK (2015), low frequency, 4 to Inf. days										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	36.69	0.28	1.35	1.20	0.37	0.86	0.69	0.04	0.60	0.98
FSI_EG	2.11	54.80	0.76	0.48	0.36	0.32	0.66	0.20	0.61	1.00
FSI_KW	0.32	0.25	35.36	0.77	0.60	4.51	7.91	2.96	2.17	3.56
FSI_MA	0.15	1.14	1.41	58.46	0.20	4.54	2.34	10.77	2.57	4.22
FSI_OM	0.76	0.43	2.54	0.08	45.59	3.70	0.05	2.86	1.30	2.14
FSI_QA	0.65	0.10	3.74	3.80	0.53	40.24	0.07	11.51	2.55	4.18
FSI_TR	0.42	0.04	5.13	3.18	0.52	0.55	53.73	4.78	1.83	3.00
FSI_AE	0.07	0.30	2.90	7.02	1.86	12.60	2.87	41.71	3.45	5.67
TO-ABS	0.56	0.32	2.23	2.07	0.55	3.39	1.82	4.14	15.08	
TO_WTH	0.92	0.52	3.36	3.39	0.91	5.56	3.00	6.79		**24.76**

Note: For space consideration the results of BK with no correlation are not reported here. The values of total spillover indices when correlation nullified are 4.13 and 11.42 at high and low frequency bands respectively.

Table 8 Dynamic connectedness between FSI after Arab Spring.

Panel A Connectedness as by BK (2015), high frequency, 1-4 days										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	13.79	0.00	0.17	0.02	0.05	0.01	0.03	0.12	0.05	0.17
FSI_EG	0.03	25.08	0.14	0.03	0.06	0.13	0.14	0.26	0.10	0.33
FSI_KW	0.54	0.19	47.41	0.06	1.65	1.19	0.01	2.25	0.74	2.48
FSI_MA	0.04	0.03	0.06	28.22	0.02	0.03	0.02	0.01	0.03	0.09
FSI_OM	0.08	0.07	1.39	0.02	30.14	0.84	0.16	2.14	0.59	1.98
FSI_QA	0.00	0.05	0.33	0.01	0.35	10.10	0.02	0.79	0.20	0.66
FSI_TR	0.06	0.24	0.22	0.01	0.18	0.12	31.78	0.41	0.15	0.52
FSI_AE	0.14	0.35	1.78	0.00	2.20	2.09	0.35	29.27	0.86	2.91
TO-ABS	0.11	0.12	0.51	0.02	0.56	0.55	0.09	0.75	2.71	
TO_WTH	0.37	0.40	1.72	0.07	1.89	1.86	0.31	2.52		**9.15**
Panel B Connectedness as by BK (2015), low frequency, 4 to Inf. days										
	FSI_BH	**FSI_EG**	**FSI_KW**	**FSI_MA**	**FSI_OM**	**FSI_QA**	**FSI_TR**	**FSI_AE**	**FROM-ABS**	**FROM_WTH**
FSI_BH	84.53	0.12	0.24	0.32	0.11	0.02	0.13	0.32	0.16	0.23
FSI_EG	0.01	70.87	0.10	0.09	0.35	0.39	0.35	1.96	0.41	0.58
FSI_KW	0.46	0.18	35.29	0.01	3.65	1.47	0.12	5.52	1.42	2.03
FSI_MA	0.31	0.04	0.05	68.49	0.85	0.67	1.11	0.05	0.39	0.55
FSI_OM	0.19	0.49	1.97	1.30	54.99	0.83	0.28	5.10	1.27	1.81
FSI_QA	1.00	0.12	0.68	0.30	0.44	84.07	0.14	1.58	0.53	0.76
FSI_TR	0.48	0.14	0.24	0.52	0.56	0.42	64.27	0.36	0.34	0.48
FSI_AE	0.27	0.86	4.17	0.06	3.35	2.36	0.37	52.39	1.43	2.03
TO-ABS	0.34	0.24	0.93	0.33	1.17	0.77	0.31	1.86	5.95	
TO_WTH	0.48	0.35	1.32	0.46	1.66	1.09	0.44	2.65		**8.46**

Note: For space consideration the results of BK with no correlation are not reported here. The values of total spillover indices when correlation nullified are 0.84 and 4.75 at high and low frequency bands respectively.

Table 9 Dynamic connectedness between FSI during the Global Financial Crisis.

	FSI_BH	FSI_EG	FSI_KW	FSI_MA	FSI_OM	FSI_QA	FSI_TR	FSI_AE	FROM
Panel A Connectedness as by DY (2012)									
FSI_BH	36.36	8.94	3.50	7.23	4.76	9.64	18.49	11.07	7.95
FSI_EG	7.38	37.70	2.64	5.01	4.13	8.06	26.05	9.02	7.79
FSI_KW	3.12	3.29	66.30	13.82	1.58	6.14	2.53	3.23	4.21
FSI_MA	7.52	8.35	9.12	50.90	2.18	6.43	11.95	3.55	6.14
FSI_OM	6.51	5.59	5.0	5.83	53.24	10.22	6.66	6.96	5.84
FSI_QA	9.46	8.41	7.14	6.30	6.26	42.89	9.17	10.36	7.14
FSI_TR	10.02	16.08	0.53	5.09	2.34	5.39	53.25	7.29	5.84
FSI_AE	6.33	3.84	1.50	5.01	1.97	6.17	6.44	68.74	3.91
TO	6.29	6.81	3.68	6.04	2.90	6.51	10.16	6.43	**48.83**
Panel B Connectedness as by BK (2015), high frequency (1-4 days)									
FSI_BH	11.64	0.26	0.40	0.22	0.67	1.11	0.20	1.05	2.91
FSI_EG	0.30	9.34	0.19	0.25	0.28	0.90	0.72	0.91	2.64
FSI_KW	0.39	0.38	10.28	0.10	0.14	0.58	0.08	0.49	1.60
FSI_MA	0.06	0.14	0.03	6.14	0.03	0.14	0.02	0.21	0.46
FSI_OM	1.20	0.70	0.20	0.30	22.23	2.51	0.37	1.40	4.97
FSI_QA	2.13	2.25	1.06	0.52	2.78	22.89	0.27	3.79	9.51
FSI_TR	0.14	0.38	0.06	0.05	0.13	0.08	6.86	0.23	0.79
FSI_AE	0.97	1.10	0.48	0.43	0.74	1.84	0.38	8.39	4.42
TO_WTH	3.86	3.87	1.79	1.38	3.54	5.33	1.52	6.01	**27.30**
Panel B Connectedness as by BK (2015), low frequencies (4 days to Inf.)									
FSI_BH	24.72	8.68	3.11	7.01	4.09	8.53	18.28	10.02	8.97
FSI_EG	7.09	28.36	2.45	4.77	3.85	7.16	25.32	8.11	8.83
FSI_KW	2.73	2.91	56.02	13.72	1.44	5.56	2.45	2.73	4.74
FSI_MA	7.46	8.20	9.09	44.75	2.16	6.29	11.94	3.33	7.28
FSI_OM	5.30	4.89	4.80	5.53	31.01	7.70	6.29	5.56	6.02
FSI_QA	7.34	6.16	6.09	5.79	3.49	20.00	8.91	6.56	6.66
FSI_TR	9.89	15.70	0.47	5.04	2.21	5.31	46.39	7.06	6.87
FSI_AE	5.36	2.75	1.02	4.58	1.23	4.33	6.06	60.35	3.80
TO_WTH	6.79	7.41	4.06	6.98	2.78	6.74	11.91	6.52	**53.18**

Note: For space consideration the results of both DY and BK with no correlation are not reported here. The values of total spillover indices when correlation nullified for DY is 25.54% and for BK are 4.33% and 31.86% at high and low frequency bands respectively.

Table 10 Short-, medium-, and long-term connectedness.

Period	Short-term, 1 to 4 days	Medium-term, 4 to 10 days	Long-term, 10 days to Inf.
Before Arab Spring 23/3/2006 -16/12/2010	16.61	21.76	43.69
During the Global Financial Crisis 02/07/2007 –02/07/2010	27.30	34.15	56.63
During the Arab Spring 17/12/2010 - 31/12/2012	12.02	17.15	29.32
After Arab Spring 01/01/2013 -31/07/2018	9.15	9.59	7.97
Full Sample 23/03/2006-31/07/2018	11.15	12.71	24.75

Note: Table reports the results of short-, medium, and long-term connectedness obtained for each of the sub-samples. The detailed results for each frequency bands are available upon request.

Financial Stress Dynamics in the MENA Region: Evidence from the Arab Spring

Highlights

- We analyse the financial stress transmission in the MENA region;
- The short-term connectedness is mainly driven by cross-sectional correlations;
- Results display existence of stress transmission in the long term;
- After Arab spring MENA countries became more isolated from the external shocks;
- High intensity of stress spillovers before Arab spring was due to the GFC.