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Dynamic transmissions between the U.S. and equity markets in the MENA countries: New evidence from pre- and post-global financial crisis

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ABSTRACT

In this paper we investigate equity returns and volatility co-movement between the U.S. and a group of large Middle East and North African stock markets before and after the global financial crisis in 2008. Our empirical evidence suggests that the pre-crisis relation with the U.S. was weak and negligible, before it jumped to a high level after the crisis. The large diversification in the pre-crisis period was negatively influenced by higher transmissions after the crisis. However, it did not completely disappear during periods of stress. Moreover, there is some evidence that the association with the U.S. has started to revert to its initial low level and therefore, we may conclude that the Middle East and North African equities are important diversifiers for U.S. investors; particularly in the long run.

1. Introduction

The transmission mechanism between the returns and volatilities of different stock markets, and the U.S. is important for three reasons. Firstly, it is well known that the U.S. markets have the largest equity capital traded and that these markets' interaction with other exchanges provides invaluable information for international investment and diversification. Therefore, studying transmission mechanisms with the U.S. may be useful in portfolio management, where knowledge of cross market association may help in asset allocation and market timing decisions. Secondly, there is substantial evidence of unidirectional information flows from the U.S. to global stock exchanges, and this has implications on other markets efficiency. In an efficient market it should not be possible to judge future returns and volatilities using another market's information. The finding that there are significant transmissions may indicate market inefficiency and the possibility of generating profits in one market based on another market's information. Thirdly, knowledge of the nature of information transmission may help in building more accurate models of conditional volatility. For instance, if transmission from the U.S. is substantial, including the U.S. as a factor in a conditional volatility model may improve accuracy. This is important for some financial applications such as option pricing, portfolio optimization, and risk measurement and hedging.

This paper investigates returns dynamic conditional correlations and temporal volatility spillovers between a group of MENA[1] countries, and the U.S. before and after the collapse of Lehman

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[1] The MENA region consists of the following countries: Egypt, Turkey, Iran, Jordan, Libya, Tunis, Morocco, Algeria, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. From the MENA region we chose only those countries that have old and well developed financial markets with large capitalization. The countries we have chosen are Turkey, Saudi Arabia, Jordan, Tunis and Egypt. The capitalization of these markets together consists of 58% of the total capital traded in the MENA region as of December 2012. For more details on the capitalization of individual markets see the World Bank, Financial Development Database in 2012 that is available at http://data.worldbank.org/data-catalog/global-financial-development.

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Brothers; a period that marked the global financial meltdown in 2008.[2] The paper focuses on quantifying the consequences of varying market association on the diversification benefits of U.S. investors who are venturing into MENA equities. It also considers the influence on intra diversification among MENA countries. The results show that MENA equities are weakly associated with U.S. equities and that there is substantial diversification benefit in terms of return enhancement and risk reduction between the two regions. A 30% allocation into MENA equities would triple the Sharpe ratio of a portfolio that was fully invested in U.S. equities. The increased association spotted following the financial crisis has negatively impacted the benefits of diversifying into MENA equities. However it did not completely eliminate it, and the same combination that contains U.S. and MENA equities has continued to succeed and to have the highest Sharpe ratios even after the crisis. Furthermore, the correlations and spillovers have started to revert to their pre-crisis level toward the end of the sample period in 2011. Therefore, the diversification benefits between the two regions are expected to be restored as we head into the future and as the U.S. economy recovers.[3]

We found similar results for diversification within the MENA region. Stock markets were segmented in the pre-crisis period and therefore there were substantial benefits of diversification for all countries. However, these benefits were country specific in the post-crisis period as sharp declines swept over all MENA equities except for Tunisia and Turkey. Therefore for these two countries there are no diversification benefits of investing in other MENA equities.

These results highlight the importance of the MENA region in the strategic asset allocation of international investors. The equities of MENA are weakly associated with themselves and with the U.S.; and therefore they offer great diversification potential. Despite the increased association of these equities during stress there are still some diversification benefits to be reaped in terms of risk reduction. Over the longer term the chance of reversion in dynamic correlations after crisis is great; and hence the benefits of diversification may well be restored eventually.

The literature on MENA has focused on information transmissions and cross market dependence with little attempts to analyze or quantify the influence on the diversification of an international portfolio. In terms of cross market linkages, the evidence on segmentation from global markets has been provided by Cheng, Jahan-Parvar, and Rothman (2010), Darrat, Elkhal, and Hakim (2000), Grahama, Kiviahob, Nikkinenb, and Omran (2013) and Neaime (2012). These empirical studies indicated that MENA stocks are good candidates for international diversification from the perspective of a global investor. There are also some results on the intra market segmentation of MENA exchanges that was provided by Lagoarde-Segot and Lucey (2007) and Neaime (2005). All these authors had stressed the low correlations and intra linkages among regional stock markets' returns and volatilities.

Our results on dynamic association during the pre-crisis period conform very well to these findings. However, we differ because we looked into the nature of dynamic association in stress and afterwards. We have also spotted higher than believed transmissions and correlations during the global financial crisis, and we noticed a mean reversion thereafter. Moreover, unlike previous studies, our paper has used the dynamically estimated correlations to quantify the influence of changed association on international diversification. Surprisingly, and as mentioned previously, we found that the same combination that contains MENA and U.S. equities continue to perform well even after the global crisis in 2008.

From the international evidence on dynamic association, we are similar to Pesaran and Pesaran (2010) who found that changes in volatilities are become more correlated across markets during and after the global financial crisis in 2008. Similarly, we are in line with Diebold and Yilmaz (2009) who recorded spikes in returns and volatility transmissions across 18 stock exchanges around the globe. We also conform very well with the works of Samarakoon (2011) and Lahrech and Sylwester (2011) who indicated that association among Latin American stock exchanges has increased post-crisis; and with Aloui, Alissa, and Nguyen (2011) who found increased transmissions in the BRICS[4] block of countries; and finally with Kazi, Guesmi, and Kaabia (2013) who recorded higher interdependence among OECD stock markets.[5]

We differ to these studies as we found MENA markets are only driven by the U.S. stocks in stress, while its association is negligible in normal times.[6] Furthermore, higher transmissions and interdependence with U.S. stocks has not continued following the crisis. On the contrary, it had fallen by the end of the sample period as growth was restored in the U.S. economy. The mean-reversion tendency in the relationship indicates that MENA equities are long term diversifiers from the perspective of international investors.

To assess return association we used dynamic conditional correlations (DCC) as in Engle (2002).[7] The estimated correlations from the DCC model were then used to optimize portfolios and to measure the influence on the Sharpe ratios. The cross spillover of volatility was analyzed by decomposing forecast errors of a generalized vector autoregressive model of conditional volatility. These decompositions were then aggregated to compute spillover indices as in Diebold and Yilmaz (2012). Two virtues of these indices are that they are intuitive and they can be used to reveal the direction of the transmission besides its strength. Specifically, the net directional transmission to a market (or a group of markets) from another market (or even from a group of markets) can be easily computed. Thus these indices are used to measure the volatility information crossover to MENA stock markets from the U.S. and vice versa.

The previous studies inferred MENA stock market correlations using various methodologies. For instance, Darrat, Elkhal, and Hakim (2000) and Neaime (2005) used a traditional cointegration analysis. On the other hand, Lagoarde-Segot and Lucey (2007) optimized and constructed a re-sampled efficient frontier by the block bootstrap of returns to derive diversification potential among MENA markets. Cheng, Jahan-Parvar, and Rothman (2010) used an alternative method; they estimated variants of the CAPM model

[2] In fact, the crisis began to unfold on July 2007 with the credit crunch and the crisis rapidly developed and spread into a global financial shock with the collapse of Lehman Brothers in September 2008.

[3] This point has been raised to us thankfully by one of the referees.

[4] The BRICS group contains the following countries: Brazil, Russia, India, China and South Africa.

[5] The evidence on increased transmissions is not unanimous. For instance Dajcman, Festic, and Kavkler (2012) argued that the global financial crisis did not uniformly increase the degree of co-movement across the stock markets of the U.K., Germany, France, and Austria.

[6] Significant interdependence with U.S. equities was found by many: Janakiramanan and Lamba (1998) and Hsiao, Hsiaob, and Yamashita (2003) in the Pacific Basin and Asia Pacific regions; Elyasiani, Perera, and Puri (1998) in emerging markets; Gilmore and McManus (2002) in Central Europe; Fernandez-Serrano and Sosvilla-Rivero (2003) in Latin America; Chuang, Lu, and Tswei (2007), Gallo and Otranto (2007), Dao and Wolters (2008), and Lee (2009) in East Asian markets; and Kanas (1998), Eger and Kočenda (2007), and Morana and Beltratti (2008) in Europe.

[7] The Engle (2002) DCC model has been widely used in the literature to investigate the common movements in international financial markets (e.g., Felipe & Diranzo, 2006; Chiang, Jeon, & Li, 2007; Celic, 2012; Dimitriou, Kenourgios, and Simos (2013); Baumöh & Lyócsa, 2014).

that allow for time-varying degree of integration with international equity. Grahama, Kiviahob, Nikkinenb, and Omran (2013) used another alternative; they applied wavelet squared coherency with simulated confidence bounds to infer association. Finally, Neaime (2012) used a fitted GARCH type model of conditional volatility to estimate simple correlations.

In this paper, we measure association using a standard dynamic conditional correlation model. However, it is well documented that the correlation measure is biased and inaccurate as it depends on the state of volatility. Forbes and Rigobon (2002), for example, claim that markets appear to be more associated during stress only because correlations are biased; when genuine interdependence has not increased. Therefore, in this paper we also infer interdependence using the spillover index measure of Diebold and Yilmaz (2012) in addition to correlations. The measure is simple to compute and it reveals time varying directional linkages among MENA stock exchanges and the U.S. during normal periods as well as during stress.

The rest of the paper is organized as follows. In Section 2 we outline our methodology. A description of the sample and some preliminary statistics can be found in Section 3. In Section 4 we present our empirical results and we discuss the influence on the diversification potential of MENA from the perspective of a U.S. investor. Finally, Section 5 contains some concluding remarks.

2. Empirical methods

2.1. Measuring dynamic return co-movements

In this paper we initially use the DCC model to estimate time-varying linear interdependence across financial markets. The dynamic correlations are generated using two steps. First, the conditional volatility is specified and estimated as a univariate GARCH process. Then the standardized residuals from the previous step are corrected and subsequently used to construct conditional correlations. The advantage of this simple approach is that it can directly measure the extent of return co-movement across markets by looking into the time-varying behavior of the data; and hence, it can detect changes in return association.

Specifically, let $r_t = (r_{1t}, \ldots, r_{Nt})'$ be a (6×1) vector of stock market index return at time $t = 1, \ldots, T$. The conditional mean equation in the model is specified as an autoregressive process of order one. It takes the following form[8]:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t \quad \text{and} \quad \varepsilon_t|\xi_{t-1} \sim N(0, H_t) \tag{1}$$

where ε_t is a (6×1) vector of errors that are estimated conditional on the information available up to time $t-1$ (ξ_{t-1}). The error term is assumed to be conditionally normal with zero mean and conditional covariance matrix, H_t. The conditional covariance matrix in the DCC is expressed as follows:

$$H_t = D_t R_t D_t \tag{2}$$

where $D_t = diag(h_{11,t}^{1/2}, \ldots, h_{NN,t}^{1/2})$ is a diagonal matrix that contains the time-varying volatilities of the univariate GARCH models (i.e. $h_t = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 h_{t-1}$),[9] and R_t is the time-varying correlation matrix of standardized returns ($\varepsilon_t = D_t^{-1} r_t$), which is specified as:

$$R_t = \{diag(Q_t)\}^{-1/2} Q_t \{diag(Q_t)\}^{-1/2} \tag{3}$$

The correlation driving process Q_t is defined by

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon_{t-1}' + \beta Q_{t-1} \tag{4}$$

where $\bar{Q}$ is a (6×6) unconditional covariance of the standardized residuals (i.e. $\bar{Q} = E[\varepsilon_{t-1} \varepsilon_{t-1}']$).[10] The parameters α and β are non-negative scalars that satisfy the following conditions: $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$.[11]

Therefore, the conditional returns correlation for a pair of markets i and j at time t is computed using the following formula:

$$\rho_{ij,t} \frac{(1 - \alpha_{ij} - \beta_{ij})\bar{Q}_{ij,t-1} + \alpha_{ij} \varepsilon_{t-1} \varepsilon_{t-1}' + \beta_{ij} \rho_{ij,t-1}}{\sqrt{\{(1 - \alpha_{ii} - \beta_{ii})\bar{Q}_{ii,t-1} + \alpha_{ii} \varepsilon_{i,t-1}^2 + \beta_{ii} \rho_{ii,t-1}\}\{(1 - \alpha_{jj} - \beta_{jj})\bar{Q}_{jj,t-1} + \alpha_{jj} \varepsilon_{j,t-1}^2 + \beta_{jj} \rho_{jj,t-1}\}}} \tag{5}$$

Under the Gaussian assumption, the DCC can be estimated by maximizing the following log-likelihood function:

$$L = -0.5 \sum_{t=1}^{T} (N \log(2\pi)) + 2 log|D_t| + \log|R_t| + \varepsilon_t R_t^{-1} \varepsilon_t' \tag{6}$$

It is well known, that inference on cross stock market co-movement using correlation analysis could be biased and inaccurate due to the dependence of the correlation measure on the state of volatility (see Forbes and Rigobon, 2002). Specifically, during market stress, volatility is high and correlation estimates tend be upwardly biased. Therefore, if volatility is not accounted for, the rise in correlations may reflect only an increase in market volatility and not higher interdependence. The term used to differentiate the influence of conditional volatility is contagion, and not interdependence. Therefore, before any inference is made on interdependence, we have also checked for any significant contagious effects by running the following regression[12]:

$$\rho_{ij,t} = \alpha_{ij,0} + \alpha_{ij,1} T + \sum_{p=1}^{p} \vartheta_{ij,p} \rho_{ij,t-p} + \beta_{i.t} h_{i.t} + \beta_{j.t} h_{j.t} + \varepsilon_{ij,t} \tag{7}$$

where $\rho_{ij,t}$ is the estimated pair-wise conditional correlations and $h_{i.t}$ and $h_{j.t}$ are the conditional volatilities of the U.S. and MENA stock markets respectively. The time trend (T) is included in the model as

[8] Based on the Akaike (AIC) and Schwarz Bayesian information (BIC) criteria, an autoregressive process of order one was found to be optimal in describing all return series. To conserve space, the results are not reported here but they are available from the authors upon request.

[9] We estimated GARCH using a standard QMLE estimator with Gaussian innovations. The results have not changed when volatilities are generated from other GARCH-type models. For instance, we estimated the following models: the exponential GARCH (EGARCH), the threshold GARCH (TGARCH), the nonlinear asymmetric GARCH (NGARCH), the asymmetric power GARCH (APGARCH), the fractionally integrated asymmetric power ARCH (FIAPARCH), and the hyperbolic GARCH (HYGARCH). All gave the same pattern of conditional correlations. These results are not reported, but are available from the authors upon request.

[10] In Aielli (2013), it is claimed that estimates of the unconditional covariance of standardized residuals (i.e. $\bar{Q}$) from the sample is biased and inconsistent. Therefore, he proposed an ad hoc correction of the correlation driving process Q_t (called cDCC) that preserves tractability in large systems. Unlike Aielli (2013), we found that both estimators have generated the same pattern of dynamic correlations, and therefore, we may conclude that the extent of bias in our data set is small. The results of the cDCC estimator are available from the authors upon request.

[11] Note that if we set $\alpha = \beta = 0$, we will get the constant conditional correlation measure of returns.

[12] Similar regressions were used by Syllignakis and Kouretas (2011), Ahmad, Sehgal, and Bhanumurthy (2013), and Baumöhl and Lyócsa (2014).

conditional correlations may exhibit an increased integration with time. The lagged value of the dependent variable is also included to incorporate persistent conditional correlations. A positive and significant $\beta_{j.t}$ indicates that the conditional correlations between the MENA stock markets and the U.S. stock market depends significantly on the conditional volatility of the U.S. market and therefore, a significant contagion effect may be concluded.

2.2. Measuring volatility spillovers

To examine the nature of cross market volatility association we utilize a new spillover index approach introduced by Diebold and Yilmaz (2012).[13] Let market volatilities, y_i be modeled as a vector autoregressive process, $VAR(p)$ that can be written as[14]

$$y_i = \sum_{i=1}^{p} \Phi y_{t-i} + \varepsilon_t \tag{8}$$

where $y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N,t})$, and Φ is an $(N \times N)$ matrix of parameters to be estimated. Also, assume that the vector of error terms ε is identically and independently distributed with zero mean and Σ covariance matrix. A transformation of coefficients in the associated moving average representation of Eq. (8) above can be used to compute variance decompositions.[15] The aggregation of these can be subsequently used to measure the extent of transmissions across financial markets. Hence, a factorization scheme is needed prior to the computation of spillovers, and hence, in this paper we generate decompositions by using the generalized VAR scheme that was first proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) (the KPPS hereafter).[16] The forecast error variance decomposition (H step ahead) is computed as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' h_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' h_h \sum e_j)} \tag{9}$$

where $\sum$ is the variance matrix of the vector of errors ε, and σ_{jj} is the standard deviation of the error term of the jth market. Finally, e_i is a selection vector with one on the ith element, and zero otherwise. As these decompositions do not sum to one, we normalize each entry of the matrix by the row sum as[17]

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{10}$$

Therefore, the decomposition including own shocks in each market sums to one, i.e. $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$, and the total decomposition over all markets sums to N, i.e. $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ by definition.

We use the KPPS variance decomposition to compute the extent of transmissions as follows:

A. The total volatility spillover index is calculated as

$$S^{g}(H) = \frac{\sum_{i,j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j-1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{11}$$

This index measures the extent of volatility spillovers across all stock markets. It is the sum of proportions of the forecast error variance of y_i due to shocks to y_j, for all $i \neq j$.

B. The volatility transmission received by market i from all other markets j is computed as

$$S_{i\circ}^{g}(H) = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{12}$$

C. The volatility transmitted by market i to all other markets j is calculated as

$$S_{\circ i}^{g}(H) = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{13}$$

D. Then, we compute the net transmission of volatility from market i to all other markets j by offsetting (12) and (13) as

$$S_{i}^{g}(H) = S_{i\circ}^{g}(H) - S_{\circ i}^{g}(H) \tag{14}$$

A positive net transmission indicates that i market is a net giver of volatility to all other markets, while a negative value points out that market i is a net receiver.

E. Finally, the net pairwise volatility spillover between markets i and j is given by

$$S_{ij}^{g}(H) = \left(\frac{\theta_{ij}^{g}(H)}{\sum_{k=1}^{N} \theta_{ik}^{g}(H)} - \frac{\theta_{ji}^{g}(H)}{\sum_{k=1}^{N} \theta_{jk}^{g}(H)} \right) \times 100 \tag{15}$$

3. Data description and preliminary statistics

In this paper we used weekly closing index prices of the five biggest and most active stock exchanges in the MENA region. They are: Egypt, Jordan, Saudi Arabia, Tunisia, and Turkey. All indices are capital weighted and include all companies traded in each market. For the U.S. market, we used the S&P 500 index, which represents a well-diversified stock portfolio of a U.S. investor. Our dataset covers the period January 2nd, 1998 to February 15th, 2013, and it includes market indices in local currencies. The data was retrieved from Thomson Reuters DataStream. We computed weekly continuously compounded returns as the change in log prices, Friday to Friday, over the whole sample which resulted in 788 weekly return observations. The weekly frequency was chosen to overcome any non-synchronous trading bias that could arise between MENA countries and the U.S. as they operate on different calendars.[18] A lower frequency might not be able to capture intermediate transmission, as spillovers are temporary and may only last for few weeks.

To detect any changes in the nature of spillovers following the financial turmoil in 2008 we split our data into two sub-periods: a pre-crisis period, January 1998 to August 2008, followed by a

[13] For the application of this approach, refer to, for example McMillan and Speight (2010), Antonakakis (2012), and Awartani and Maghyereh (2013).

[14] Note that the text and notation in this sub-section are extensively quoted from Diebold and Yilmaz (2012).

[15] Note that the moving average representation of the VAR in Eq. (6) only exists if it is covariance stationary.

[16] We could have used Cholesky factorization instead; we did not as it is sensitive to ordering of markets.

[17] Unlike Cholesky factorization, which sums up to one, the KPPS decomposition may not. Thus, normalization is needed to enable an intuitive computation of the contribution of markets.

[18] Trading in the MENA countries closes on Thursday and resumes on Sunday; whereas the U.S. operates on a Monday Friday Calendar. The number of trading hours is also different and there are substantial time differences, let alone the different national and religious holidays for which trading stops.

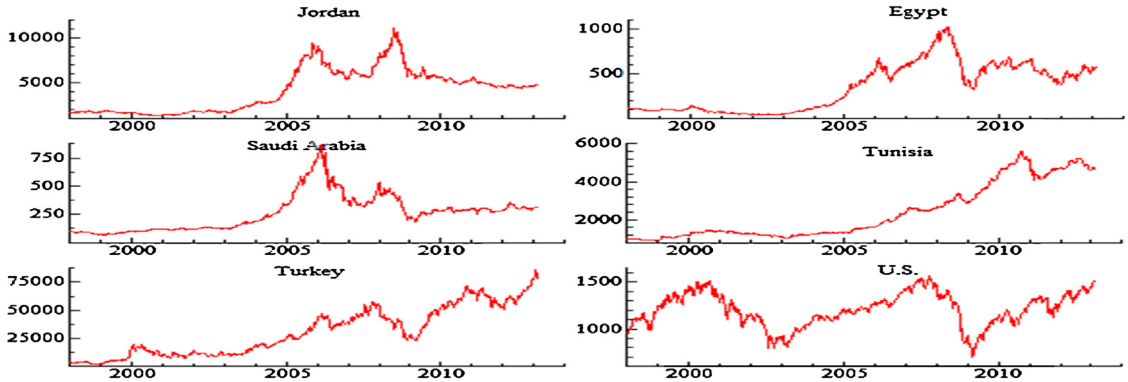

Fig. 1. Time-variations in stock price indices (02/01/1998–15/02/2013).

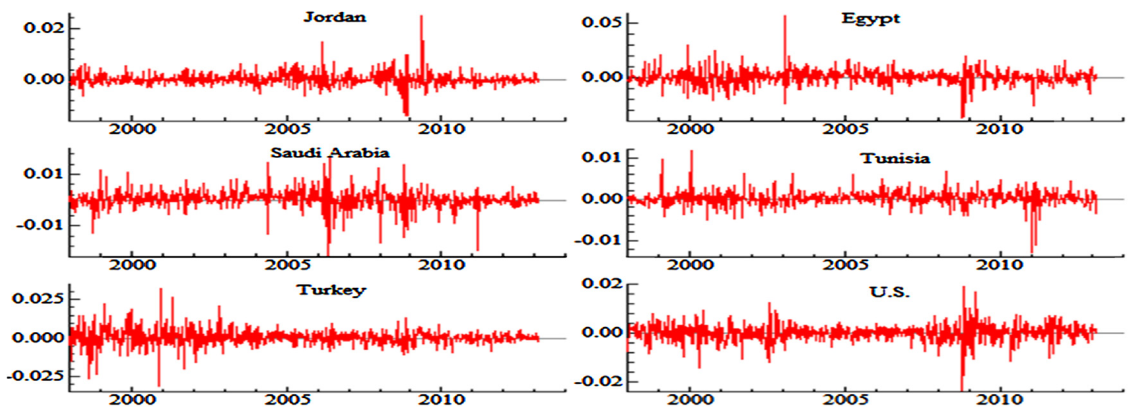

Fig. 2. Time-variations in weekly stock market returns (02/01/1998–15/02/2013).

post-crisis period from September 2008 to February 2013.[19] To measure the latent volatility we used a simple range based estimator. The estimator employs weekly high, low, opening and closing prices from Monday open to Friday close. Specifically, for any stock market i, the volatility in week t is computed as[20]

$$\sigma_{i,t}^2 = 0.51(H_{i,t} - L_{i,t})^2 - 0.019[(C_{i,t} - O_{i,t})(H_{i,t} + L_{i,t} - 2O_{i,t})2(H_{i,t} - O_{i,t})(L_{i,t} - O_{i,t})] - 0.383(C_{i,t} - O_{i,t})^2,$$

where H, L, O and C, are the Monday to Friday open, high, low, the Monday open and the Friday close respectively.

Figs. 1–3 plot the indices, returns and volatilities respectively. Fig. 1 shows that all stock markets in the MENA were rallying until 2005. The strong growth was supported by high corporate results and substantial public sector structural reforms. The optimism, however, began to drop in Egypt, Jordan, and Saudi Arabia by the end of 2005 and sharp declines swept all these markets in early 2006. These declines were partially reversed by a subsequent rise that had started by the end of 2007 and continued until the outbreak of the global financial crisis in October 2008. Afterwards, markets recovered marginally at a slow pace. With the exception of Turkey, previous losses were never recouped. The Arab Spring, the bleak picture of the global economy, and the continuing fallout of the financial distress have all contributed to weak stock market performances after 2008. Upward trends were short lived in most of these markets.

Figs. 2 and 3 show stock market returns and volatilities, respectively. These figures show a pronounced volatility clustering effect. Most noticeable were the spikes in volatility during October 2008 after the collapse of Lehman Brothers (15th September 2008). This reflects the large uncertainty and the severe loss of confidence that hit the market during that period. The volatility of the U.S. market had also peaked during that time and this stimulated further volatility in all MENA markets. Volatility also jumped in the Egyptian and Tunisian markets after December 2011. This illustrates the impact of the Arab Spring and the political transformation that swept the two countries and the Middle East during that period.[21]

Recall that we split the sample into two subperiods: pre-crisis and post-crisis. Table 1, Panel A, reports the summary statistics of the return series. The table shows that there are significant differences between the two sub-periods. All pre-crisis MENA returns were positive and significantly higher than U.S. returns. However, following the crisis, mean returns were all negative except for Tunisia and Turkey, who recorded reduced but positive returns. As expected for stocks, returns are negatively skewed except for Tunisia. The Saudi Arabian financial market has exhibited the largest negative skewness of −1.4424 and −1.5687 in both periods respectively.

[19] We used Chow test to detect any structural breaks in the markets. The tests show that significant shifts in market volatilities have occurred at the end of August and the beginning of September 2008. The timing of these breaks coincides nicely with the collapse of Lehman Brothers. For more details, see Fig. 1.

[20] This measure was first proposed by Garman and Klass (1980).

[21] Note that Fig. 1 shows that the Turkish stock returns have also demonstrated high volatility over the period 2000–2004. This has also reflected the economic and political instability that hit Turkey during that period.

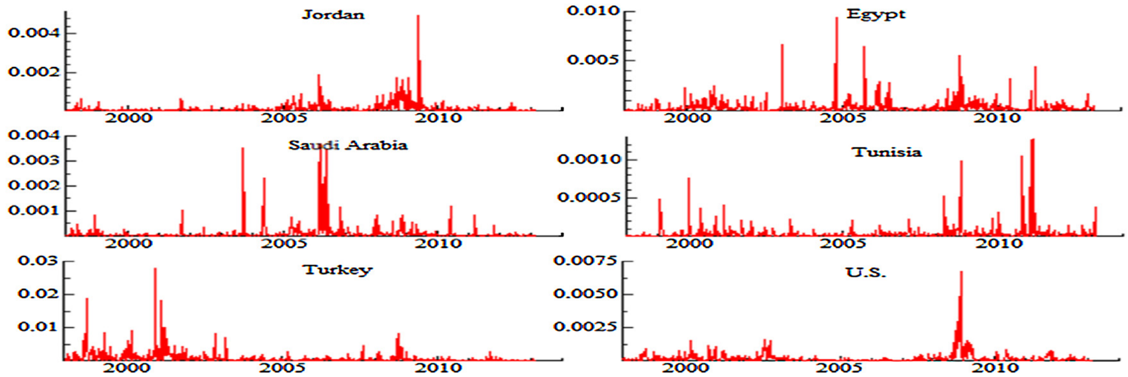

Fig. 3. Time-variations in weekly stock market volatilities (02/01/1998–15/02/2013).

Note that skewness and kurtosis were significantly larger in magnitude post-crises in all countries. This suggests a higher frequency of extreme performance during the troubled period. Moreover, in the table all indices show significant linear and non-linear serial correlation as indicated by the Ljung–Box statistics of serial correlation. A variety of summary statistics of the natural logarithm of volatilities is also included in Panel B of Table 2. The data show that cross market volatility co-movement is higher

Table 1
Descriptive statistics, stock market returns, and volatilities.

	Jordan	Egypt	Saudi Arabia	Tunisia	Turkey	U.S.
Panel A: summary statistics of return series[a]						
Pre-crisis period, 02/01/1998–09/09/2008 (558 observations)						
Mean	0.0013	0.0014	0.0011	0.0019	0.0009	0.0002
Maximum	0.038	0.073	0.057	0.100	0.037	0.053
Minimum	−0.041	−0.070	−0.102	−0.110	−0.020	−0.052
Std. dev.	0.010	0.016	0.015	0.027	0.006	0.010
Skewness	0.118	−0.275	−1.442	1.1604	−0.254	−0.078
Kurtosis	1.806	1.565	8.454	6.0366	1.523	2.903
$Q(10)$	29.379** (0.001)	20.710*** (0.023)	27.808*** (0.002)	24.466*** (0.006)	14.56 (0.1485)	40.257*** (0.000)
$Q^2(10)$	145.067*** (0.000)	76.240*** (0.000)	160.786*** (0.000)	24.552*** (0.006)	115.496*** (0.000)	163.974*** (0.000)
Post-crisis period, 16/09/2008–15/02/2013 (231 observations)						
Mean	−0.001	−0.0004	−0.0003	0.0013	0.0006	0.0004
Maximum	0.048	0.051	0.043	0.071	0.034	0.034
Minimum	−0.061	−0.091	−0.076	−0.075	−0.032	−0.068
Std. dev.	0.012	0.020	0.015	0.018	0.0077	0.013
Skewness	−0.422	−0.629	−1.568	1.448	−0.306	−0.538
Kurtosis	4.1210	2.618	8.074	7.030	2.093	3.726
$Q(10)$	37.191*** (0.000)	26.649*** (0.003)	19.314** (0.036)	26.375** (0.003)	22.692** (0.012)	25.870*** (0.004)
$Q^2(10)$	681.158*** (0.000)	100.633*** (0.000)	258.990*** (0.000)	197.069*** (0.000)	209.170*** (0.000)	165.967*** (0.000)
Panel B: summary statistics of return volatilities[b]						
Pre-crisis period, 02/01/1998–09/09/2008 (558 observations)						
Mean	−4.522	−3.918	−4.488	−4.943	−3.284	−4.071
Maximum	0.000	−2.028	0.000	0.000	0.000	−2.635
Minimum	−8.125	−6.081	−6.647	−10.071	−5.344	−5.9508
Std. dev.	0.9053	0.6546	1.0797	0.7254	0.7134	0.521
Skewness	5.0589	7.597	6.706	6.288	7.144	3.097
Kurtosis	37.470	79.919	51.562	54.226	70.182	12.893
$Q(10)$	300.961*** (0.000)	12.685 (0.241)	344.170*** (0.000)	32.912*** (0.0002)	131.112*** (0.0000)	412.254*** (0.0000)
$Q^2(10)$	39.606*** (0.000)	0.3192 (0.999)	140.486*** (0.000)	2.27780 (0.993)	8.880 (0.543)	179.014*** (0.000)
Post-crisis period, 16/09/2008–15/02/2013 (231 observations)						
Mean	−4.436	−3.654	−4.345	−4.682	−3.742	−4.019
Maximum	0.000	0.000	0.000	0.000	0.000	−2.168
Minimum	−6.712	−5.780	−7.885	−7.054	−5.433	−6.248
Std. dev.	0.821	0.912	1.098	0.837	0.592	0.639
Skewness	8.163	4.445	4.740	5.996	6.255	6.302
Kurtosis	87.690	25.281	26.688	38.429	47.746	50.070
$Q(10)$	87.294*** (0.000)	36.746*** (0.000)	46.053*** (0.000)	43.102*** (0.000)	98.700*** (0.000)	286.683*** (0.000)
$Q^2(10)$	0.2281 (0.999)	12.892 (0.229)	4.277 (0.933)	41.897*** (0.000)	57.060*** (0.000)	62.183*** (0.000)

Notes: $Q(10)$ and $Q^2(10)$ are the Ljung–Box statistics for serial correlation in raw series and squared series, respectively. The values in parentheses are the actual probability values.

[a] Returns are measured weekly from Friday-to-Friday returns.

[b] Volatilities are measured weekly as range based for Monday-to-Friday returns and in logs.

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

Table 2
Unconditional correlations.

	Jordan	Egypt	Saudi Arabia	Tunisia	Turkey	U.S.
Panel A: unconditional correlations of return series[a]						
Pre-crisis period, 02/01/1998–09/09/2008 (558 observations)						
Jordan	1.000					
Egypt	0.174***	1.000				
	(0.000)					
Saudi Arabia	0.223***	0.154***	1.000			
	(0.000)	(0.000)				
Tunisia	0.039	0.152***	0.098**	1.000		
	(0.350)	(0.000)	(0.019)			
Turkey	0.095**	0.124***	0.111***	0.022	1.000	
	(0.023)	(0.003)	(0.008)	(0.607)		
U.S.	0.033	0.084**	0.072*	0.019***	0.050	1.000
	(0.427)	(0.045)	(0.089)	(0.130)	(0.236)	
Post-crisis period, 16/09/2008–15/02/2013 (231 observations)						
Jordan	1.000					
Egypt	0.360***	1.000				
	(0.000)					
Saudi Arabia	0.356***	0.377***	1.000			
	(0.000)	(0.000)				
Tunisia	0.200***	0.343***	0.457***	1.000		
	(0.002)	(0.000)	(0.000)			
Turkey	0.151***	0.140**	0.210***	0.157**	1.000	
	(0.020)	(0.032)	(0.001)	(0.016)		
U.S.	0.285***	0.355***	0.582***	0.501***	0.044	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.507)	
Panel B: unconditional correlations of return volatilities[b]						
Pre-crisis period, 02/01/1998–09/09/2008 (558 observations)						
Jordan	1.000					
Egypt	0.078*	1.000				
	(0.063)					
Saudi Arabia	0.256**	0.012	1.000			
	(0.000)	(0.77)				
Tunisia	0.107**	0.144***	0.050	1.000		
	(0.011)	(0.000)	(0.235)			
Turkey	−0.170***	0.059	−0.094	0.008	1.000	
	(0.000)	(0.162)	(0.025)	(0.838)		
U.S.	−0.129***	−0.001	−0.174***	0.088**	0.214***	1.000
	(0.002)	(0.969)	(0.000)	(0.036)	(0.000)	
Post-crisis period, 16/09/2008–15/02/2013 (231 observations)						
Jordan	1.000					
Egypt	0.443***	1.000				
	(0.000)					
Saudi Arabia	0.256***	0.299***	1.000			
	(0.000)	(0.000)				
Tunisia	0.213**	0.117*	0.077	1.000		
	(0.015)	(0.076)	(0.246)			
Turkey	0.341***	0.3065***	0.191***	0.065	1.000	
	(0.000)	(0.000)	(0.003)	(0.325)		
U.S.	0.345***	0.309***	0.382***	−0.109*	0.426***	1.000
	(0.000)	(0.000)	(0.000)	(0.099)	(0.000)	

Notes: The values in parentheses are the actual probability values.
[a] Returns are measured weekly from Friday-to-Friday returns.
[b] Volatilities are measured weekly as range based for Monday-to-Friday returns and in logs.
[*] Significance at 10% level.
[**] Significance at 5% level.
[***] Significance at 1% level.

and more significant in the post-crisis periods. This is expected and consistent with the empirical observation of higher volatility during troubled times.

Table 2 Panels A and B display pairwise simple return and volatility correlation across markets. The correlations among MENA returns are all significant during the two periods; however, their levels have doubled post-crisis. The largest increase in return correlation was between Saudi Arabian returns and Tunisian and Egyptian returns where correlations have risen by 36% and 22% respectively. Panel B of Table 2 contains volatility correlations among MENA markets, and it describes a similar story. It also reveals that the highest increase in the volatility correlation was between Jordan and Turkey, which has risen from negative −17.0% to positive 34.1% post-crisis. The second highest rise was between Egypt and Saudi Arabia, which has increased from a low of 1.2% to 29.9% following the crisis.

The simple correlation analysis also indicates a clear change in correlations of returns and volatility between MENA stock markets and the U.S. market. As can be seen in the table, pre-crisis all MENA markets showed little association with the U.S. However, post-crisis, association is substantial in all countries other than of Turkey. In particular the return correlations of the U.S. have jumped from almost nothing pre-crisis to 28.5%, 35.5%, 58.2% and 50.1% with Jordan, Egypt, Saudi Arabia, and Tunisia respectively.

Table 3
Jennrich test for equality of correlation matrices.

	χ^2	P-value
$\rho_{\text{Egypt–Jordan}}$	19.317***	(0.0093)
$\rho_{\text{Saudi Arabia–Jordan}}$	77.333***	(0.0004)
$\rho_{\text{Tunisia–Jordan}}$	6.424*	(0.0580)
$\rho_{\text{Turkey–Jordan}}$	12.709***	(0.0048)
$\rho_{\text{U.S.–Jordan}}$	29.657***	(0.0005)
$\rho_{\text{Saudi Arabia–Egypt}}$	25.444***	(0.0096)
$\rho_{\text{Tunisia–Egypt}}$	47.252***	(0.0001)
$\rho_{\text{Turkey–Egypt}}$	9.666***	(0.0019)
$\rho_{\text{U.S.–Egypt}}$	77.218***	(0.0000)
$\rho_{\text{Tunisia–Saudi Arabia}}$	2.500	(0.2937)
$\rho_{\text{Turkey–Saudi Arabia}}$	48.750***	(0.0044)
$\rho_{\text{U.S.–Saudi Arabia}}$	132.598	(0.0000)
$\rho_{\text{Turkey–Tunisia}}$	4.187*	(0.0790)
$\rho_{\text{U.S.–Tunisia}}$	2.376	(0.1902)
$\rho_{\text{U.S.–Turkey}}$	121.397***	(0.0000)

Notes: The table reports the Jennrich (1970) tests for equality of correlation matrices between the pre- and post-crisis periods. The Jennrich statistics have an asymptotic χ^2 distribution with $((k-1)p(p-1))/2$ degree of freedom, where p is number of countries and k is number of $p \times p$ correlation matrices tested. The null hypothesis of equal correlation matrices between two periods is rejected at 1%, 5%, and 10% significance levels if the p-value is less than 1%, 5%, and 10% respectively.

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

Similarly, the volatility correlations of Jordan, Egypt, and Saudi Arabia with the U.S., have changed signs from negative pre-crisis to positive following the crisis. The volatility correlation between Turkey and the U.S. has also increased from 21.4% to 44.6% after the crisis.

In Table 3, we test for equality in correlation matrices in the two periods using the Jennrich (1970) Chi squared test statistics. The test was implemented over the two correlation matrices as in Bracker and Koch (1999).[22] The results are presented in Table 2, and they show that correlations have changed significantly in the post-crisis period. This reaffirms the significant rise in post-crisis correlations in the MENA region.

To summarize, the preliminary evidence reveals that association within the MENA is moderate, and it strengthens in a crisis. This indicates little diversification potential within the MENA markets. The minor diversification benefit disappears partially during periods of stress. On the contrary the association with the U.S. is weak and hence, great diversification may be realized by combining U.S. and MENA equities. However, diversification with the U.S. is affected once we enter into a crisis period, as returns and volatility correlations jump to high levels.

4. Empirical results

In this section we present results on time varying linear interdependence of MENA countries calculated using the DCC model. As mentioned previously, the volatility spillovers are inferred by aggregating variance decompositions to compute a spillover index as in Diebold and Yilmaz (2012).

4.1. Results of time-varying correlations

Table 4 reports the estimation results of the DCC model in the pre- and post-periods of the 2008 financial crisis. Panel A of Table 4 contains the GARCH parameters estimation results, as well as the diagnostics of the model. The Ljung–Box statistics of the 10th order fails to reject the null of no serial correlation in the standardized residuals and their squares, thus indicating an appropriate specification for all countries.[23] Table 4 also shows that volatility is persistent because the sum of GARCH parameters is close to unity (i.e. $\theta_1 + \theta_2$) in all markets and for both considered periods. Panel B of Table 4 includes the DCC model's estimates and the constant conditional correlation. As can be seen in the Panel, the DCC model seems to be a good fit, as its estimated parameters, α and β, are significant. The sum of the parameters in the model is less than unity (i.e. $\alpha + \beta < 1$), and this shows that conditional pairwise correlations are mean reverting. This feature was documented by many researchers.

As mentioned above, Panel B reports the conditional average correlations coefficients of the DCC model in the pre- and post-crisis periods. In the pre-crisis period correlations among MENA markets were low. The averages lie between −0.1% and 32.5%. This is surprising given the geographical proximity, common economic and political driving factors (for instance oil), and the cultural similarities among countries of the region.[24] From a portfolio strategy viewpoint, these findings imply intra diversification benefits in the MENA countries.

In the post-crisis period correlations of stock returns have substantially increased. The biggest rise in conditional correlations was between Egypt and Jordan, where association rose from 6.7% to 36.5%. The lowest increase was between Turkey and Jordan, where correlation increased from −0.1% to 15.2%. The only exception was the pairwise association with the Tunisian stock market, which was found in most cases to be statistically insignificant, and weakly correlated with other MENA stock markets in both sub-periods.[25] The low correlation between Tunisia and other MENA markets could possibly be explained by its geographical segmentation from regional and global markets. Note also that the conditional correlation evidence reconfirms the unconditional correlation results in Table 3, and that both suggest that diversification has weakened in the MENA markets following the global financial turmoil in 2008.

It is quite possible that oil returns may explain changes in interdependence among MENA markets. To rule out that possibility we regressed the pairwise dynamic conditional correlations on oil returns and we found no significant relationship.[26] In all markets oil has no significant impact on pairwise correlation and we conclude that, the time varying correlation in these markets is not driven by

[22] Jennrich (1970) statistics are used to test the null hypothesis of no equality in correlation matrices. The test statistics are given by: $J = 1/2tr(Z_i^2) = [dg(Z_i)]'W^{-1}[dg(Z_i)]$ where for i to k, R_i is the sample correlation matrix for p countries computed over n_i observations; the elements w_{ij} of W are defined as $w_{ij} = (\delta_{ij}) + r_{ij}r^{ij}$, in which δ_{ij} denotes Kronecker's delta; the $dg(Z)$ stacks the main diagonal of Z into a column vector, which is defined by $Z_i = \sqrt{n_i}\bar{R}^{-1}(R_j - \bar{R})$; and $R = (n_1R_1 + \cdots + n_kR_k)/n = r_{ij}J$ can be shown to be asymptotically distributed as a chi-square with $(k-1)p(p-1)/n$ degrees of freedom.

[23] We used the information criteria AIC and BIC for lag selection. Both have chosen one lag.

[24] The low association points to the fact that countries of the region have failed to develop frameworks to improve intra-regional portfolio investment flows and financial and economic integration.

[25] Note however that the conditional correlation between Tunisia and Saudi Arabia has dropped from a significant 10.5% in normal times to 2.2% in stress.

[26] To test whether changes of market linkages are caused by changes in oil prices we regressed the pairwise conditional correlation on a constant, time trend, lagged correlation, oil returns, and a dummy for the U.S. subprime crisis. The estimated model reads as: $\rho_{ij,t} = c_{ij,0} + c_{ij,1}T + \sum_{p=1}^{p}\delta_{ij,p}\rho_{ij,t-p} + \gamma_{i,t}O_{i,t} + \tau_{j,t}dummy + e_{ij,t}$ where $\rho_{ij,t}$ is the estimated pair-wise conditional correlations, T is the time trend, $O_{i,t}$ is the first log difference of the price of WTI crude, and dummy takes a value of 1 from 15 September 2008 onwards and zero otherwise.

Table 4
Estimation results of DCC–GARCH model $r_t = \varphi_0 + \varphi_1 r_{(t-1)} + \varepsilon_t$ and $\varepsilon_t|\xi_{(t-1)} \sim N(0, H_t)$ $h_t = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \theta_2 h_{t-1}$ $Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}^{*}\varepsilon_{t-1}^{*'} + \beta Q_{t-1}$ $\varepsilon_t^{*} = diag\{Q_t\}^{1/2}\varepsilon_t$.

	Pre-crisis period, 02/01/1998–09/09/2008						Post-crisis period, 16/09/2008–15/02/2013					
	Jordan	Egypt	Saudi Arabia	Tunisia	Turkey	U.S.	Jordan	Egypt	Saudi Arabia	Tunisia	Turkey	U.S.
Panel A: univariate GARCH estimates and univariate diagnostic tests												
Conditional mean equation												
φ_0	0.002***(0.002)	0.008***(0.000)	0.006*** (0.000)	0.000 (0.726)	0.005*** (0.001)	0.000 (0.176)	0.000 (0.941)	0.000 (0.757)	0.000 (0.968)	0.001*** (0.009)	0.000 (0.134)	0.000 (0.174)
φ_1	0.040 (0.428)	0.0222 (0.644)	0.183*** (0.001)	0.1256 (0.172)	−0.121*** (0.010)	−0.106** (0.023)	0.094 (0.359)	0.134 (0.125)	0.003 (0.980)	0.192** (0.020)	0.018 (0.821)	−0.007 (0.929)
Conditional variance equation												
θ_0	0.232*(0.064)	0.695* (0.019)	0.085** (0.021)	0.960*** (0.001)	0.092 (0.390)	0.360* (0.059)	0.028 (0.585)	2.620 (0.510)	0.618 (0.209)	0.125 (0.238)	0.132 (0.647)	0.586* (0.099)
θ_1	0.132** (0.012)	0.157** (0.014)	0.312*** (0.000)	0.539* (0.070)	0.042** (0.047)	0.156*** (0.001)	0.060* (0.086)	0.052 (0.495)	0.308 (0.180)	0.114* (0.099)	0.073** (0.028)	0.097** (0.048)
θ_2	0.832*** (0.000)	0.686*** (0.000)	0.643*** (0.000)	0.206** (0.027)	0.953*** (0.000)	0.813*** (0.000)	0.928*** (0.000)	0.869*** (0.000)	0.666*** (0.000)	0.864*** (0.000)	0.907*** (0.000)	0.846*** (0.000)
θ_1+θ_2	0.964	0.843	0.955	0.745	0.999	0.969	0.988	0.921	0.974	0.978	0.980	0.946
Univariate diagnostic												
Q(10)	13.053 (0.220)	12.1 41 (0.238)	14.653 (0.223)	17.600 (0.102)	11.008 (0.356)	10.769 (0.375)	5.695 (0.840)	17.189* (0.058)	9.345 (0.499)	8.652 (0.565)	6.251 (0.793)	9.636 (0.472)
Q^2(10)	6.540 (0.767)	1.009 (0.999)	9.904 (0.448)	4.986 (0.892)	7.194 (0.706)	10.579 (0.391)	1.590 (0.998)	4.00 (0.947)	1.275 (0.999)	3.180 (0.976)	11.574 (0.314)	1.987 (0.996)
Panel B: conditional correlation estimates and multivariate diagnostic tests												
Multivariate cDCC equation												
α	0.005**	(0.021)					0.014**	(0.012)				
β	0.890***	(0.000)					0.863***	(0.000)				
Dynamic conditional correlations												
$\rho_{\text{Egypt–Jordan}}$	0.067	(0.122)					0.365***	(0.000)				
$\rho_{\text{Saudi Arabia–Jordan}}$	0.034	(0.490)					0.166**	(0.024)				
$\rho_{\text{Tunisia–Jordan}}$	0.024	(0.631)					0.112*	(0.054)				
$\rho_{\text{Turkey–Jordan}}$	−0.001	(0.036)					0.152**	(0.017)				
$\rho_{\text{U.S.–Jordan}}$	−0.016	(0.714)					0.130*	(0.088)				
$\rho_{\text{Saudi Arabia–Egypt}}$	0.069	(0.203)					0.224***	(0.010)				
$\rho_{\text{Tunisia–Egypt}}$	0.011	(0.817)					0.098*	(0.093)				
$\rho_{\text{Turkey–Egypt}}$	0.100**	(0.027)					0.333***	(0.000)				
$\rho_{\text{U.S.–Egypt}}$	0.086**	(0.041)					0.398***	(0.000)				
$\rho_{\text{Tunisia–Saudi Arabia}}$	0.105**	(0.012)					0.027	(0.716)				
$\rho_{\text{Turkey–Saudi Arabia}}$	0.146***	(0.000)					0.147**	(0.017)				
$\rho_{\text{U.S.–Saudi Arabia}}$	0.111***	(0.008)					0.235***	(0.001)				
$\rho_{\text{Turkey–Tunisia}}$	0.015	(0.765)					0.116	(0.104)				
$\rho_{\text{U.S.–Tunisia}}$	0.054	(0.203)					0.018	(0.759)				
$\rho_{\text{U.S.–Turkey}}$	0.325***	(0.000)					0.535***	(0.000)				
Multivariate diagnostic												
Li–McL Q(10)	434.802	(0.521)					364.484	(0.409)				
Li–McL Q^2(10)	295.944	(0.992)					536.858	(0.419)				

Notes: Q(10) and Q^2(10) are the univariate Ljung–Box test statistics for serial correlation in standardized and squared residuals, respectively. Li-McL Q(10) and Li-McL Q^2(10) are the multivariate Li and McLeod's (1981) test statistics for serial correlation in standardized and squared residuals, respectively. The values in parentheses are the actual probability values.

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

oil. Similar results were found in Hammoudeh, Yuana, and Smimou (2008).[27]

Furthermore, Panel B in Table 4 shows a substantial change in co-movement with the U.S. following 2008. The association with the U.S. jumped from insignificant pre-crisis to become relatively high and significant in the period that followed the crisis. The average conditional correlation between the U.S. and Egypt increased from 8.6% to 39.8%. Similarly the average with Saudi Arabia increased from 11.1% to 23.5%, and finally with Turkey it increased from 32.5% to 53.5%. These results imply that the MENA stock markets are more integrated to the U.S. market during stress when volatility is high. The implication for a U.S. investor is clear failure of diversification during uncertain conditions.

Fig. 4 displays the time series of conditional correlations generated by the DCC model during the period 1998–2013. As seen in the figure, pair-wise correlations reached their peak during the second half of 2008. Compared to previous associations, the conditional correlation across MENA markets have increased by 100% on average. The spike in association has continued and started to revert back to its initial lower levels only after 2010. The plot of correlations of returns to equities over the entire sample period shows that time varying correlations demonstrate less fluctuation, and that the pattern of these fluctuations is relatively stable for all combinations of U.S. equity and other MENA equity markets. In the pre-crisis period all markets show relatively low positive conditional correlations with the U.S. market. The greatest correlation was in the Turkish market. These correlations trended downward in the run up to the financial turmoil in 2008 reflecting the deterioration in the importance of the U.S. in the information transmission of returns. However, during the crisis year, correlations increased sharply to a higher level, and they have not recovered their initial levels. Thus there is substantial evidence of a rise in transmissions and correlations with the U.S. over the last few years. Based on the magnitude of conditional correlation mean values in percentage terms, Turkey, Egypt, and Saudi Arabia seem to be the most influenced by U.S. financial crisis.

To check contagious effects between the U.S. and MENA markets we regressed the time varying correlations on conditional volatility (see Eq. (7)). Table 5 contains the regression results across all MENA and U.S. markets. As can be seen in the table, the coefficients associated with the U.S. conditional volatility were all found to be positive and statistically significant at conventional levels, with the exception of Tunisia. Thus we may conclude that contagious effects are significant and that the pairwise correlation with the U.S. depends significantly on the conditional volatility of U.S. equities. This implies that the computed conditional correlations between the U.S. market and the MENA markets rise with the volatility of the U.S. market. Therefore, we hope that the induced bias on conditional correlations due to these contagious effects will only be small and that inference on interdependence can still be derived from dynamic conditional correlations.

The same contagious influence is not relevant to our analysis of volatility transmissions and interdependence in MENA markets. As mentioned previously, the inference here is derived using a spillover index methodology that is independent of conditional volatilities and therefore the spillover results are not biased. We turn to discuss volatility spillovers.

[27] Using the same methodology, Awartani and Maghyereh (2013) have shown significant co-movement between oil and GCC equities. Unlike MENA countries, the GCC are all net exporters of oil and their economies are more closely dependent on its revenues.

4.2. Results of volatility spillovers

Volatility spillovers results are shown in Table 6. All results are based on vector autoregressions of lag-length of 2,[28] and generalized variance decompositions of the 10 week ahead forecast errors. The (i, j) entry in each panel is the estimated contribution to the forecast error variance of market i coming from innovations to market j (see Eq. (9)). Those labeled "Contribution to others" correspond to the directional spillovers from a market to all other markets (see Eq. (12)) and finally "Contribution from others" corresponds to the directional spillovers from all markets to a particular market (see Eq. (13)). The total spillover index as in Eq. (11) is reported in the lower right corner of each panel, expressed as a percentage.

Panels A and B of Table 6, reports the estimates of volatility spillover for the pre- and post-crisis sample periods respectively. Several interesting findings emerge from this table. First, in all cases, the results clearly show that the highest share of volatility forecast error is originating from own-market volatility rather than from volatility of other markets. This stresses the importance of local political and economic factors as sources of volatility in MENA markets. However, the importance of own-market volatility has decreased significantly in the post-crisis period, which witnessed an increase in the importance of external factors in driving local volatility. For instance, own-volatility innovations explained around 94% of total variation in most countries in the pre-crisis period. This figure has dropped to around 74% post-crisis. Thus it can be said that the influence of regional and global markets has increased in the post-crisis period.

Second, there was a dramatic increase in the influence of the U.S. in the post-crisis period. In the pre-stress period the influence of the U.S. on all other markets was small and negligible, even in comparison to the contribution of other countries. For instance, the U.S. contribution was 6%, which was smaller than the contribution of Jordan, Saudi Arabia, and Turkey at 9%, 7%, and 8% respectively. However, after the Lehman Brothers' shock, the U.S. contribution rose to 78%. The evidence points to a switch in the U.S. role in the information transmission mechanism of the MENA region following the financial turmoil in 2008. The increased influence of the U.S. can also be spotted by looking into net pairwise volatility spillovers with U.S. market. From almost nothing pre-crisis, the U.S. suddenly became a net giver of volatility to MENA countries post-crisis. Its volatility contribution to others was highest for Turkey and Egypt, and lowest for Tunisia; a net spillover of 35.5%, 16%, and 1.2% for the three countries respectively. A high volume of trade between the U.S. and Turkey and Egypt is a possible explanation for the impact of U.S. market stress on the variances of these two markets.

Third, in the MENA region, the Saudi market is the driving force, and its influence was even more pronounced in the post-crisis period. In particular the matrix shows that in every pairwise comparison of directional spillovers with a particular MENA country, the Saudi market was a net giver. For instance, transmissions from the Saudi market to the Turkish and Egyptian markets in the post-crisis period were 6.0% and 6.1% for the two countries respectively. However, transmissions in the opposite direction were around 3.9% and 2.7% for Turkey and Egypt respectively. This pattern and information transmission holds true for every country's stock market in the MENA countries.

Lastly, and most importantly, the total volatility spillover index, which is reported in the bottom corner of Panels A and B of Table 6, and which effectively summarizes volatility spillovers in a single measure, suggests that volatility spillovers in post-crises were

[28] This lag-length is chosen based on the AIC and BIC criteria.

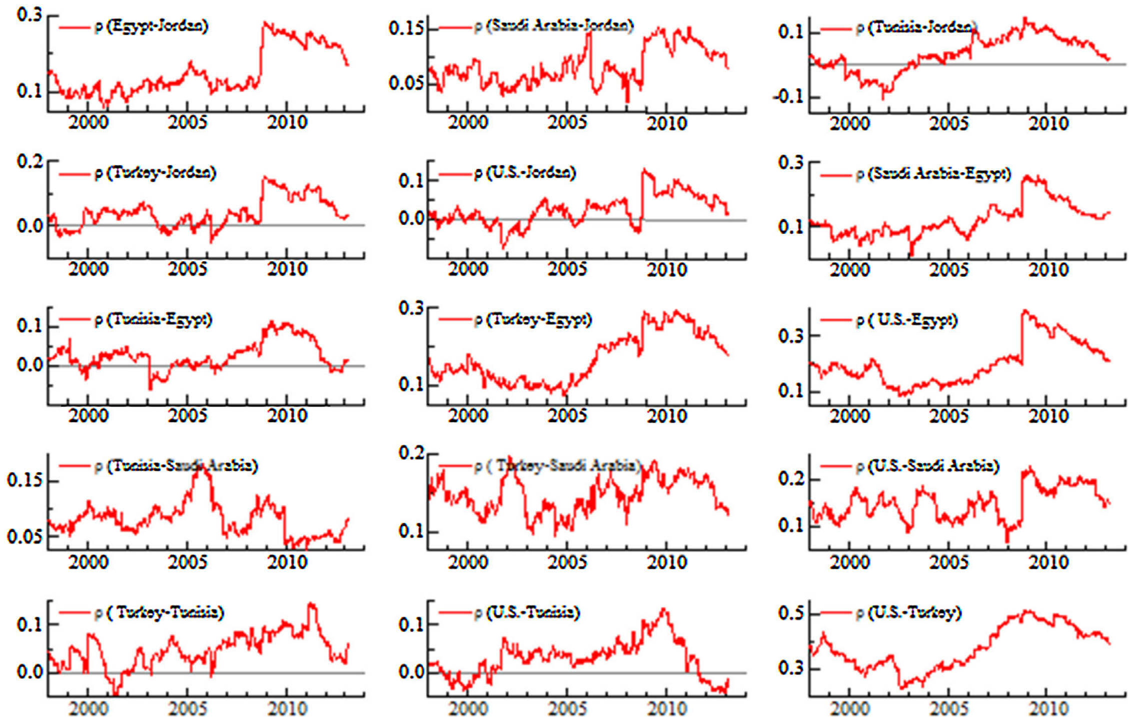

Fig. 4. Estimated time-variations of conditional correlations from the DCC–GARCH model (02/01/1998–15/02/2013).

Table 5

Dynamic conditional correlation and contagion effect test $\rho_{i,j,t} = \alpha_{ij,0} + \alpha_{ij,1}t + \sum_{k=1}^{p} \rho_{ij,t-k}\beta_{i,t}h_{i,t} + \beta_{j,t}h_{j,t} + \varepsilon_{ij,t}$.

	$\alpha_{ij,0}$	$\alpha_{ij,1}$	$\beta_{i,t}$	$\beta_{j,t}$	$Adj.R^2$
$\rho_{\text{Jordan–U.S.}}$	−0.003** (0.014)	3.4e−6*** (0.007)	0.002 (0.990)	0.658*** (0.000)	0.495
$\rho_{\text{Egypt–U.S.}}$	−0.004*** (0.000)	6.0e−6*** (0.000)	0.515*** (0.001)	1.021*** (0.000)	0.538
$\rho_{\text{Saudi Arabia–U.S.}}$	0.001 (0.374)	1.9e−6* (0.081)	0.277* (0.069)	0.557*** (0.000)	0.294
$\rho_{\text{Tunisia–U.S.}}$	−0.000 (0.592)	−1.9e−7 (0.836)	−0.060 (0.821)	0.263* (0.053)	0.120
$\rho_{\text{Turkey–U.S.}}$	0.002 (0.110)	−7.2e−8 (0.971)	−0.199 (0.270)	0.298** (0.026)	0.522

Notes: The regression model is estimated using the OLS method. The coefficients of lagged dependent variable are not reported; however, the first lags are significant at 1% level in all cases with coefficient estimates of more than 0.95. We reported *adj.R*^{2} without lagged dependent variable in the regression model. The values in parentheses are the actual probability values.

* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

significantly higher than in the pre-crisis period. Particularly, 5.6% of volatility originating in MENA markets is due to spillovers in the pre-crisis period. This number has risen fivefold and to 25.1% post-crisis. This indicates the increased volatility spillovers among the MENA markets in stress.[29]

It is well known that at any time the information transmission may change. For instance, when potential risks are substantial; linkages spike and spillovers increase. Moreover as stock markets open up for foreign investment, or as these markets receive more attention, the risk of shock transmission increases. Hence the computation over the whole sample will not be able to capture these important cyclical and secular changes. Thus to obtain dynamics of transmission, we now estimate the vector autoregression using a 100-week rolling window and we assess the extent and nature of spillover variation over time by analyzing the corresponding time series of the spillover index. Fig. 5 displays a time series of the total spillover index in Eq. (11) that is generated from rolling samples.

Fig. 5 shows that in the pre-crisis period, volatility spillovers moved relatively smoothly and fluctuated between 10% and 25%. However, with the advent of the financial crisis, spillovers jumped to reach 50% by February 2008. Then they remained above 45% until the end of 2010 at which time they started to subside to the pre-2008 levels. A two week forecast horizon in the VAR model or even the exclusion of the U.S. market from the system could not have changed these results.[30]

To investigate the directional spillovers from the U.S. market to the MENA stock markets more, we computed the corresponding time series of gross spillovers as in Eqs. (12)–(14). The bar charts of these measures are presented in Fig. 6. The volatility spills from the U.S. market to all MENA stock exchanges as in Eq. (12) are plotted in Panel A. The opposite spills in returns as in Eq. (13) are plotted

[29] An exclusion of the U.S. market could not have changed these results. The estimates without the U.S. are not presented and are available from the Authors upon request.

[30] Various lags in the VAR models show similar results as well; thus we are also robust to lag selection.

Table 6
Volatility spillovers.

To market i	From market j						
	Egypt	Jordan	Saudi Arabia	Tunisia	Turkey	U.S.	Contribution from others
Panel A: pre-crisis period, 02/01/1998–09/09/2008							
Egypt	97.6	1.0	0.7	0.5	0.3	0.1	2
Jordan	0.4	91.4	6.0	0.6	0.8	0.8	9
Saudi Arabia	0.2	5.0	93.4	0.0	0.2	1.1	7
Tunisia	0.3	1.5	0.1	96.5	1.2	0.4	4
Turkey	0.5	0.9	0.1	0.2	94.4	3.5	6
U.S.	0.0	0.1	0.5	0.9	5.5	92.9	7
Contribution to others	2	9	7	2	8	6	34
Contribution including own	99	100	101	99	102	99	Total spillover Index = 5.6%
Post-crisis period, 16/09/2008–15/02/2013							
Egypt	72.7	1.4	6.1	2.5	1.1	16.0	27
Jordan	4.8	75.3	1.9	1.2	5.3	11.6	25
Saudi Arabia	2.7	0.4	73.5	4.2	5.4	13.9	26
Tunisia	3.2	0.1	0.7	94.6	0.2	1.2	5
Turkey	6.4	1.6	6.0	3.9	46.6	35.5	53
U.S.	0.4	2.0	7.9	1.1	1.9	86.8	13
Contribution to others	17	5	23	3	14	78	151
Contribution including own	90	81	96	98	60	165	Total spillover index = 25.1%

Notes: The underlying variance decomposition is based on a weekly VAR system with two lags. The (i, j) value is the estimated contribution to the variance of the 10 step ahead stock return (volatility) forecast error of country i coming from innovations to stock returns volatility of country j. The decomposition is generalized, and thus it is robust to the ordering shown in the column heading.

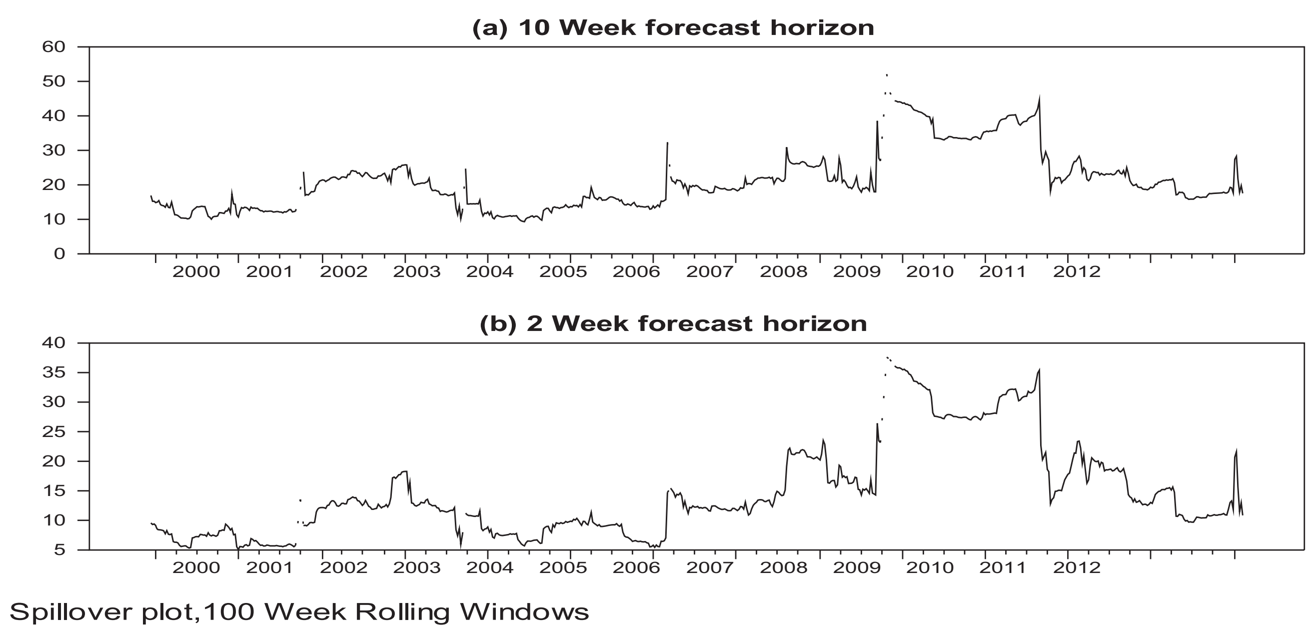

Fig. 5. Dynamic volatility spillover index.

in Panel B. Finally, the net spills as in Eq. (14) are plotted in Panel C.

Fig. 6 shows that volatility transmission from the U.S. to MENA was low in the period that preceded the financial crisis in 2008. However, transmissions from the U.S. to the rest of MENA exploded during September and October of 2008. The increase in transmission has never reverted to their initial levels.[31]

Fig. 7 presents the net volatility spillovers from the U.S. market to each of the MENA markets. The figures were obtained by estimating Eq. (15) using 100-week rolling windows. Initially, from 1998 to 2007, the net volatility spillovers from the U.S. market to each of the MENA markets were very weak and fluctuated around zero. However, with the first drizzles of the subprime financial crisis and the credit crunch at the end of 2006,[32] the transmission of volatility from the U.S market to each of the MENA markets suddenly jumped. The climax was reached for most markets during the collapse of the Lehman Brothers in mid-September 2008. Thus, we may conclude that the U.S. is a leading indicator of other markets,

[31] Note that spills from the U.S. to MENA have increased by more than fivefold during the crisis period.

[32] The first sign of the subprime mortgage crisis appeared in November 2006, when the Commerce Department reported that new home permits dropped by 28% from the year before.

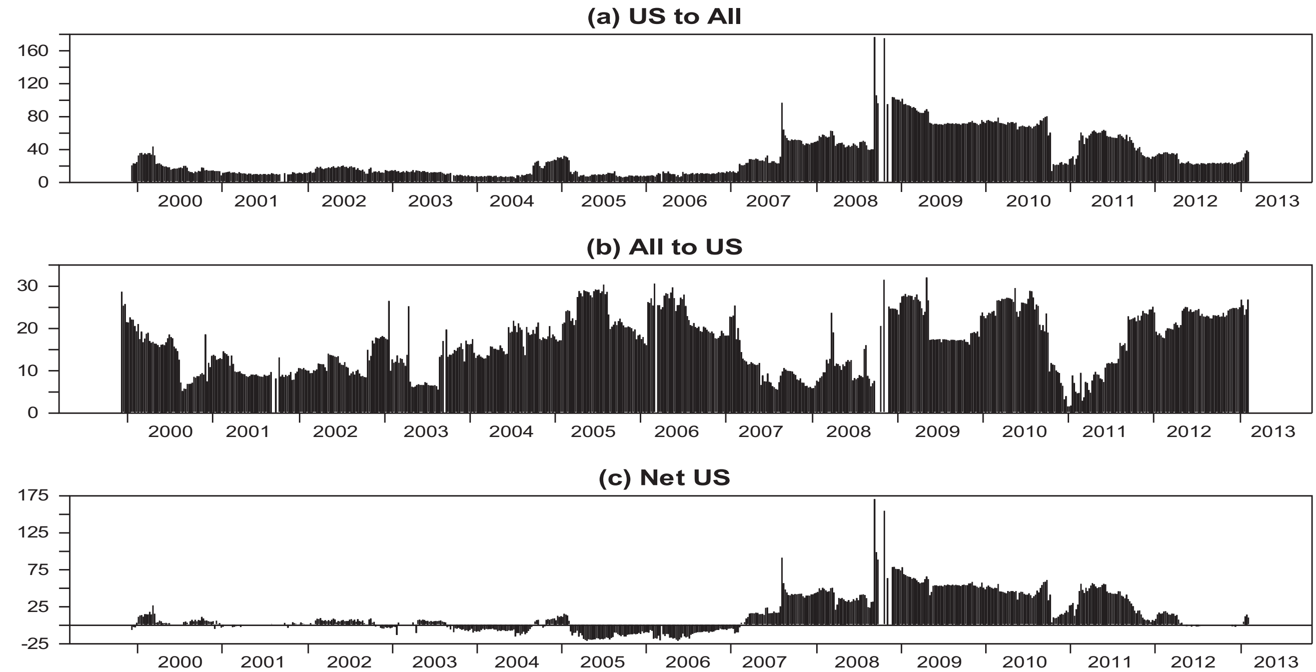

Fig. 6. Dynamic volatility spillovers from the U.S. market to the MENA markets.

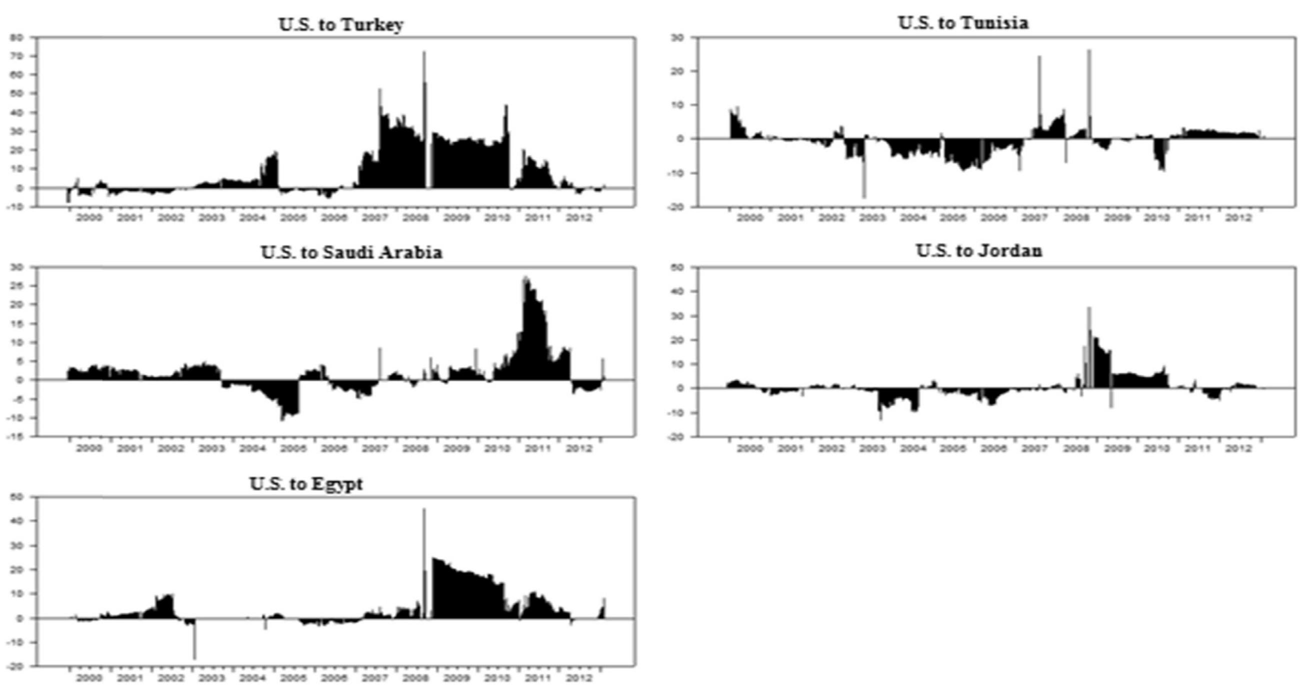

Fig. 7. Pairwise directional net volatility spillovers between the U.S. market and MENA markets.

and that the U.S. has had a far reaching impact on other markets during the financial crisis period.

4.3. Implications for portfolio diversification

The results reported above indicate that the diversification benefits between the U.S. and the MENA countries were reduced due to an increased level of spillovers and association between the two regions. To quantify the loss in diversification potential we simulated portfolios consisting of U.S. and MENA equities. The hypothetical portfolios were constructed by imposing limit restrictions on the weights allocated to individual countries.[33] The actual weights of minimum variance portfolios were then computed using a standard Markowitz (1952) mean variance procedure.[34]

[33] The market regulations in MENA exchanges prohibit short selling. Therefore, we imposed restrictions on the weights to be positive in the optimization exercise.

[34] Specifically, let w be $n \times 1$ vector of portfolio weights, H be the conditional variance-covariance matrix of DCC model, and n be the number of countries. The

Table 7
Performance of minimum variance portfolios.

Country	Optimal weights (%)						Return (%)	St. dev. (%)	Sharpe ratio
	Jordan	Egypt	Saudi Arabia	Tunisia	Turkey	U.S.			
Panel A: pre-crisis period, 02/01/1998–09/09/2008									
U.S. only	0.000	0.000	0.000	0.000	0.000	100.0	0.921	7.665	0.120
U.S. with MENA markets (unrestricted)	14.254	2.607	5.026	34.371	4.000	39.741	4.388	3.543	1.238
U.S. with MENA markets (min 70% in U.S. and 10% MENA markets)	10.000	4.283	5.115	10.000	0.602	70.000	2.343	5.676	0.413
U.S. with MENA markets (min 70% in U.S. and 20% MENA markets)	9.042	0.466	0.277	20.000	0.214	70.000	2.257	5.557	0.406
U.S. with MENA markets (max 10% in MENA markets)	10.000	10.000	10.000	10.000	1.256	58.744	2.926	5.294	0.552
U.S. with MENA markets (max 20% in MENA markets)	20.000	13.758	8.185	20.00	0.000	38.056	3.918	4.453	0.879
MENA only (unrestricted)	16.863	8.407	11.882	57.662	5.187	0.000	5.229	3.865	1.353
Jordan only	100.0	0.000	0.000	0.000	0.000	0.000	6.432	9.865	0.651
Egypt only	0.000	100.0	0.000	0.000	0.000	0.000	6.700	11.849	0.565
Saudi Arabia only	0.000	0.000	100.0	0.000	0.000	0.000	4.726	11.099	0.425
Tunisia only	0.000	0.000	0.000	100.0	0.000	0.000	4.862	4.422	1.099
Turkey only	0.000	0.000	0.000	0.000	0.000	100.0	8.998	19.641	0.458
Panel B: post-crisis period, 16/09/2008–15/02/2013									
U.S. only	0.000	0.000	0.000	0.000	0.000	100.0	2.207	9.303	0.237
U.S. with MENA markets (unrestricted)	12.733	3.000	8.000	46.138	2.000	28.129	1.585	5.504	0.288
U.S. with MENA markets (min 70% in U.S. and 10% MENA markets)	10.000	6.252	3.048	10.000	0.000	70.000	1.260	7.755	0.163
U.S. with MENA markets (min 70% in U.S. and 20% MENA markets)	10.000	0.000	0.000	20.000	0.000	70.000	1.683	7.133	0.235
U.S. with MENA markets (max 10% in MENA markets)	10.000	7.665	9.171	10.000	4.323	58.841	0.026	1.068	0.024
U.S. with MENA markets (max 20% in MENA markets)	20.000	4.362	1.942	20.000	3.373	50.323	0.941	6.682	0.140
MENA only (unrestricted)	21.107	3.608	5.971	65.962	3.352	0.000	1.682	5.096	0.330
Jordan only	100.0	0.000	0.000	0.000	0.000	0.000	−5.305	10.681	−0.496
Egypt only	0.000	100.0	0.000	0.000	0.000	0.000	−1.077	14.386	−0.074
Saudi Arabia only	0.000	0.000	100.0	0.000	0.000	0.000	−0.435	11.261	−0.038
Tunisia only	0.000	0.000	0.000	100.0	0.000	0.000	8.239	12.605	0.653
Turkey only	0.000	0.000	0.000	0.000	0.000	100.0	3.343	5.520	0.605

Table 7, Panel A, presents the weights, the mean return, the standard deviation and the Sharpe ratio of the simulated portfolios in the pre-crisis period. The panel shows that a reallocation to MENA in a portfolio that is fully invested in U.S. equities significantly improves the risk-return trade off of U.S. investors. For instance, if we begin with a portfolio consisting of 100% U.S. equities, portfolio returns would have been approximately 0.921%, and its standard deviation would have been 7.665%. However, because the mean return on MENA equities is larger, and they are weakly associated; return on this portfolio could have been increased and risk could have been reduced by substituting MENA equities for U.S. equities. For instance, by allocating 30% to MENA equities, portfolio returns are more than doubled and risks are reduced by more than 26%. The gains in returns and the drop in portfolio volatility led to a big increase in the Sharpe ratio, which has jumped more than threefold and from 0.12 to 0.4.

If we optimize a portfolio that includes U.S. and MENA equities without imposing any weight restrictions; the diversification benefits is even greater. In the minimum variance unrestricted portfolio in Panel A, an allocation of 60% to MENA equities has resulted in more than a fourfold increase in returns; while volatility has dropped to half its value compared to a portfolio that is fully invested in the U.S. The positive influence on returns and volatility has translated into an even stronger effect on the Sharpe ratio, which has increased tenfold, and from 0.12 to 1.2 for the portfolio that contains MENA equities. The upshot here is that in the period before the global financial crisis, venturing into MENA equities could substantially improved a U.S. portfolio due to higher returns and weaker association and spillovers.

The pre-crisis intra diversification benefits among MENA equities were also significant, but only to a lower extent; and they were unanimous across all countries. As can be seen in Panel A, Table 7, the greatest benefits are realized by Saudi investors, as the Sharpe ratio jumped by three folds compared to a portfolio that is only invested in the Saudi market. On the other hand, the benefits for Tunisian investors were marginal as the Sharpe ratio was only slightly improved. In most countries, return enhancement was not substantial and most of the benefits were achieved in terms of risk reduction. The greatest risk reduction was enjoyed by Turkish investors when diversification reduced the standard deviation from 19% to 3.8% only. The cost of dissipating these 15% points of risk was only a 4% drop in returns, and therefore the risk return tradeoff of Turkish investors had significantly improved.

These relationships and their associated diversification benefits were not carried forward in the period after the financial crisis. Panel B, Table 7 shows the weights, the mean return, the standard deviation and the Sharpe ratio of optimal portfolios in the post-crisis period. As can be seen in the Panel, the portfolio return enhancement of rebalancing toward MENA equities has completely disappeared. On the contrary, portfolio returns are higher when it is fully invested in U.S. equities. The expected return on a portfolio that is fully invested in the U.S. is 2.207%, while the expected return of reallocating 30% to MENA equities is only 1.26%. The reason for that is the bad performance of MENA equities

optimal weights are then calculated by solving the following optimization problem:

$$\text{Minimize}_w w'H_t w \quad \text{s.t.} \sum_{i=1}^{n} w_i = 1, 0 \leq w_i \leq 1 \quad \text{for } i = 1, \ldots, n.$$

compared to U.S. equities, which had recovered soon after the crisis.

On the contrary of the negative influence on returns, risk can still be reduced by investing in other MENA equities, albeit risk reduction is lower due to increased correlation in the post-crisis period. For instance, a 30% allocation to MENA equities would have reduced volatility from 9.303% to 7.755%. This constitutes a reduction of 16% compared to 26% reduction in the same portfolio before the crisis. The volatility of all simulated portfolios is higher compared to portfolios in Panel A, and while risk can still be reduced by diversification, the extent of the reduction is less.

The increased spillovers eliminated some of the diversification benefits that could have been collected by U.S. investors. However the Sharpe ratios of the simulated portfolios that included both U.S. and MENA equities continued to beat other portfolios even in the periods of stress. Furthermore, as correlations started to drop following 2010; we expect a full recapture of diversification benefits between the two regions in the near future.

In a similar fashion, relationships and diversification potential was dramatically changed across MENA equities. Table 7 shows a total reversal of the portfolio that contains MENA equities following the crisis. The Sharpe ratio of this portfolio has dropped by three quarters and from 1.353 to 0.330. Compared to the portfolio that includes both U.S. and MENA equities; the deterioration in the Sharpe ratio of the MENA portfolio was greater.[35]

Table 7 also shows that diversification had a negative impact on the risk return tradeoff in Tunis and Turkey. It had only positive effect on Jordan, Saudi Arabia and Egypt. These benefits are only marginal when they are compared to the pre-crisis period. In the post-crisis period, the Turkish and the Tunisian stocks grew by 3.3 and 8.2% respectively. Moreover, the volatility of the Turkish market had subsided compared to the pre-crisis period. Therefore, compared to other portfolios, the Sharpe ratios of Turkey and Tunis were higher. Moreover, the stock performance in the rest of MENA was poor. There was a drop in the value of equities in Jordan, Egypt and Saudi Arabia, and this explains their poor performance in terms of the Sharpe ratios. To reiterate, most of the realized improvement in diversification toward other countries in the block came from the risk reduction associated with diversification.

The changed performance, risk and relationships in the post-crisis period has negatively influenced inter and intra diversification benefits of MENA equities. Therefore, we conclude that the addition of MENA equities to a U.S. portfolio would have unambiguously and significantly improved portfolio performance but only in the period that preceded the global financial crisis. The bad performance of MENA equities and the increased association among stock markets post-crisis have negatively influenced risk reduction and risk return tradeoffs of portfolios that contain MENA and U.S. equities.

5. Conclusion

In this paper we show that MENA stock markets are moderately correlated and that they are weakly integrated with the U.S. market in normal conditions. Furthermore we show that this structure of relationships changes dramatically during periods of stress; especially in terms of the relation with the U.S. market. In stress, the transmission of information from the U.S. explodes to a much higher level and MENA markets become more integrated among themselves.

Our results are consistent with those previously obtained and stressed the unidirectional transmission from U.S. stock market to the rest of stock markets around the globe.[36] However, our results differ in that we find the unidirectional relationship is only pronounced in periods of stress; while in normal conditions the relationship can be safely ignored.

Similar increases in transmissions during stress were recorded in South American and East Asian stock exchanges by Diebold and Yilmaz (2009), and Yilmaz (2010). Correlation increases among stocks, bonds, and commodities were also found in Diebold and Yilmaz (2012). Our results are similar to Diebold and Yilmaz's (2012) because we found that volatility spillover has increased following the global financial crisis in 2008.

These results have important implications on the benefit of diversifying into MENA equities. In particular MENA equities are returns enhancers and risk diversifiers during normal conditions. The Sharpe ratio of a portfolio that contains MENA stocks is ten times higher than a portfolio that is fully invested in the U.S. The benefits of diversification remain even during modes of stress, albeit it is less. Over the longer term, the diversification benefits of a global portfolio that is venturing into MENA equities are recaptured as correlations revert to their initial low level.

The fast growth potential of MENA equities following the rise in oil prices, the shift in global growth toward developing countries, the high corporate profits realized in the region, and the structural reforms implemented across countries could potentially enhance the return and reduce the risk of a global portfolio and thus, improve the associated risk adjusted performance in normal periods.

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[35] This point has been raised to us thankfully by one of the referees.

[36] From the recent literature, see for instance Muherjee and Mishra (2005), Kim, Moshirian, and Wu (2005), Wang, Gunasekarage, and Power (2005), Baur and Jung (2006), Chuang et al. (2007), Chen, Huang, and Lin, (2007), Elyasiani and Zhao (2008), Morana and Beltratti (2008), Yu and Hassan (2008), and Sosvilla-Rivero and Rodríguez (2010).

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