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Full Length Article

# Causality and contagion in emerging stock markets

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**Abstract**

Given the evidence of occasional discrete shifts in the conditional variance process, it is essential to test the volatility transmission between financial markets when a reasonable suspicion exists for structural change. This paper aims to study the interdependencies in terms of stock market volatility and to assess the impact of Global Financial Crisis (GFC) on these interdependencies. We found evidence of structural breaks in the volatility of time series for the majority of markets. The results show also that, in view of the crisis, new significant causal linkages appeared together with the intensification of the causal relationship in 40% of the cases in which we find causality during both the tranquil and crisis period. These additional linkages during crisis periods in excess of those that arise during non-crisis periods contributes significantly in amplifying the international transmission of volatility and the risk of contagion.


*Keywords:* Causality; Contagion; Structural breaks; Global financial crisis; Emerging stock markets; Granger causality test

## 1. Introduction

In light of the calm and turbulence of the global stock markets during the recent years due to domestic, macroeconomic and political events, and financial crises, the models which take into consideration structural breaks, may prove to be a more appropriate characterization of stock return volatility than the ones ignoring structural shifts. In parallel, periods of high and low volatility have been succeeding. These spectacular volatilities may lead to instability of economies ready to be exported through a contagion effect given the fact that the interdependence of the different financial markets are bound in terms of returns and volatility.

The succession of crises during the 1990s, from the Mexican crisis (1994–1995), the Asian crisis (1997), the Russian crisis (1998) and the Argentinean crisis (2001) to the recent Subprime crisis, the global financial crisis (GFC) showed that financial shocks in one country can quickly affect other countries and have bad effects on several other financial markets. More specifically, during the subprime crisis of the summer 2007 when the financial markets of developed and emerging countries have been seriously affected. This has fueled the debate on the contagious character of these financial crises and highlighted its importance. Generally the terms stock market 'relations', 'linkages' and 'interdependence' are used synonymously. Recent authors though (Baele & Inghelbrecht, 2010; Billio & Caporin, 2010; Corsetti, Pericoli, & Sbracia, 2005; Forbes & Rigobon, 2002; and; Gębka & Karoglou, 2013) subdivide stock market 'linkages' or 'relations' into 'interdependence' and 'contagion'. In contrast to that, the state of 'contagion' is characterized by strong and sudden changes in measured market linkages. To be more precise, by saying contagion we refer to a significant increase in co-movement across markets after a shock. This definition goes back to Forbes & Rigobon (2002), 'Interdependence' thereby stands for a state of 'continuous', 'normal' or 'tranquil-period' relation between markets.

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In this context, this paper is structured as follows. Section 2 presents a brief overview of the literature. Section 3 provides a brief explanation of our econometric methodology. Section 4 describes the data and the descriptive results. Section 5 presents and discusses the empirical results. Finally, the last section concludes the paper.

## 2. Literature review

Despite the strand of research, which is specifically concerned on stock prices in the well-developed financial markets, less is known about it in other markets, specifically in emerging markets. Research on these markets has focused on the issue of efficiency as well as on their integration with international markets. Sensoy (2013) examined the efficiency of MENA stock markets, the study covers the period from January 2007 to December 2012. The results show that all stock markets have different long-term degrees of dependence that vary over time and that the political transition had a negative effect on the efficiency of the markets in the region. Moreover, Hammoudeh & Li (2008) tested sudden changes in volatility for five Gulf area Arab stock markets, they found that most of these stock markets were more influenced by major international events than local and regional factors. Neaime (2016) examined contagion vulnerability of the MENA stock markets by using the Granger causality tests. The results show that the GCC is relatively less vulnerable to global and regional financial crises. However, the remaining MENA stock markets of Egypt, Morocco and Tunisia, that have been matured and are financially integrated with the world stock markets, show more vulnerability to regional and international financial crises. Abdmoulah (2010) examined Arab stock markets, and concluded that all markets are highly sensitive to past shocks and are judged inefficient. In addition, returns react to contemporary crises, except some temporary sub-periods advancements of improvement for larger markets. Chau, Deesomsak, & Wang (2014) found that Arab Spring and the political turbulence have an impact on volatility of MENA stock markets, in particular for the Islamic indices. Nevertheless, there is little or no significant effect on their interaction and integration with the World market. Guyot et al. (2014) studied whether foreign financial shocks had an impact on the cost of equity in emerging markets. Based on theoretical discussion, they had developed annual metrics for the international cost of equity, financial integration, spillovers and shift-contagion vulnerability in a sample of 535 Middle East and North African firms from Egypt, Tunisia, Morocco and Jordan for the 1998–2011 period. They examined the effect of foreign shocks on the international cost of equity, using SGMM and PVAR techniques. They found that external shocks could increase the cost of equity in mature emerging markets. Assaf (2016) examined the MENA stock markets with taking into consideration the shift dates and corresponding to the 2008 financial crisis, and found that the returns and volatility measures display less evidence of long memory in the after crisis period as opposed to the before crisis period.

Many reasons suggest that this subject is essential and relevant. First, according to the relatively long sample period of our study which includes various crisis events, it seems logical to investigate the structural stability of financial markets. Then, the researches made on emerging financial markets are minimal and do not receive much attention as that given to developed financial markets. However, few studies focused on the causality and the direction of the interactions which might link the emerging stock markets. More specifically, a particular attention is paid to explore the contagion through examining the intensification or the reduction of causal relationships.

The importance of the Middle East and African stock markets is that, in recent years, many African markets offer very high returns for investors. There was at least an African stock market in the top Ten of the best performing markets in the world every year since 1995 (Giovannetti & Velucchi, 2013).

To our knowledge, previous researches which used the Granger Causality test, concentrated on the investigation of changes in cross-market interdependencies, but in our paper, we make use of Final Predictive Error and thus assess the intensification or reduction in the causal relationship.

The purpose of this study is to identify sudden breaks in volatility of financial time series and to examine the interdependencies in terms of stock market volatility between financial markets between emerging stock markets during the period 2005–2015, in the context of the Global Financial Crisis (GFC).

By applying the Granger-causality approach, we have investigated changes in the existence and the directions of causality between these countries. Our strategy is based on the comparison of the interdependencies on two phases (before and after the GFC). We found evidence for new and changed causality patterns, considered as a proof of volatility transmission.

$$y_t = a_0 + \sum_{i=1}^{M} \phi_1 y_{t-i} + \varepsilon_t \tag{1}$$

$$y_t = a_0 + \sum_{i=1}^{M} \phi_i y_{t-i} + \sum_{j=1}^{N} y_j X_{t-j} + \varepsilon_t \tag{2}$$

## 3. Econometric methodology

### 3.1. Testing for causality

Granger causality or G-causality is named after the econometrist Clive Granger, it is a technique for determining whether one time series is useful in forecasting another G-causality which is grounded in econometric and time-series analysis and is defined using predictability and temporal precedence. According to Granger causality, if a signal $X_1$ "Granger-causes" (or "G-causes") a signal $X_2$, then past values of $X_1$ should include information which would be of assistance to predict $X_2$ above and beyond the information contained in past values of $X_2$ alone.

Granger-causality tests are sensitive to lag length and, therefore, it is important to select the suitable lengths. Hence it is important that the lengths selected should be the appropriate ones to avoid inconsistently estimating the model and drawing misleading inferences Thornton & Batten (1985). In this paper, we follow Hsiao's (1981) sequential method to test for causality generalization, which combines.

Akaike's (1974) final predictive error (FPE) and the definition of Granger-causality. Essentially, the FPE criterion trades off the bias that emerges from under-parameterization of a model against the loss in efficiency that emanates from its over-parameterization.

Hsiao's variant of Granger-causality proceeds as follows. Suppose we want to test Granger-causality for two stationary variables, $X_t$ and $Y_t$. Consider the following models:Where $X_t$ and $Y_t$ are covariance-stationary variables [i.e., they are $I(0)$ variables]. The procedure is divided into six steps:

i. Consider $Y_t$ as a one-dimensional autoregressive process (1), and compute its FPE with the order of lags $m_i$ varying from 1 to M.

$$FPE_y(m_i, 0) = \frac{T + m_i + 1}{T - m_i + 1}\frac{SSR}{T}$$

where T is the total number of observations and SSR is the sum of squared residuals of OLS regression (1). Choose $m_i$ for the value of m that minimizes the FPE, say m, and denote the corresponding value as $FPE_y(m, 0)$.

ii Treat $Y_t$ as a controlled variable with m number of lags, and treat $X_t$ as a manipulated variable as in (2). Compute again the FPE of (2) by varying the order of lags $n_i$ of $X_t$ from 1 to N.

$$FPE_y(m_i, 0) = \frac{T + m_i + n_i - 1}{T - m_i - n_i - 1}\frac{SSR}{T}$$

choose the order $n_i$ which gives the smallest FPE, say n, and denote the corresponding FPE as $FPE_y(m, n)$.

iii Compare $FPE_y(m, 0)$ with $FPE_y(m, n)$ [i.e., compare the smallest FPE in step (i) with the smallest FPE in step (ii)]. If $FPE_y(m, 0) - FPE_y(m, n) > 0$, then $X_t$ is said to cause $Y_t$. If $FPE_y(m, 0) - FPE_y(m,n) < 0$, then $Y_t$ is an independent process.

iv Repeat steps i) to iii) for the $X_t$ variable, treating $Y_t$ as the manipulated variable.

When $X_t$ and $Y_t$ are not stationary variables, but is first-difference stationary [i.e., they are $I(1)$ variables] and cointegrated (see Dolado, Jenkinson, & Sosvilla-Rivero, 1990), it is possible to investigate the causal relationships from $\Delta X_t$ to $\Delta Y_t$ and from $\Delta Y_t$ to $\Delta X_t$, using the following error correction models:

$$\Delta y_t = a_0 + \beta Z_{t-1} + \sum\nolimits_{i=1}^{M} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

$$\Delta y_t = a_0 + \beta Z_{t-1} + \sum\nolimits_{i=1}^{M} \phi_i \Delta y_{t-i} + \sum\nolimits_{j=1}^{N} y_j \Delta X_{t-j} + \varepsilon \tag{4}$$

where $Z_t$ is the OLS residual of the cointegrating regression ($y_t = \mu + \lambda X_t$), known as the error-correction term. Note that, if $X_t$ and $Y_t$ are $I(1)$ variables but are not cointegrated, then $\beta$ in (3) and (4) is assumed to be equal to zero.

In both cases [i.e., $X_t$ and $Y_t$ are $I(1)$ variables, and they are or they are not cointegrated], we can use Hsiao's (1981) sequential procedure substituting $Y_t$ with $\Delta Y_t$ and $X_t$ with $\Delta X_t$ in steps (i) to (iv), as well as substituting expressions (1) and (2) with Eqs. (3) and (4).

### *3.2. Structural break tests: Bai and Perron's tests (1998, 2003)*

We use Bai and Perron (1998, 2003) test to detect both the change of mean and variance of emerging stock index returns from April 2005 to March 2015. One of the main advantages of this technique is that it permits us to estimate multiple structural shifts endogenously. It also enables us to generalize specifications, like for instance, determining whether to allow for heterogeneity and autocorrelation in the residuals. We employ a two-step procedure to identify structural break points in the mean and volatility of emerging stock index returns.

We begin our analysis by constructing the Autoregressive (AR) model to describe a time series $r_t$ of stock returns. The general mean return series equation equals the following:

$$r_t = a_0 + \sum\nolimits_{i=1}^{2} a_1 r_{(t-1)} + \varepsilon_t \tag{5}$$

First, we estimate Eq. (5), allowing for the possibility of structural breaks in its coefficients,[1] without prior knowledge of when those breaks occur. After finding some breaks in the parameters of $r_t$ we obtain the residuals from this estimation process. Next, following Cecchetti & Debelle (2006), we identify breaks in the variance through Eq. (6).

$$\sqrt{(\pi/2}|\widehat{\varepsilon}| = c + \mu_t \tag{6}$$

Each set of residuals is assumed to follow a normal distribution and the transformations are unbiased estimators of the standard deviation of $\varepsilon_t$.

In order to select the number of breaks, a common procedure should be used by considering the information criterion. However, the BIC always chooses a much higher value than the true one in the presence of a serial correlation case, as documented by Bai and Perron (2003). We use the "sequential" method, which is described by Bai and Perron (2003) and may prove to be a more appropriate characterization for detecting breaks than the other methods, which they conducted based on simulations. We start by estimating up to 5 breaks in the series for each country. Then, we apply the method

[1] We have applied the Bai and Perron's test to both the constant term and the AR persistence parameters in the mean Eq. (5) to determine the appropriate number of lag length of the VAR model, the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) are employed.

advanced by Bai and Perron (1998), based on the sequential application of the sup $F(k+1/k)$ test, which is performed to detect the presence of $(k+1)$ conditional breaks of having found $k$ breaks ($k = 0, 1, ..., 5$). In the process, rejecting $k$ breaks favors a model with $(k+1)$ breaks, if the overall minimal value of the sum of squared residuals (over all the segments where an additional break is included) is sufficiently smaller than the sum of squared residuals from the model with $k$ breaks. The dates of the breaks selected are the ones associated with this overall minimum.

### 3.3. Testing for causality intensification

In order to investigate possible causal relationships between stock markets, we undertake a Granger causality analysis. A clear causal relationship between the variables could offer insight as to where information discovery takes place. Our study adopts a comprehensive approach to obtain some insights on different patterns of contagion transmission across emerging markets, by applying Granger causality. Since the statistic that we use to detect Granger-causality is $FPE_y(m, 0) - FPE_y(m,n)$, we can measure this statistic before and after the endogenously identified breakpoint (GFC). Using this methodology allows us to identify contagion, by estimating the intensification or reduction in the causal relationship for those pairs in which we have found Granger-causality in both period, and testing for the presence of new significant links among countries after this shock. Hence, an increase of Granger causality signifies an amplification of the statistical predictability of one time series over another one, as evidence of intensification in the transmission mechanism between them.

For this reason, we detect causality both in the tranquil and crisis period, then we compare $FPE_y(m,0) - FPE_y(m,n)$ in these periods. We can talk about an intensification that occurred in the causal relationship if this statistic is higher in the crisis than in the quiet period. Indeed, this result shows that in the crisis period, even though the uncertainty is by definition higher, the $X_t$ (or $\Delta X_t$) in Eq. (2) [or in Eq. (4)] includes relatively more useful information for forecasting the $Y_t$ (or $\Delta Y_t$) which is not included in past values of $Y_t$ (or $\Delta Y_t$), than during the pre-crisis period. Contrarily, we can talk about reduction in the causal relationship, only when this statistic is lower in the crisis period than in the tranquil one, as long as the utility of the delayed additional variables, in the present time, during the process of informing us about the future behavior of the performance examined is less during the crisis period than during the pre-crisis period. Thereby, we are first examining the "forecast conditional efficiency" in the terminology of Granger & Newbold (1973, 1986) [or "forecast encompassing" in accordance with Chong & Hendry (1986) and Clements & Hendry (1993)] of the manipulated variable $X_t$ (or $\Delta X_t$) in Eq. (2) [or Eq. (4)] for the two sub-periods, by evaluating if $X_t$ (or $\Delta X_t$) encloses helpful information for forecasting $Y_t$ (or $\Delta Y_t$) which is not contained in past values of $Y_t$ (or $\Delta Y_t$) and then comparing them and evaluating the relative gains in forecasting exactitude in each period.

## 4. Data presentation and preliminary study

The study period runs from April 2005 to March 2015 with daily data (closing prices) from datastream. For holidays, we based our study on the adjustment of dates where there are holidays to expose themselves against the risk of break in the series of each variable. For the indices used, we converted the value of the indices in dollars so that the evolution of its indices is comparable.

This list is constructed emerging and US stock markets (See Table 1).

Summary statistics for daily returns of various stock markets are presented in the Table 2. This table shows clear evidence of deviations from normality as it can be seen by the high values of skewness and kurtosis. This statistics (LB) for the returns is very significant at 5% for all markets, indicating the presence of serial correlation.

## 5. Empirical results

### 5.1. Structural changes

First, we identified at least one break in the mean equation for 4 of these 11 countries, with two breaks for Bahrain. Then, we found at least 3 breaks in volatility in Egyptian and Tunisian markets, and 4 breaks for the rest of markets. We allowed for as many as 5 breaks as possible, but in no country we have found more than 4. While for the dating of the breaks, we can note that for both mean and variance equations, dates are almost synchronized across countries. Out of the total of 47 breaks in volatility that we have identified, only 3 are in 2006, 4 take place in each one of these years 2007, 2010 and 2012, 6 are in the 2009, 8 occur in both 2011 and 2013, and 10 others are in 2008 (Table 3).

This is clearly consistent with some previous researches, confirming the existence of structural shifts in the financial markets of emerging countries that may be caused by global or regional effects. For instance, Assaf (2016) shows that the global financial crisis has affected all countries, the MENA's relatively low integration into global financial markets have minimized some of the downturn on MENA's economies. The change in the returns and volatility dynamics of these markets was caused by financial and economic conditions that have

Table 1
A list of countries and indexes included in the empirical research.

| Country | Stock Market Index |
|---|---|
| Bahrain | Bahrain All Share (BHSEASI) |
| Dubai | Dubai Financial Market (DFM) |
| Egypt | EGX 100 (EGX100) |
| Jordan | Amman Se Market (ASE) |
| Kuwait | Kuwait SE Market (KSE) |
| Oman | Oman Muscat Securities Mkt (MSM) |
| Saudi Arabia | Saudi Tadawul All Share (TASI) |
| South Africa | FTSE/JSE All Share |
| Turkey | Borsa Istanbul (BIST National 100) |
| Tunisia | Tunisia Stock Exchange (Tunindex) |
| USA | Morgan Stanley Capital International |

Table 2
Summary statics for daily returns.

| Country | Mean | Min | Max | Median | Std | Kurtosis | Skewness | J-B | Q (12) | Qs (12) |
|---|---|---|---|---|---|---|---|---|---|---|
| Bahrain | −0.007 | −4.918 | 3.612 | −0.002 | 0.592 | 9.3514 | −0.4456 | 4579.57* (0.0000) | 109.57* (0.0000) | 347.30* (0.0000) |
| Dubai | 0.011 | −12.157 | 12.203 | 0.002 | 1.904 | 8.5389 | −0.0994 | 3420.079* (0.0000) | 27.749* (0.006) | 1101.8* (0.0000) |
| Egypt | −0.010 | −16.521 | 7.288 | 0.040 | 1.601 | 14.9636 | −1.5615 | 15358.21 (0.0000) | 106.83* (0.0000) | 139.59* (0.0000) |
| Jordan | −0.002 | −20.541 | 19.964 | 1.4338e-04 | 1.238 | 59.2572 | −0.2848 | 352391.8* (0.0000) | 10.344* (0.000) | 638.77* (0.000) |
| Kuwait | −0.001 | −9.115 | 5.036 | 0.037 | 0.826 | 13.7233 | −1.2177 | 13462.51* (0.0000) | 159.84* (0.000) | 347.05* (0.000) |
| Morocco | 0.023 | −6.4808 | 6.126 | 0.017 | 0.984 | 7.6413 | −0.2477 | 2425.578* (0.0000) | 135.50* (0.0000) | 906.43* (0.0000) |
| Oman | 0.023 | −8.697 | 8.039 | 0.005 | 1.096 | 17.9103 | −0.9064 | 25117.10* (0.0000) | 126.34* (0.0000) | 2408.6* (0.0000) |
| Saudia Arabia | 0.002 | −11.686 | 16.215 | 0.068 | 1.688 | 14.384 | −0.632 | 14608.09* (0.0000) | 50.995* (0.0000) | 1192.4* (0.0000) |
| South Africa | 0.024 | −12.852 | 12.889 | 0.099 | −0.251 | 8.3228 | 1.896 | 3182.390* (0.0000) | 33.284* (0.0000) | 2141.3* (0.0000) |
| Turkey | 0.019 | −14.761 | 15.852 | 0.116 | 2.293 | 7.478 | −0.388 | 2300.534* (0.0000) | 23.052* (0.027) | 717.21* (0.0000) |
| Tunisia | 0.033 | −6.357 | 3.839 | 0.030 | 0.708 | 9.067 | −0.263 | 4050,587* (0.0000) | 89.955* (0.000) | 714.27* (0.000) |
| USA | 0,019 | −8200 | 10,508 | 0,050 | 1168 | 14,015 | −0,081 | 13249,89* (0.0000) | 70,595* (0.000) | 3069,3* (0.000) |

Note: * Significant at the 5% level.

occurred in the MENA region after the crisis. Moreover, Hammoudeh & Li (2008) tested sudden changes in volatility for five Gulf area Arab stock markets, over the period 1994–2001 and found that most of these stock markets were more influenced by major international events than local and regional factors. However, Neaime (2012) analyzed the impact of the recent financial crisis in the MENA region, The results show a higher correlation with the U.S. stock market during the crisis, the index of the place of Egypt, the CASE30, ended 2008 with a change of −56.43%. Alkulaib, Najand, and Mashayekh (2009) investigated the lead-lag relationship between the MENA countries and regions and found that there is more interaction and linkage in the Gulf Cooperation Council (GCC) region than in North Africa and Levant regions. Bahloul and Abid (2014) studied MENA stock market, and found that volatility can be described by three regimes: tranquil period with low volatility, turmoil regime with high volatility and crisis regime with extremely high volatility. Although, regimes were instable, the results show some common patterns in the switching dates among all series especially around May 2008, when there is an increase in the probability of crisis regime.

Table 3
Empirical results of Bai and Perron's (1998, 2003) test.

| Tests [a] | Bahrain | Dubai | Egypt | Jordan | Kuwait | Morocco | Oman | Saudi Arabia | South Africa | Turkey | Tunisia |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Structural break test in mean** | | | | | | | | | | | |
| **Number of breaks selected** | | | | | | | | | | | |
| Sequential: | 2 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| LWZ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| BIC | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| Break dates | 16/06/2008 21/12/2012 | | | | 25/06/2008 | 18/03/2008 | | | | | 04/10/2010 |
| **Panel B:Structural break test in volatility** | | | | | | | | | | | |
| **Number of breaks selected** | | | | | | | | | | | |
| Sequential: | 4 | 4 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 3 |
| LWZ | 3 | 3 | 2 | 2 | 3 | 3 | 3 | 2 | 3 | 2 | 2 |
| BIC | 2 | 4 | 4 | 3 | 3 | 3 | 4 | 4 | 3 | 4 | 2 |
| Break dates | 03/10/2006 11/09/2008 16/07/2010 13/01/2012 | 03/10/2006 06/08//2008 09/02/2010 28/08/2013 | 13/08/2008 29/07/2011 26/04/2013 | 28/01/2008 28/07/2009 28/04/2011 26/07/2013 | 01/01/2007 09/09/2008 12/07/2010 02/05/2013 | 06/11/2007 06/05/2009 13/01/2011 14/08/2012 | 28/11/2007 28/05/2009 12/04/2011 29/03/2013 | 14/12/2006 14/05/2009 05/04/2011 28/08/2013 | 17/01/2008 17/07/2009 08/02/2011 08/08/2012 | 27/07/2007 16/03/2009 30/11/2011 30/05/2013 | 01/04/2008 03/06/2011 15/08/2013 |

Notes: We search for up to five breaks and use a trimming parameter of 0.15; * Significant at the 5% level.
[a] We sequentially test the hypothesis of $l$ breaks vs. $l+1$ breaks, employing the *Sup FT(l+1/l)* statics.

So, two remarks can be deduced from this, the year that has the highest number of structural breaks is 2008, this is not surprisingly because the year 2008 is associated with the break of the American investment bank Lehman Brothers on the day 09/15/2008, the crisis has become more critical and its transmission to emerging markets has become more intensely.

Also, the Arab world knew from the end of the year 2009 a great political transitions that have effects on the financial, economic plans; And it can be seen that even from this year onwards these countries have not experienced the same frequency of ruptures as the year 2008, this can be explained in part by the effect of external shocks on the financial markets. The results are confirmed by Hammoudeh & Li (2008), who have tested the volatility of the Gulf area in Arab stock markets, over the period 1994–2001 and found that most of these stock markets were more influenced by major international events than local and regional factors.

Hence, we can consider the 15th of September 2008 as a break-point in order to identify the GFC occurrence and divide the full sample period into pre and post-crisis Periods. The pre-crisis period spans the period April 1, 2005 to September 15, 2008, while the post-crisis period ranges from September 16, 2008 up to the end of the sample (March 31, 2015).

### *5.2. VAR modeling and Granger Causality test*

This method includes VAR test, Granger-causality tests, the computation of impulse response functions and the forecast error variance decompositions.

To have a clear picture on the interdependencies between the volatility series, firstly, it makes use of VAR model, combined with a standard GARCH model in order to analyze the causal relationships in terms of volatility across stock markets (see Table 4).

The estimation results of a VAR model on the second difference[1] VAR (2), of the stock indices is able to describe and evaluate suitably the interdependence between the volatility series. The adjusted R-squared is high, it is larger than 80% for all markets, indicating that the model fits the data quite well.

Also, the results of the Granger non-causality test, depicted on Supplemental Appendix Table S1, show a strong volatility interdependence. This can be noted through the results of Changes in the number and intensity of Granger-causal relationships.

#### *5.2.1. Changes in the number of Granger-causal relationships*

The resulting FPE statistics for the two sub-samples are reported in Supplemental Appendix Table S1. This method that we used, allowed us to gain insights into the Granger-causality between the 132 (12 × 11) possible relationships in emerging stock market. In each estimation, we apply Hsiao's (1981) sequential procedure outlined above to determine the optimum FPE (m, 0) and FPE (m, n) statistics in each case. Therefore, the sample was decomposed in two sub-periods: the pre-crisis period which runs from 1 April 2005 to 28 September 2008 and the crisis period from 29 September 2008 to 31 March 2015.

Note that if the difference is positive in the case XX- > YY, this indicates the existence of a statistically significant Granger-causality relationship running from country XX towards country YY.

As the results show for the two subsamples of countries, the number of causal relationships increases as the financial crisis develops in the markets. Considering the evolution of causality relationships between countries, the results indicate that in the post-crisis period, the number of bidirectional Granger-causality has increased in 17 relations.

There is clear evidence that during the crisis period, even though the number of causal relationships detected increases in both directions, these latter are more frequent for Gulf markets than African ones, in other words the Gulf countries are the most influential and the most impacted at the same time. This can be noticed by observing the number of Granger-causal relationships which runs generally from Gulf countries (they are influential in 50% of the cases in the post crisis period and almost 63% in the pre-crisis period).

We can also note, that the number of causality linkages of impacted Gulf countries, rises from 46% to almost 62% for the crisis period. Interestingly, in the two periods, the Saudian and Oman markets are the most influential in stock markets of the Middle East and African region. By contrast, Moroccan and South-African are the less influential markets in our sample. However, in the post crisis period, the results have changed, so we can note that the Moroccan market became the most influential, while the Saudian one is still among the most influential markets in our sample.

Our results are similar to those of Abbes and Trichilli (2015), showing that for MENA stock markets, Islamic indices of Bahrain and Egypt cause the dynamic of other Islamic indices (Kuwait, Oman, Jordan and Morocco). Jordan and Morocco are not influential in stock markets of MENA region. Giovannetti & Velucchi (2013) investigates the effects of external shocks (the 2008–09 crisis) on emerging African financial markets, over the period 2005–2012, focusing on the role of financial markets' volatility. The results show that South Africa turn out to be net "absorbers". In view of these negative contagion effects, regional integration of financial markets should remain among the main objectives of all countries in the MENA region in general and the GCC countries in particular where there is an acceleration of liberalization.

With the maturity of emerging markets and their increasingly rapid integration into global markets, an increase in their sensitivity to the volatility spillovers of stock markets, as well as a decrease in their ability to diversify can be noticed,. In addition to that, their portfolio diversification ability decreases and they become more vulnerable to external shocks Alotaibi and Mishra (2015). Also, Dania & Spillan (2013) found evidence of different level of volatility spillover and leverage effect. This varying response to global stock market shocks reveals that MENA stock markets are not fully integrated with global economy. According to Assaf (2016), the MENA's relatively low integration into global financial markets have minimized some of the downturn on MENA's economies.

Table 4
Estimate results of VAR (2) model (whole sample).

| Independant variables | Estimated parameters $\Phi_{t-1}$ | Dependant variables: Bahrain | Dubai | Egypt | Jordan | Kuwait | Morocco | Oman | Saudi | South-Africa | Tunisia | Turkey | USA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bahrain | $\Phi_{t-1}$ | **0.9(0.02)***** | −0.5 (0.263)*** | −0.75 (0.310) | −1.23 (0.486) | 0.63 (0.099) | 0.01 (0.26) | 0.097 (0.161) | −0.08 (0.284) | **−0.4(0.17)***** | −0.06 (0.04) | **0.00(0.000)***** | **0,003(0.001)*** |
| | $\Phi_{t-2}$ | −0,07 (0.02) | **0.17(0.21)***** | **0.62(0.31)**** | 1.52 (0.49) | **−0.61(0.1)***** | −0.03 (0.03) | −0.18 (0.16) | **0.084(0.28)**** | **0,18(0.17)**** | −0.001 (0.04) | 0.00 (0.000) | **−0,03(0.003)*** |
| Dubai | $\Phi_{t-1}$ | **0.00(0.002)***** | **1.17(0.22)**** | 0.09 (0.03) | **0.00(0.05)**** | **−0.12(0.01)***** | −0.001 (0.002) | 0.09 (0.017) | 0.04 (0.03) | 0.06 (0.02) | **0.01(0.005)**** | **0.00(0.000)**** | 0,00 (0.015) |
| | $\Phi_{t-2}$ | 0.00 (0.002) | −0.15 (0.02) | **−0.1(0.03)***** | **0.00(0.05)***** | **0.01(0.01)***** | 0,00 (0.003)*** | −0.08 (0.01) | −0.01 (0.03) | **−0.04(0.02)*** | −0.01 (0.004) | **0.00(0.000)*** | **0,09(0.04)**** |
| Egypt | $\Phi_{t-1}$ | **0.00(0.001)*** | **0.01(0.013)***** | **0.1(0.02)**** | **−0.01(0.03)***** | **0.00(0.007)***** | **0.00(0.001)**** | **0.00(0.01)***** | **0.00(0.02)***** | 0.02 (0.01) | **0.00(0.003)***** | 0.00 (0.000) | 0,00 (0.01) |
| | $\Phi_{t-2}$ | **0.00(0.001)***** | **0.00(0.01)***** | **−0.07(0.02)***** | 0.03 (0.03) | 0.002 (0.005) | −0.001 (0.002) | 0.153 (0.01) | −0.006 (0.02) | −0.016 (0.01) | −0.002 (0.003) | 0.00 (0.000) | −0,023 (0.05) |
| Jordon | $\Phi_{t-1}$ | **0.001(0.001)*** | −0.001 (0.008) | **0.002(0.01)**** | **1.31(0.02)**** | **−0.004(-0.004)**** | −0.001 (0.001) | 0.0001 (0.005) | 0.006 (0.01) | 0.01 (0.01) | **0.001(0.002)***** | **0.00(0.000)***** | −0,046 (0.03) |
| | $\Phi_{t-2}$ | −0.001 (0.001) | 0.001 (0.01) | −0.004 (0.01) | −0.451 (0.02) | 0.002 (0.004) | 0.001 (0.001) | 0.000 (0.01) | −0.01 (0.01) | −0.01 (0.01) | −0.001 (0.002) | 0.00 (0.000) | **0,18(0.1)**** |
| Kuwait | $\Phi_{t-1}$ | −0.01 (0.004) | −0.11 (0.04) | 0.45 (0.01) | −0.1 (0.1) | **0.8(0.02)***** | **−0.08(0.06)***** | −0.07 (0.03) | 0.11 (0.06) | −0.11 (0.03) | 0.03 (0.01) | 0.00 (0.000) | −0,002 (0.01) |
| | $\Phi_{t-2}$ | 0.02 (0.004) | **0.14(0.04)***** | **−0.43(0.07)**** | −0.01 (0.1) | 0.05 (0.02) | **0.02(0.006)***** | **0.13(0.03)***** | **−0.06(0.06)**** | **0.01(0.04)**** | −0.03 (0.01)** | **0.00(0.000)***** | **−0,33(0.03)*** |
| Morocco | $\Phi_{t-1}$ | 0.08 (0.02) | 0.09 (0.17) | 2.06 (0.25)*** | **0.31(0.4)***** | 0.1 (0.08) | 1.03 (0.02) | 0.03 (0.13) | −0.32 (0.23) | −0.44 (0.14) | −0.09 (0.03) | **0.00(0.000)** | −0,003 (0.002)** |
| | $\Phi_{t-2}$ | −0.01 (0.02) | −0.05 (0.16) | −1.73 (0.25) | **−0.36(0.4)**** | **−0.08(0.08)***** | **−0.07(0.02)***** | **−0.03(0.13)**** | **0.41(0.23)***** | **0.63(0.14)*** | **012(0.036)**** | **0.00(0.000)***** | **0,03(0.004)*** |
| Oman | $\Phi_{t-1}$ | 0.01 (0.003) | **0.22(0.03)**** | **−0.02(0.04)**** | 0.13 (0.05) | 0.163 (0.01) | **0.01(0.003)**** | 1.06 (0.02) | −0.054 (0.04) | **−0.06(0.02)**** | **−0.01(0.01)** | **0.00(0.000)***** | 0,001 (0.02) |
| | $\Phi_{t-2}$ | −0.01 (0.003) | −0.19 (0.03) | 0.04 (0.04) | **−0.1(0.06)**** | **−0.15(0.01)***** | −0.01 (0.003) | −0.17 (0.02) | **0.01(0.04)***** | **0.1(0.02)***** | **0.01(0.006)***** | **0.00(0.000)***** | 0,22 (0.15) |
| Saudi | $\Phi_{t-1}$ | **0.006(0.001)**** | 0.044 (0.01) | −0.04 (0.02) | 0.03 (0.036) | **−0.02(0.01)***** | −0.003 (0.002) | **0.05(0.01)***** | 0.8 (0.02) | 0.01 (0.01) | −0.002 (0.003) | 0.00 (0.000) | 0,06 (0.03)** |
| | $\Phi_{t-2}$ | −0.004 (0.001) | −0.04 (0.01) | 0.02 (0.02) | −0.01 (0.03) | **0.02(0.01)*** | 0.006 (0.002) | −0.046 (0.01) | **0.15(0.02)*** | −0.02 (0.01) | **0.00(0.003)***** | 0.00 (0.000) | **−0,44(0.27)***** |
| South-Africa | $\Phi_{t-1}$ | **0.004(0.003)**** | **0.05(0.034)***** | **0.003(0.05)***** | **−0.02(0.08)***** | **0.05(0.02)***** | **0.09(0.004)**** | **0.06(0.03)*** | 0.23 (0.05) | **0.9(0.03)**** | **−0.02(0.01)***** | 0.00 (0.000) | **0,07(0.02)*** |
| | $\Phi_{t-2}$ | **0.00(0.003)**** | −0.05 (0.03) | −0.02 (0.045) | 0.038 (0.08) | −0.03 (0.02) | **0.00(0.004)***** | −0.04 (0.03) | **−0.2(0.05)***** | **0.05(0.03)***** | **0.03(0.01)***** | **0.00(0.000)***** | **−0,75(0.19)*** |
| Tunisia | $\Phi_{t-1}$ | −35.5 (17.35) | −300.7 (169.7) | **−25.6(255)**** | **149.(399.6)*** | 22.14 (81.6) | 47.8 (21.7) | −16 (133) | 913 (233.8) | 181 (140) | **98.5(35.9)**** | **0.83(0.03)***** | −0,07 (0.05) |
| | $\Phi_{t-2}$ | 35.7 (17.17) | 301.6 (168) | −187.3 (252) | −211.8 (395.5) | −32.2 (80.8) | −45.3 (21.5) | −50.3 (131.7) | −1.12.4 (231.4) | **−128(138.8)*** | −111.8 (35.5) | **0,08(0.03)**** | **−0,05(0.01)*** |
| Turkey | $\Phi_{t-1}$ | 0.016 (0.01) | −0.1 (0.1) | **−0.26(0.15)***** | 0.001 (0.24) | −0.20 (0.049) | **−0.00(0.013)***** | **0.27(0.08)***** | 0.34 (0.14) | −0.09 (0.08) | 1.11 (0.02) | **0.00(0.000)***** | 0,000 (0.000) |
| | $\Phi_{t-2}$ | −0.01 (0.01) | **0.17(0.1)**** | **0.13(0.15)**** | −0.05 (0.24) | 0.155 (0.05) | 0.01 (0.013) | 0.08 (0.08) | **−0.2(0.14)***** | **0.20(0.1)***** | **−0.20(0.021)**** | **0.00(0.000)**** | **0,000(0.000)*** |
| USA | $\Phi_{t-1}$ | 0,00 (0.000) | **0,00(0.000)***** | **0,000(0.000)*** | **0,00(0.000)*** | **0,8(0.03)*** | 0,05 (0.04) | **0,08(0.034)**** | 0,00 (0.000) | 0,00 (0.000) | 0,00 (0.000) | 0,00 (0.000)** | −0,32 (0.57) |
| | $\Phi_{t-2}$ | 0,10 (0.78) | 0,79 (0.58) | 0,046 (0.06) | −0,077 (0.09) | 0,047 (0.06) | 0,026 (0.03) | 0,04 (0.05) | −0,05 (0.03) | −0,018 (0.02) | 0,047 (0.04) | −0,02 (0.02) | 0,08 (0.12) |
| C | | **0.034(0.05)**** | **0.16(0.05)*** | 0.17 (0.07) | 0.07 (0.11) | **0.02(0.02)***** | **0.022(0.01)***** | **−0.1(0.04)***** | **−0.04(0.07)**** | **0.00(0.04)***** | **0.04(0.01)***** | **0.00(0.000)***** | 0,025 (0.15) |
| Adj, R-squared | | 0,855 | 0.952 | 0.896 | 0.857 | 0.831 | 0.975 | 0.946 | 0.934 | 0.970 | 0.875 | 0.902 | 0,9431 |

Notes: The standard deviations are given in parenthesis. *, ** and *** indicate that the coefficients are significant, respectively, at the 10%, 5% and 1%. The most significant linkages in the VAR system are indicated in bold.

Table 5
Changes in the number of Granger-causal relationships.

| | Pre-crisis period | Post-crisis period |
|---|---|---|
| No | 91 | 74 |
| Yes | 41 | 58 |

#### 5.2.2. Changes in the intensity of Granger-causal relationships

As the results show, for the 58 cases where causality is detected both in the period of tranquility and crisis, we have compared $FPE_y(m,0) - FPE_y(m,n)$ in the two periods. If this statistic is higher in the crisis than in the tranquil period, then we can talk about the intensification of the causal relationship in the crisis period. And it will be a reduction in the causal relationship in the case where this statistic is lower in the crisis than in the causative relationship.

The causality changes are reported in the last column of the Supplemental Appendix Table S1.[2] The results reveal that there is causality intensification in 17 cases. We can speak also of cases of reduction in the causal relationship, generally emanating from North Africa countries.

Moreover, another relevant finding is that with the crisis, some causal relationships have stayed the same, others have disappeared and 34 appeared, we can mention for instance:

Morocco- > Oman, Morocco- > Saudi, Morocco- > South-Africa, Morocco - > Tunisia, Morocco - > Turkey, Morocco- > Kuwait, Morocco - > Dubai, etc….

Emerging markets are very sensitive and vulnerable to external shocks coming from developed markets particularly the United States, due to the weakness and immaturity of their financial institutions and regulatory systems (Mensi, Hammoudeh, & Yoon, 2014).

A recapitulation of Supplemental Appendix Table S1 can be summarized in Table 5 which seeks to highlight the changes in the Grangercausal relationships. We can note that, with the crisis, some Granger-causal relationships have appeared and others disappeared.

#### 5.2.3. Impulse response functions analyses

Building on the concept of IRF, Koop, Pesaran, & Potter (1996), developed the generalized impulse response function (GIRF) tracing the effects of independent shocks on volatility through time. Unlike the traditional impulse response function, GIRF is unaffected by ordering of variables.

We report a graphical representation in which time (days since the shock hit the market) is on the horizontal axis and the volatility response (relative difference between a baseline and the response after the shock) is on the vertical axis. Figure 1 reports the impulse-response functions for the 5, 10, 20 and 60 day horizon, which are an interesting representation of how markets' j volatility responds to a (one standard deviation) shock in another market, say market i. The representation uses the model estimates to derive a time-dependent profile that describes how one market, hit by a shock (either positive or negative), spreads its volatility to other markets.

We can note that the entire figure (Fig. 1) reveals that the highest level of any country's conditional volatility is attributable to its own shocks (figures along the diagonal). Generally, the response of returns is positive on the first days, but oscillate and die out after the following days. This may be explained by the fact that in the chaotic financial environment at that time, investors would overreact not only to local news, but also to news originating in the other markets, especially when the news events were adverse (Lim, Brooks, & Kim, 2008).

The largest increase in the African markets can be observed in the Moroccan market as its expected conditional variance is the most influenced by the other stock markets volatilities shocks. From these findings, we can note that both Moroccan and the Turkish markets exhibit a higher responsiveness to the shocks than Tunisian market does.

#### 5.2.4. Analysis of the decomposition of the forecast error variance

Variance decomposition gives the proportion of the movements in the dependent variables that are due to their ‘‘own’’ shocks, versus shocks to the other variables.

The results of variance decomposition over the 5-day, 10 -day, 20- day, 30- day and 60- day forecast horizons, for different markets are presented in Table 6. As the table below suggests, the variance decomposition results are consistent with the findings of impulse responses.

There is a high degree of interactions among Gulf markets variances, we can note that the variance decomposition of Jordon stock market shows that Jordon stock market is largely explained by its own shock followed by other Gulf markets and very less by African and USA stock markets.

It stands out from the entire figure that conditional volatility forecast error variance in GULF and African markets are mainly explained by their own-volatilities innovations and the influence of the foreign markets decreases over time.

Table 6 shows also, the Kuwait market is mostly explained by its own-volatilities innovations to a percentage of 84,72% at a 5-day horizon, to decline to 55,31% on a 60-day horizon. Whereas, for the impact of the foreign markets, the Kuwait country forecast-error variances is heavily influenced by GULF stock markets volatilities shocks. At 60-day horizon, the cumulative forecast-error variance for Kuwait market is 8,21%, 6,9% and 4,09% attributable respectively to Oman, Dubai and Bahrain stock markets. The cumulative percentage of the forecast-error variance accounted for by Dubai market amounts to 11, 47% for Dubai for at 5-day horizon. By the same taken, the cumulative forecast-error variance attributable to Dubai market shocks is 12.49% for Oman, 15,53% for Saudi Arabia and 6,94% for Kuwait at 60-day horizon.

On another front, for the African markets, we found that Morocco market holds 12,33% of the variation of the Egyptian, 18% for South African and 11,86% for Tunisian markets.

[2] To save space, the test results are reported in the Supplemental Appendix Table S1.

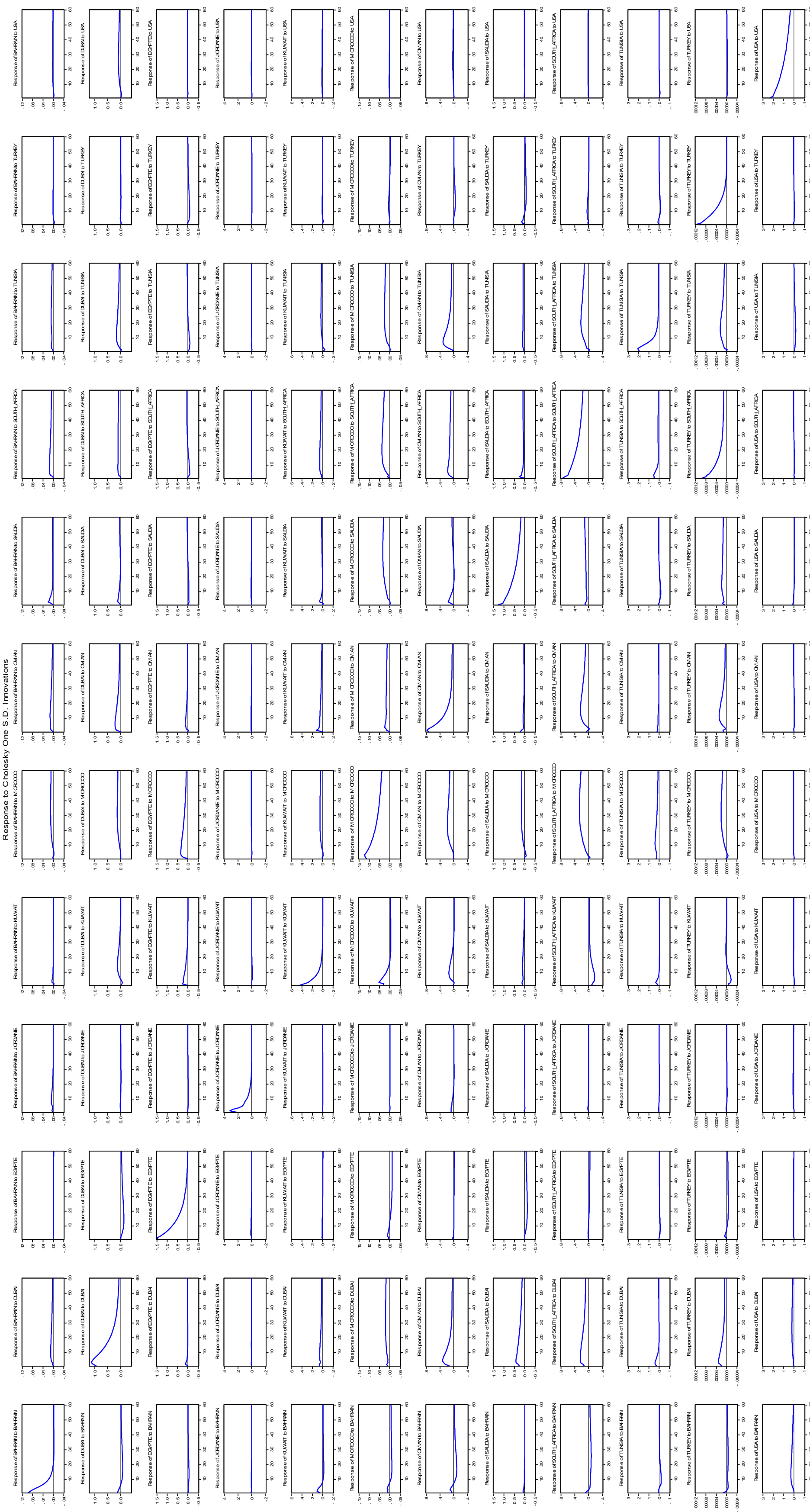


Fig. 1. Generalized impulse response function.

Table 6
Variance decompositions of stock market volatility series.

| Dependant variables | Periods | Independant variables | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Bahrain | Dubai | Egypt | Jordan | Kuwait | Morocco | Oman | Saudi Arabia | South-Africa | Tunisia | Turkey | USA |
| Bahrain | 5-period | 93,398 | 0,357 | 0001 | 0,167 | 0248 | 0,069 | 1236 | 2607 | 1394 | 0,365 | 0114 | 0,045 |
| | 10-period | 87,801 | 1390 | 0,018 | 0680 | 0,244 | 0089 | 2528 | 2997 | 3440 | 0,678 | 0096 | 0,040 |
| | 20-period | 78,341 | 3028 | 0,043 | 1119 | 0,218 | 0968 | 5026 | 2803 | 6700 | 1544 | 0,100 | 0109 |
| | 30-period | 72,029 | 3715 | 0,057 | 1071 | 0,201 | 2680 | 6075 | 2621 | 8621 | 2639 | 0,095 | 0195 |
| | 60-period | 62,975 | 4140 | 0,123 | 0935 | 0,205 | 7165 | 6512 | 2704 | 10,763 | 4087 | 0,086 | 0306 |
| Dubai | 5-period | 0,610 | 95,354 | 0,084 | 0013 | 0,142 | 0001 | 2477 | 0,613 | 0390 | 0,255 | 0020 | 0,042 |
| | 10-period | 0,389 | 92,702 | 0,469 | 0014 | 0,338 | 0041 | 3482 | 0,635 | 0726 | 1144 | 0,014 | 0046 |
| | 20-period | 0,663 | 87,539 | 1334 | 0,014 | 1137 | 0,535 | 4318 | 0,534 | 1186 | 2390 | 0,018 | 0332 |
| | 30-period | 0,885 | 84,103 | 1817 | 0,025 | 1360 | 1425 | 4519 | 0,488 | 1643 | 2975 | 0,023 | 0737 |
| | 60-period | 0,969 | 78,911 | 2133 | 0,031 | 1291 | 3682 | 4603 | 0,580 | 2787 | 3571 | 0,022 | 1420 |
| Egypt | 5-period | 0,030 | 0299 | 92,486 | 0,004 | 2183 | 3994 | 0,304 | 0096 | 0,236 | 0267 | 0,098 | 0004 |
| | 10-period | 0,070 | 0218 | 88,812 | 0,022 | 2515 | 6369 | 0,677 | 0137 | 0,387 | 0467 | 0,316 | 0008 |
| | 20-period | 0,197 | 0175 | 85,284 | 0,047 | 2566 | 9176 | 0,829 | 0207 | 0,398 | 0489 | 0,595 | 0037 |
| | 30-period | 0,257 | 0166 | 83,609 | 0,056 | 2500 | 10,738 | 0,845 | 0218 | 0,389 | 0467 | 0,687 | 0067 |
| | 60-period | 0,287 | 0207 | 81,501 | 0,058 | 2425 | 12,329 | 0,896 | 0288 | 0,657 | 0537 | 0,703 | 0111 |
| Jordan | 5-period | 0,063 | 0043 | 0,168 | 99,499 | 0,011 | 0008 | 0,134 | 0044 | 0,003 | 0017 | 0,005 | 0005 |
| | 10-period | 0,159 | 0066 | 0,375 | 98,699 | 0,124 | 0008 | 0,308 | 0195 | 0,016 | 0023 | 0,006 | 0019 |
| | 20-period | 0,250 | 0149 | 0,595 | 97,468 | 0,178 | 0044 | 0,587 | 0487 | 0,050 | 0054 | 0,034 | 0102 |
| | 30-period | 0,258 | 0217 | 0,645 | 96,822 | 0,177 | 0149 | 0,677 | 0620 | 0,087 | 0089 | 0,069 | 0188 |
| | 60-period | 0,257 | 0334 | 0,648 | 95,868 | 0,176 | 0493 | 0,725 | 0745 | 0,209 | 0146 | 0,094 | 0307 |
| Kuwait | 5-period | 5, 447 | 2278 | 0,074 | 0004 | 84,722 | 0,071 | 4836 | 1325 | 0,748 | 0385 | 0,075 | 0036 |
| | 10-period | 4644 | 3959 | 0,126 | 0011 | 80,659 | 0,222 | 5967 | 1370 | 2486 | 0,346 | 0101 | 0,108 |
| | 20-period | 4474 | 6166 | 0,161 | 0040 | 71,088 | 2108 | 7687 | 1203 | 5628 | 1015 | 0,178 | 0252 |
| | 30-period | 4419 | 6817 | 0,148 | 0062 | 64,467 | 4582 | 8246 | 1136 | 7512 | 2083 | 0,183 | 0345 |
| | 60-period | 4093 | 6940 | 0,213 | 0066 | 55,317 | 9631 | 8219 | 1585 | 9733 | 3605 | 0,159 | 0438 |
| Morocco | 5-period | 0,659 | 0825 | 0,518 | 0006 | 10,388 | 84,539 | 2151 | 0,101 | 0740 | 0,036 | 0020 | 0,017 |
| | 10-period | 0,424 | 0992 | 0,391 | 0003 | 8217 | 82,852 | 2575 | 0,750 | 2937 | 0,747 | 0069 | 0,043 |
| | 20-period | 0,572 | 1894 | 0,273 | 0004 | 5051 | 76,536 | 2802 | 2760 | 7225 | 2665 | 0,153 | 0065 |
| | 30-period | 0,673 | 2678 | 0,407 | 0006 | 3845 | 70,176 | 3050 | 5119 | 9720 | 4125 | 0,135 | 0067 |
| | 60-period | 0,732 | 4127 | 0,987 | 0007 | 2622 | 59,845 | 3377 | 9844 | 12,300 | 5994 | 0,110 | 0058 |
| Oman | 5-period | 0,941 | 11,474 | 0,053 | 0848 | 0,286 | 0012 | 77,229 | 2230 | 2344 | 4575 | 0,002 | 0006 |
| | 10-period | 0,658 | 14,307 | 0,033 | 0720 | 1800 | 0,415 | 64,357 | 1941 | 4071 | 11,653 | 0,040 | 0006 |
| | 20-period | 1458 | 14,269 | 0,034 | 0560 | 2893 | 3590 | 54,568 | 1465 | 5526 | 15,256 | 0,319 | 0061 |
| | 30-period | 1948 | 13,597 | 0,039 | 0511 | 2727 | 7207 | 50,016 | 1319 | 6619 | 15,451 | 0,427 | 0139 |
| | 60-period | 2034 | 12,496 | 0,102 | 0451 | 2399 | 12,599 | 43,960 | 1531 | 8808 | 14,984 | 0,396 | 0240 |
| Saudi Arabia | 5-period | 0,195 | 10,001 | 0,019 | 0016 | 0,777 | 0229 | 1125 | 84,720 | 1899 | 0,346 | 0665 | 0,009 |
| | 10-period | 0,130 | 12,754 | 0,257 | 0015 | 0,797 | 0169 | 0,865 | 82,523 | 1482 | 0,569 | 0433 | 0,005 |
| | 20-period | 0,091 | 14,395 | 1051 | 0,013 | 1063 | 0,697 | 0765 | 79,484 | 1118 | 0,799 | 0522 | 0,004 |
| | 30-period | 0,079 | 15,003 | 1727 | 0,011 | 1129 | 1608 | 0,690 | 77,011 | 1068 | 0,947 | 0719 | 0,008 |
| | 60-period | 0,082 | 15,531 | 2630 | 0,009 | 1005 | 3880 | 0,672 | 72,380 | 1599 | 1339 | 0,838 | 0035 |
| South-Africa | 5-period | 0,547 | 8290 | 0,021 | 0055 | 3870 | 0,243 | 0450 | 1142 | 84,734 | 0,566 | 0065 | 0,017 |
| | 10-period | 0,598 | 10,601 | 0,017 | 0034 | 5397 | 1347 | 3271 | 0,972 | 75,617 | 1934 | 0,191 | 0020 |
| | 20-period | 0,864 | 11,072 | 0,026 | 0019 | 4452 | 5101 | 8230 | 1111 | 62,704 | 6169 | 0,218 | 0034 |
| | 30-period | 1170 | 10,368 | 0,073 | 0018 | 3508 | 9528 | 9770 | 1323 | 55,261 | 8765 | 0,167 | 0049 |
| | 60-period | 1438 | 8976 | 0,278 | 0022 | 2522 | 18,247 | 9417 | 2667 | 45,759 | 10,471 | 0,132 | 0071 |
| Tunisia | 5-period | 0,055 | 3253 | 0,052 | 0047 | 1240 | 1551 | 0,614 | 0132 | 5716 | 87,041 | 0,200 | 0099 |
| | 10-period | 0,647 | 3236 | 0,232 | 0042 | 1031 | 3560 | 0,781 | 0456 | 5482 | 84,141 | 0,268 | 0123 |
| | 20-period | 1379 | 2974 | 0,408 | 0042 | 0,939 | 7923 | 0,910 | 0822 | 5244 | 78,614 | 0,629 | 0118 |
| | 30-period | 1483 | 2875 | 0,450 | 0044 | 0,954 | 9979 | 0,904 | 0821 | 5442 | 76,264 | 0,671 | 0114 |
| | 60-period | 1479 | 2866 | 0,499 | 0043 | 0,995 | 11,858 | 1018 | 1118 | 6202 | 73,170 | 0,642 | 0109 |
| Turkey | 5-period | 0,290 | 4861 | 0,133 | 0015 | 1268 | 0,095 | 0734 | 0,837 | 36,536 | 0,399 | 54,792 | 0,040 |
| | 10-period | 0,310 | 6352 | 0,101 | 0019 | 1643 | 0,168 | 2860 | 1492 | 34,749 | 1448 | 50,759 | 0,098 |
| | 20-period | 0,384 | 7110 | 0,284 | 0046 | 1322 | 1323 | 6366 | 3176 | 32,197 | 4458 | 43,156 | 0,179 |
| | 30-period | 0,551 | 7093 | 0,522 | 0059 | 1209 | 3369 | 7243 | 4308 | 30,578 | 6103 | 38,743 | 0,223 |
| | 60-period | 0,734 | 6911 | 0,880 | 0064 | 1055 | 7853 | 7004 | 6363 | 28,465 | 7044 | 33,374 | 0,252 |
| USA | 5-period | 0,138 | 0064 | 0,068 | 0040 | 0,053 | 0014 | 0,011 | 0159 | 0,027 | 0186 | 0,015 | 99,225 |
| | 10-period | 0,880 | 0196 | 0,114 | 0082 | 0,036 | 0053 | 0,056 | 0097 | 0,074 | 0418 | 0,038 | 97,956 |
| | 20-period | 2035 | 0,618 | 0150 | 0,179 | 0048 | 0,113 | 0118 | 0,087 | 0104 | 0,778 | 0049 | 95,721 |
| | 30-period | 2485 | 1084 | 0,158 | 0251 | 0,057 | 0158 | 0,115 | 0145 | 0,092 | 0920 | 0,042 | 94,495 |
| | 60-period | 2670 | 1861 | 0,152 | 0309 | 0,068 | 0302 | 0,115 | 0331 | 0,125 | 0893 | 0,045 | 93,130 |

Like we've seen that Gulf countries-have them interact or, albeit much more than in the case of Africa.

In contrast, The USA market remain not very sensitive to volatility of emerging markets regardless of the time horizons, but it can be observed that the highest level of USA's conditional volatility is attributable to its own shocks, and its reaction is long-lasting as at the first period horizon (5-day), the cumulative percentage of the forecast-error variance accounted to 99,65% and 93% for 60-day forecast horizons, while for the other markets, most often the own effect lasts slightly except for the Jordon market.

### 5.3. Volatility transmission

The above analysis results lend support to the hypothesis of volatility transmission between emerging stock markets. It also appears that the GFC is likely to enhance the transmission of volatility. In the crisis period, we do find not only some new causality patterns which had been absent before its start, but also an intensification of causality in many cases,indeed, almost 26% of new significant causal linkages appeared among the potential 132 (11 × 12) linkages between emerging markets.

The results regarding volatility transmission and contagion point to the existence of unidirectional as well as bidirectional spillovers between emerging stock markets. The 34 new causality patterns, together with the intensification of the causal relationship represent almost 40% of the cases in which we find causality both in the tranquil and in the crisis period.

These interdependencies appear to be responsible for transmission of volatility, which may inform us about the state of contagion in these countries. These results may be consistent with the financial literature which has focused on studying the volatility movements that may lead to instability of economies which may become international through contagion because of the growing interdependence linking the different financial markets at the returns and volatility levels, and may be represented by additional linkages during crisis periods in excess of those that arise during non-crisis periods (see Baele & Inghelbrecht, 2010; Billio & Caporin, 2010; Corsetti et al., 2005; Forbes & Rigobon, 2002; Gębka & Karoglou, 2013).

## 6. Conclusion

The paper examined the volatility of the financial markets of emerging financial markets by exploring the implications of the recent global financial crises on these markets through the verification of existence and the evolution of possible Granger-causal relationships. The empirical methodology of this paper uses is based on two main econometric models. Firstly, it makes use of VAR model, combined with a standard GARCH model in order to analyze the causal relationships in terms of volatility across stock markets. To sum up our results, the findings appear quite consistent with what is expected. This leads us to reflect on the phenomenon of volatility transmission in times of crisis (contagion). However, we find an intensification of the causal relationship in 17 out of the 24 cases. These 34 new causality patterns, together with the intensification of the causal relationship represent almost 40% of the cases. The GFC reinforce the interdependencies between markets, such interdependence is a high indicative of volatility transmission between markets, and may be considered as an important operative measure of contagion. Finally, in this paper, we have focused on the study of bivariate analysis series. In the future research, the study may be extent to multivariate analysis series.

## Appendix. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.bir.2018.07.001.

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