Uncertainty and Volatility in MENA Stock Markets During the Arab Spring

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27 August 2014

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ABSTRACT

This paper sheds light on the economic impacts of political uncertainty caused by the civil uprisings that swept across the Arab World and have been collectively known as the Arab Spring. Measuring documented effects of political uncertainty on regional stock market indices, we examine the impact of the Arab Spring on the volatility of stock markets in eight countries in the Middle East and North Africa (MENA) region: Egypt, Lebanon, Jordon, United Arab Emirate, Qatar, Bahrain, Oman and Kuwait. This analysis also permits testing the existence of financial contagion among equity markets in the MENA region during the Arab Spring. To capture the time-varying and multi-horizon nature of the evidence of volatility and contagion in the eight MENA stock markets, we apply two robust methodologies on data from November 2008 to March 2014: MGARCH-DCC, Continuous Wavelet Transforms (CWT). Our results tend to indicate two key findings. First, the discrepancies between the volatile stock markets of countries directly impacted by the Arab Spring and the countries that were not directly impacted indicate that international investors may still enjoy portfolio diversification and investment in MENA markets. Second, the lack of financial contagion during the Arab Spring suggests that there is little evidence of cointegration among MENA markets implying the opportunities of portfolio diversification. Providing a general analysis of the economic situation and the investment climate in the MENA region during and after the Arab Spring, this study bears significant importance for the policy makers, local and international investors, and market regulators.

Keywords: Portfolio Diversification, MENA Region, Stock Market Indices, MGARCH-DCC, Wavelet Analysis, (CWT) .

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INTRODUCTION

Over the last thirty years, the world witnessed many major events such as the United States' Black Monday of October 1987, the Asian financial crisis of 1997-1998, the dot.com tech bubble, the September 11 terrorist attack on the World Trade Center in New York, and the global financial crisis of 2008, to name a few. These incidences have all been saturated with research from experts of a wide spectrum of fields and specialties.

The recent political upheavals in the Arab world, coined the Arab Spring, have not received adequate attention from experts in various fields of research. Analysts and researchers have failed to provide nuanced discussions of the root causes of the unrests or thorough assessments of the future of countries that have seen their governments replaced within weeks. The exceptions are a few studies that attempted to explore the effects of the Arab Spring on the economic, political and social establishments of the host countries (O'Sullivan et al. 2012; World Bank, 2011). Yet, much remains unstudied. This is particularly puzzling for a region that produces one third of the world's oil and represents one of the most diverse and interesting mixture of political and economic configurations, ranging from monarchies with rentier economies to parliamentary-based republics with capitalist, laissez-faire, albeit corrupt, economies.

The Arab Spring presents a fertile ground for informative and instrumental research. On the one hand, the revolutionary movements represent a departure from archaic political establishments and decaying economic arrangements and provide an opportunity for Middle East and North African (MENA) countries to establish accountable, effective, and transparent governance. On the other hand, political uncertainty caused by the unrest could have economic repercussions, manifesting in stock market cycles and volatile reactions capable of quivering international investors' confidence in the region's markets.[3]

This research attempts to rectify part of this problem by shedding light on the effects of the Arab Spring on regional stock market and the volatilities that spread across MENA markets. This research also attempts to provide a topographic analysis of MENA financial sectors before and during the Arab Spring by measuring contagion among regional markets and finding variance and

[3] The political unrest has taken a toll on financial markets in many MENA countries since early January 2011. For example, the Egyptian stock exchange (North Africa's second-largest exchange) fell by 16% to the lowest level in two years shortly after reopening its stock market closure as political unrest led to the overthrown of the country's president. The Tunisia stock exchange has also declined substantially following the unrest.

co-variance profile to understand the risk and return of portfolio diversification and investment in the region's markets.[4]

Although it has come to be popularly known as the Arab Spring, not all MENA countries experienced the revolutions or riots that swept across the region. Why some Arab countries experienced revolutions while others did not is a subject for another research. What is important to our discussion is the effect the Arab Spring, as a political movement, had on the investment climate in the region. Like its political systems, the MENA region is rich with a diverse array of market and financial arrangements – ranging from conventional to Islamic ones. In this research, we look into which sectors were affected the most over a period of four years before and during the uprisings: from 2008 to 2011.

To analyze the effects of the uprising on the economies of the region and the market volatility they caused, we rely on cautiously selected economic techniques suitable to capture sequential data and highlight substantial market volatilities. Methods such as DCC-GARCH and Wavelet techniques permit analyzing the mean-variance profile, the time intervals and other key market indicators over a specific period of time. Using these results, we present an analysis of the short-term and long-term effects of the Arab Spring on regional stock market, noting the appropriate time to enter and invest in MENA markets. Additionally, this research analyzes the time frame of market instabilities and equilibriums before and during the uprisings.

The structure of the paper is as follow. Section 2 provides a review of the related literature, placing the discussion within the larger corpus of literature about political unrest and their effects on economies and stock markets. Section 3 describes the data, statistics and methodologies employed in the research. Section 4 presents the data and discusses the empirical results. And, finally, section 5 concludes the paper with a summary of the main findings and their practical implications.

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[4] Political turmoil, the cause of market uncertainty, is difficult to decipher and explain without relying on theoretical arguments to put forward any affirmative conclusion. Rather, this paper concentrates on the effects of the political unrest on the economies of the region, particularly the financial sectors (represented here by stock market indices). This permits the use of robust and sophisticated economic instruments and technique such as DCC-GARCH and Wavelet (MODWT, CWT)

LITERATURE REVIEW

The concept of studying the linkage among global stock markets is incremented by the globalization of capital markets (Forbes and Rigobon, 2002), and, thereafter, the advancement of information technology. A crisis that used to affect only the local economy starts to affect other related economies. Capital movements, common economic ties, and regional policy coordination across countries are among the factors that can interlink stock prices (Valadkhani and Chancharat, 2008). Globalization could be in favor of portfolio diversification. Often, this is in the interest of investors, but only to the extent that it does not increase the correlation among national stock markets.

The literature in the financial sector supports the notion that this correlation has strengthened after the increment of financial integration, making the gain of portfolio diversification less effective (Longin and Solnik, 1995; etc.). However, this phenomenon of increasing correlation between the global equity stock markets remains ambiguous with regards to the emerging markets of the Middle East and North African (MENA) region. Recent studies and discussions focused on linkages within the emerging stock markets (Chau et al 2014). Local and international investors have gained clear views in the emerging markets (Bhaskaran et al., 2005) supported by better relative growth prospects, abundant global liquidity (Institute of International Finance, 2011) and safe haven status – as was the case during the financial crisis of 2008 (Neaime, 2012). The discussion about conventional stock market indices, however, has not been conclusive. On the other hand, and due to recent crises over the last decades – starting with the terrorist attack of September 11 and then the supreme debt crises following the European sovereign debt crisis (Aroni and Deck 2010) – local investors have concentrated on their own local markets (Bouri 2014). The local markets of the MENA region are a case in point. With potential growth in equity, especially in the sector of Islamic capital market – which the global financial market has witnessed its rapid expansion[5] – the area is a beacon of hope. A recent study in this realm using DCC-Garch was the subject of volatility has been under close scrutiny for the last three decades, as it gets a big boost of improving the technique of

[5] The Islamic financial system is based on the fundamentals of Shari'ah (Islamic Law) that requires gains from investments to be earned in an ethical and socially responsible manner that comply with teachings of Islam (DeLorenzo, 2000). Equities traded under Shari'ah indices undergo a screening process to ensure they are free from prohibitive elements as dictated by Shari'ah. The common elements screened for are riba (interest rates), gharar (uncertain outcomes), maysir (gambling), prohibited commodities (liquour, pork, etc.) and fulfillment of contractual requirements as required in Islamic Law of Contracts (Rosly, 2005).

ARCH model in the following section will give the reason why this technique is suitable to solve our issue here and we justified how it's the most relevant one as well.

By going over this literature review its clear there are insufficient empirical evidences showing a clear result of volatility in the MENA region in conventional indexes and there are no such studies up to 2014 data set especially in the Islamic indices. So the literature here is not conclusive. My study is a humble attempt to add up to the literature and answer some important question usually an international investor like to have. More than that, by using the most suitable technique DCC-GARCH for Volatility and CWT we are filling a small gap there. By using daily data for academicians, it would provide better insights of what time can investor take decisions to be reflected in making better asset allocation of the portfolio.

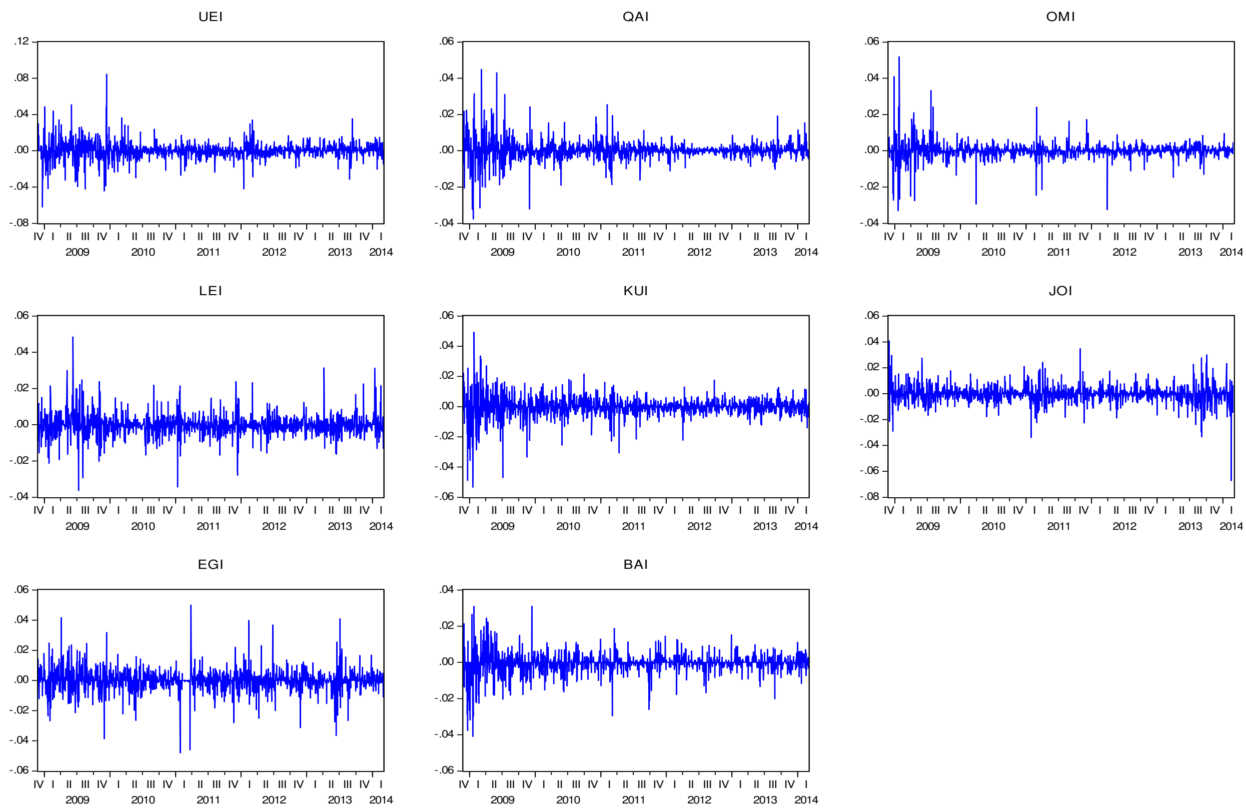
METHODOLOGY

A-Multivariate GARCH – Dynamic Conditional Correlation

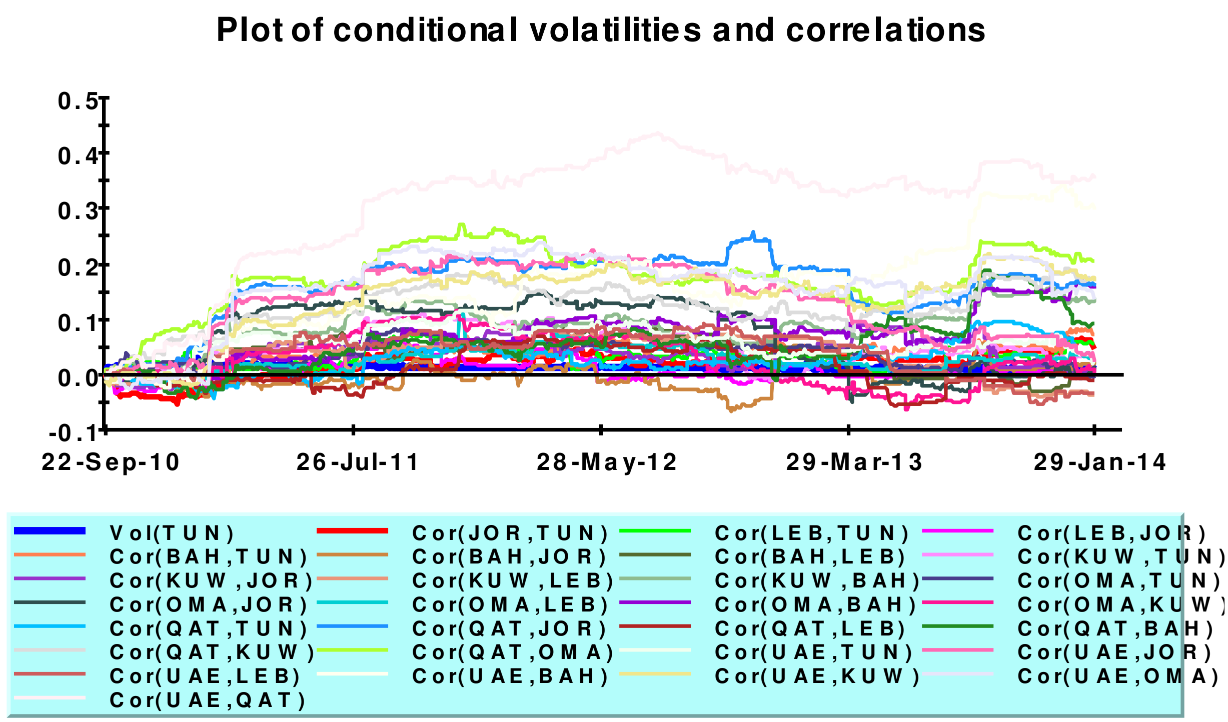
There are two conditions to use arch model, there should be clustered volatility in the residuals and there should be Arch effect. By proceeding one by one and running one by one to find out the clustering volatility and the arch effect, we test two variable against each other, one of them representing the exogenous the other indigenous, then checking the residual. Plotting the graph as shown below, we can notice period of low volatility seemed to be followed by a period of low volatility in the same time period of high volatility is followed by a period of high volatility for long period and that's called volatility clustering.[6]

[6] Volatility Clustering in Financial Markets: Empirical Facts and Agent–Based Models Rama Cont ,Centre de Math´ematiques appliqu´ees, Ecole Polytechnique ,F-91128 Palaiseau, France

Volatility plot showing individual countries' data how it is clustering



What usually occurs during crises compared to what was the condition before and after the crises is why this multi variants garch can be applied, what this multi variat garch can give us is some correlation variance and covariance metrics. Many unique ccc model in the real words are always time variance and the correlation always changes as conditional means vary from one day to the next. What this means is that every day's correlation depends on data of the day before



Multivariate GARCH – Dynamic Conditional Correlation[7]

This section presents the structure of the multivariate model to be used in order to capture means and volatilities of returns dynamics across markets.

The DCC_MGARCH model is suitable to apply for analyzing economic time series with time-varying volatility .It indicates market integration .Market become more integrated when the conditional correlation increases over time (Yu et al., 2010). This model is able to capture the volatility, correlation between two markets, either directly through its conditional variance or indirectly through its conditional covariance.

“MGARCH is more real life – application as mean and variance is varying. We have to relax these assumptions in order to close real life activities .The lowest volatility means high returned unfortunately there is a flow in normal distribution as the financial activities is not normal anymore ”[8]

[7] Faiq najeep
[8] Lecture for Rumi Masih , 7/4/2012 at INCEIF Campus ,

The DCC_MGARCH model can consider n stock's return volatility and correlation with time-dependent. It's also dynamic model with time-varying means, variances and co variances of return series, Hooi and KEE (2013)t for index i at time t, with the following equations

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t},$$

and

$$\mu_{i,t} = E\left(r_{i,t}|\Psi_{t-1}\right) = E_{t-1}\left(r_{i,t}\right), \varepsilon_{i,t}|\Psi_{t-1} \sim N(0, \mathrm{H_t}),$$

where Ψ_{t-1} is the set of information available at time $t-1$.

The conditional variance–covariance matrix H_t can be written as $H_t = D_t R_t D_t$, where H_t is also denoted as a conditional correlation estimator. D_t is an (n × n) diagonal matrix of time-varying conditional standard deviations of the return in the mean equation at time t

from the univariate GARCH (1, 1) model. $D_t = diag(\sqrt{h_{i,t}})$, where $h_{i,t}$ is the time-varying conditional volatility of return series for index i at time t. Thus, D_t for a multivariate model is expressed as $D_t = diag(\sqrt{h_{1,t}}, \ldots, \sqrt{h_{n,t}})$ with $h_{i,t} = \tau_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$, where τ_i

Is a constant term, αi is the ARCH effect, and βi is the GARCH effect. A positive coefficient of βi implies volatility clustering and persistency in the positive changes of a stock index. The sum of αi and βi indicates the persistency of the volatility shock. Rt is a time-varying conditional correlation matrix. It contains the coefficients of conditional correlation as follows

$$R_t = diag[Q_t]^{-1} Q_t d^t iag[Q_t]^{-1},$$

where $Q_t \equiv \left[q_{ij}\right]_t = (1-\alpha_{dcc} + \beta_{dcc})\overline{Q} + a_{dcc}(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta_{dcc} Q_{t-1}$ is a

Conditional covariance matrix. Q denotes the unconditional covariances of the standardized error matrix, which is an (n × n) symmetric positive definite matrix, and εt = (ε1,t,…,εn,t)' are the standardized residual terms[9].Engle (2002) suggested the estimation of time-varying conditional correlation (qij,t) for any two return series by

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Selected Indexes for Research

[9] Positive covariance implies that the tested variables were strongly linked and moved in the same direction and vice versa

the following GARCH (1, 1) process:

$$q_{ij,t} = E\left(\varepsilon_{i,t}\varepsilon_{j,t}|\Psi_{t-1}\right) = \frac{E\left(\varepsilon_{i,t}\varepsilon_{j,t}|\Psi_{t-1}\right)}{\sqrt{E\left(\varepsilon_{i,t}^2|\Psi_{t-1}\right)E\left(\varepsilon_{j,t}^2|\Psi_{t-1}\right)}}$$

$$= \frac{E\left(r_{i,t}r_{j,t}|\Psi_{t-1}\right)}{\sqrt{E\left(r_{i,t}^2|\Psi_{t-1}\right)E\left(r_{j,t}^2|\Psi_{t-1}\right)}} = Corr\left(r_{i,t}r_{j,t}|\Psi_{t-1}\right) = \rho_{ij,t} = [R_t]_{ij},$$

Now, after we have done for the whole period time long term and short term I am going to move to a new method where I can answer the question of Investors for what the risk estimated for different time scale to find out if there is different or not by taking a decision in a week or month or year etc.

B -Continuous Wavelet Transformation (CWT)

There are some limitation for DCC-Garch as its only work for long term and short time analyses .But investors didn't work only for short and long term time periods. But market full of investors interested in different time periods, we consider the large number of investors who participate in the international stock market and make decisions over different time scales. International stock market participants are a diverse group and include Intraday traders, market makers, hedging strategists, international portfolio managers, commercial banks, large multinational corporations, and national central banks. It also seeks to find empirical evidence as to whether regional and/or international markets have a greater or lesser cross-correlation in comparison with local conventional equity investments.

Many authors have used continuous wavelet transform (CWT) in finance research (e.g.Averal Kumar et al (2013), Masih et al. (2009),Chaker Aloui, Besma Hkiri(2013),etc..The CWT scans the original time series, representing only one variable time-separate into function of two different variable such a time and frequency.

At least one clear value added over the method MODWT is that not to define the number of wavelet (time-scale) in CWT its generate itself based on length of data .Also, it shows the figure in two-dimensional, which allows us to easily identify and interpret patterns or hidden information. We use Daubechies(1992) least an asymmetric wavelet filter of length L=8 denoted by LA (8) eights journal article have used this approach (LA8) IN and Kim Book (An Introduction to Wavelet Theory In Finance). In literature, it is argued that this filter generates smoother wavelet coefficients than other filters such as Haar wavelet filter. The continuous wavelet transform (CWT) $W_X(u,s)$ is obtained by projecting a mother wavelet ψ onto the examined time series $x(t) \in L^2(\mathbb{R})$,that is:

$$W_X(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) dt$$

In order to study the interaction among the series, how x and y are related by Linear transformation , we need to implement the method so called wavelet coherence. Which defined as :

$$R_n^2(s) = \frac{\left|S(s^{-1}W_n^{xy}(s))\right|^2}{S(s^{-1}|W_n^x(s)|^2 . S(s^{-1}\left|W_n^y(s)\right|^2}$$

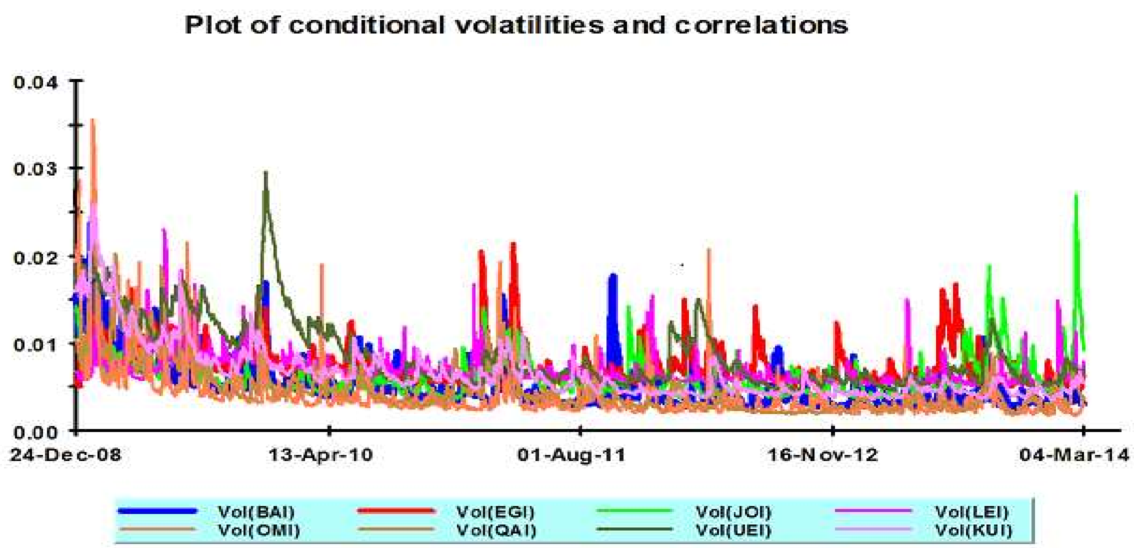
Where S is a smoothing operator, so is a wavelet scale, $W_n^x(s)$ is the continuous wavelet transform of the time series X, $W_n^y(s)$is the continuous wavelet transform of the time series Y, $W_n^{xy}(s)$is a cross wavelet transform of the two time series X and Y (Madaleno and Pinho, 2012). For brevity, we omit further detailed mathematical equations and interested readers may refer to Gencay et al (2001; 2002) and In and Kim (2013) for full methodological models.

Data Analysis and Empirical Results

To conduct this study, we extract daily data from Morgan Stanley Capital International (MSCI) indices. Our data consists of daily closing prices for Islamic stock Indices for eight countries representing MENA region, namely Egypt, Jordon, Lebanon, Kuwait, Oman, Qatar,Bahrain and United Arab Emirates. This countries were chosen to give us a clear picture of two spectra of the area in the MENA countries representing the side has lived the incident of the uprising, the other one is the countries didn't witness the revolution, but get affected by it, in somehow (will be proven later) to eliminate the currency effects, the value of all indices is in the US dollars, the continually decomposed returns are calculated as return on stock priced which is equal to the price of today divided by the price of yesterday minus one

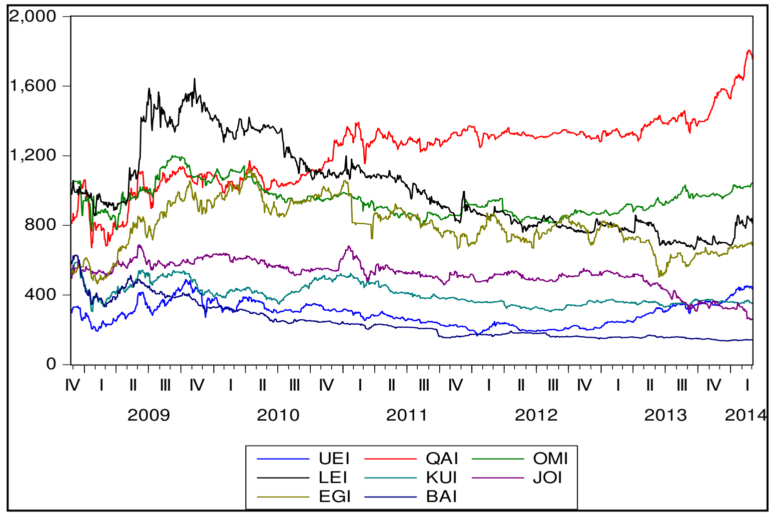
Return of Market = price of today /price of yesterday -1

Considering the viewpoint of international investor and based on the availability of datasets maintained by these prominent providers, we collect our daily data on Islamic stock indies from the MSCI database for the value started together [10] in the Islamic sector the data start matrix together for the indicated countries from November 2008 up to 4th of march 2285 as will, with a total of 1379 observations.

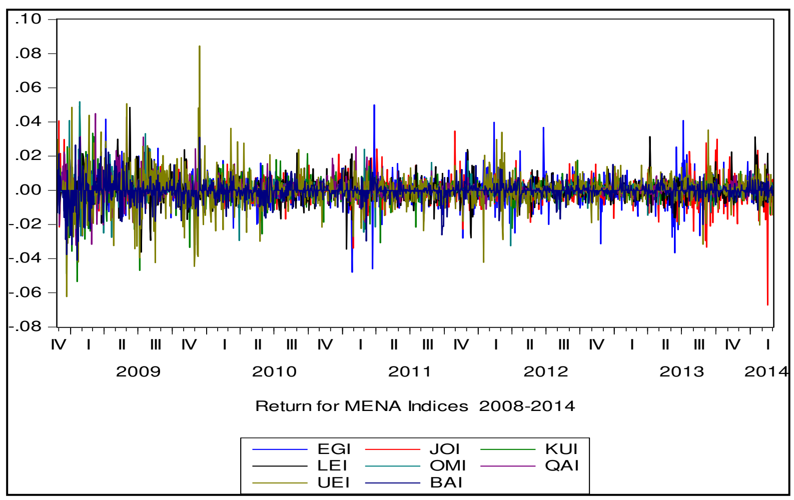


[10] In this point the researcher was lucky to find such data in Islamic finance index from those countries, especially it reflected three years ahead of Arab Spring and three years later of its beginning. That will give us comfortable view in order to describe our pieces of research in such a clear view of what have been happening before and after Arab spring.

Plot of the price of MENA stock indices from Nov 2008 to Mar 2014



Plot of the return of MENA stock indices from Nov 2008 to Mar 2014



Selected Indexes for Research

Symbol	Definition
BHI	**Bahrain Islamic Stock Exchange Index**
EGI	**Egypt Islamic Stock Exchange Index**
JOI	**Jordan Islamic Stock Exchange Index**
KUI	**Kuwait Islamic Stock Exchange Index**
LEI	**Lebanon Islamic Stock Exchange Index**
OMI	**Oman Islamic Stock Exchange Index**
QAI	**Qatar Islamic Stock Exchange Index**
UEI	**United Arab Emirate Islamic Stock Exchange Index**

Table 2: Descriptive Statistics of Indices Returns Series

Descriptive	UEI	QAI	OMI	LEI	KUI	JOI	EGI	BAI
Mean	0.000122	0.000238	2.81E-07	-6.56E-05	-0.00013	-0.00021	9.31E-05	-0.00045
Median	0	0	0	-2.89E-05	0	0	0	0
Maximum	0.084585	0.04496	0.051921	0.048554	0.049327	0.040723	0.05005	0.031031
Minimum	-0.06229	-0.03771	-0.03311	-0.03624	-0.05347	-0.06721	-0.04804	-0.04097
Std. Dev.	0.009233	0.005578	0.004745	0.006316	0.006733	0.006658	0.007424	0.005694
Skewness	0.224198	0.476403	0.506107	0.671417	-0.88658	-0.45909	-0.09571	-0.86822
Kurtosis	14.52569	16.90677	30.30245	10.59828	15.55738	15.00333	11.38419	12.25248
Jarque-Bera	7622.235	11132.12	42765.28	3410.976	9214.334	8302.884	4029.397	5077.392
Probability	0	0	0	0	0	0	0	0
Sum	0.168261	0.327459	0.000386	-0.09022	-0.17479	-0.28802	0.128059	-0.62366
Sum Sq. Dev.	0.117131	0.042746	0.030935	0.054807	0.06229	0.060904	0.075727	0.044543
Observations	1375	1375	1375	1375	1375	1375	1375	1375

The table 2 provides descriptive statistics of return series. All the return series are non-normally distributed.For every index, the Jarkue-Bera statistic rejects the null hypothesis of normality of returns .The skewness is divided into positive and negative four indices has negative signs Bahrain, Egypt, Kuwait and Lebanon, which means that large negative returns are more common than large positive returns in these four countries. Also, the kurtosis value of every market exceeds by far 3, particularly in Oman Market where it reaches 30.30. Thus the distribution of return in every market is leptokurtic in relation to Gussian distribution. This is a usual result, finding for stock market returns.

As DCC allows for the analysis of time variation in both mean and variance equations we can read our result of putting our data into Microfit 5 and getting the results computed pass on iterations we are presented with the following results:

```
       Multivariate GARCH with underlying multivariate t-distribution
                        Converged after 199 iterations
*******************************************************************************
 Based on  1315 observations from 18-Feb-09 to 04-Mar-14.
 The variables (asset returns) in the multivariate GARCH model are:
 BAI  EGI  JOI  KUI  LEI  OMI  QAI   UEI
 Volatility decay factors unrestricted, different for each variable.
 Correlation decay factors unrestricted, same for all variables.
*******************************************************************************
```

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda1_BAI	.68255	.043052	15.8543[.000]
lambda1_EGI	.77856	.042863	18.1639[.000]
lambda1_JOI	.78930	.051429	15.3474[.000]
lambda1_KUI	.85791	.075998	11.2886[.000]
lambda1_LEI	.37598	.10154	3.7027[.000]
lambda1_OMI	.56149	.057598	9.7484[.000]
lambda1_QAI	.83669	.032946	25.3956[.000]
lambda1_UEI	.92555	.017083	54.1793[.000]
lambda2_BAI	.26524	.034027	7.7949[.000]
lambda2_EGI	.12941	.022823	5.6702[.000]
lambda2_JOI	.13624	.029148	4.6741[.000]
lambda2_KUI	.11370	.057664	1.9718[.049]
lambda2_LEI	.19342	.031948	6.0541[.000]
lambda2_OMI	.38219	.048248	7.9213[.000]
lambda2_QAI	.14946	.028919	5.1683[.000]
lambda2_UEI	.066094	.014150	4.6708[.000]
delta1	.99549	.8969E-3	1109.9[.000]
delta2	.0044079	.7074E-3	6.2307[.000]
df	2.3872	.022091	108.0631[.000]

```
*******************************************************************************
 Maximized Log-Likelihood =    42886.0
*******************************************************************************
df is the degrees of freedom of the multivariate t distribution
```

Estimated Unconditional Volatility Matrix

```
     1315 observations used for estimation from 18-Feb-09 to 04-Mar-14
   Unconditional Volatilities (Standard Errors) on the Diagonal Elements
          Unconditional Correlations on the Off-Diagonal Elements
*******************************************************************************
```

	BAI	EGI	JOI	KUI	LEI	OMI	QAI	UEI
BAI	.0049174	.17062	.061919	.21850	.033222	.12441	.14744	.25344
EGI	*.17062*	.0072992	.077163	.16810	.036320	.13772	.19466	.27865
JOI	.061919	.077163	.0064329	.081197	.060616	.071641	.22031	.19024
KUI	.21850	.16810	.081197	.0056679	.084802	.075109	.21287	.24480
LEI	.033222	.036320	.060616	.084802	.0061976	.017479	.054331	.12152
OMI	.12441	.13772	.071641	.075109	.017479	.0038364	.19805	.22923
QAI	.14744	.19466	.22031	.21287	.054331	.19805	.0049439	.40027
UEI	.25344	.27865	.19024	.24480	.12152	.22923	.40027	.0087189

For the time-varying conditional volatilities and correlations see the Post Estimation Menu.

The upper panel of the above results presents the maximum likelihood estimates of Pita 1 and pita 2 (volatility Parameters) for the eight market index returns. We can notice that all volatilities are highly significant, which implies gradual volatility decay for instance, the high riskiness of the future return gradually decays (dies out) following a shock in the market, which makes the return highly volatile .Even by adding Lamda1-BAI to Lamda2-BAI (0.68255+0.26524=0.94779<1) Which is less unity, implies that the volatility of the Bahrain stock market future returns is not following IGARCH i.e. the shock to volatility is not permanent.

The lower panel of the results, reports the estimated unconditional volatilities and unconditional correlation, cross correlation between future returns the off diagonal elements represent unconditional correlation and diagonal elements represent unconditional volatilities of the stock market returns. We can find out unconditional volatility is highest in United Arab Emirates(.0087189) followed by Egypt(.0072992) and lowest in Oman (0.0038364) and Qatar (0.0049439), which implies that Oman futures returned are more stable followed by Qatar as well. While, less stable stock markets in the future, is going to be UAE and EGI. Investors should be aware of that before investing in these stock indices. Also, by reading the cross return correlation, we observe that UEI and QAI (+40%) are the most correlated, which shows the possible direction of movement and the degree of association between the two market return. It is also a concern for the investors as any movement in the return of either of the two causes another to move in the same direction.

By applying the DCC –GARCH tool above,we decompose the data into two periods only (long term period and short term period) but in the real market the participants are more than two categories they are many investors in the market each one of them has his own reason to buy or sale at different holding stock period , there are the market maker and the hedger etc... That is the first reasons enforced us to employ a wavelet technique the second one, even though, the correlation coefficient technique for a better estimating and reading data as sophisticated tools was GARCH Model which relaxed most of those assumptions, but still has some restrictions to be applied. Most finance variables (including stock market indices) are non-stationary. This means that performing ordinary regression on the variables will render the results misleading, as statistical tests like t-ratios and F statistics are not statistically valid when applied to non-stationary variables. Performing regressions of the difference form of these variables will solve one problem, at the expense of committing an arguably even graver one. When variables are regressing in their difference from, the long-term trend is effectively removed. Thus, the regression only captures short term, cyclical or seasonal effects. In other words, regression fails to test long-term (theoretical) relationships. Here we come to the latest one called Wavelet[11] .

What is Wavelet: it's that kind of technique which decomposes relationships into different time scales (more than two levels) while in the case of a VECM decomposed only two levels of relationships (long –term and short-term between variables.

In terms of concern wavelet implementations in finance, main recent works applied the wavelet analysis for assessing the volatility transmission between the main developed stock markets. In fact, wavelets are considered as a powerful mathematical tool for signal processing which can provide more insights to co-movement among international stock markets via a decomposition of the time series into their time scale component. With reference to GCC stock markets, Masih et al. (2010) had used the wavelet tool to estimate the systematic risk via the "beta parameter". They concluded that on average the beta coefficients in all the GCC markets exhibit a multiscales tendency. That result comes to an agreement with the theoretical argument that stock market investors have different time horizons due to different trading strategies and that is also reflecting the characteristics

[11] Lecture for Rumi Masih 7/4/2012 at INCEIF Campus. KL Malaysia

of the GCC markets.[12] In our study it has the same characterized, as we are working in the MENA region with the same period the only extra on Masih studies; we concentrate here on the effects of Arab spring revolution on the volatility of the Index on 8 countries in the area. Empirical results by applying the Wavelet coherence on the data of 8 Islamic indices of the stock market co-movement. The wavelet coherence analysis can provide interesting insight into MENA stock market has evolved over time and across frequencies.

[The 28 figures about to be here but rather not to cut the paper into half because they are so many I attached them (as an appendix) with the rest of the results from DCC-GARCH]

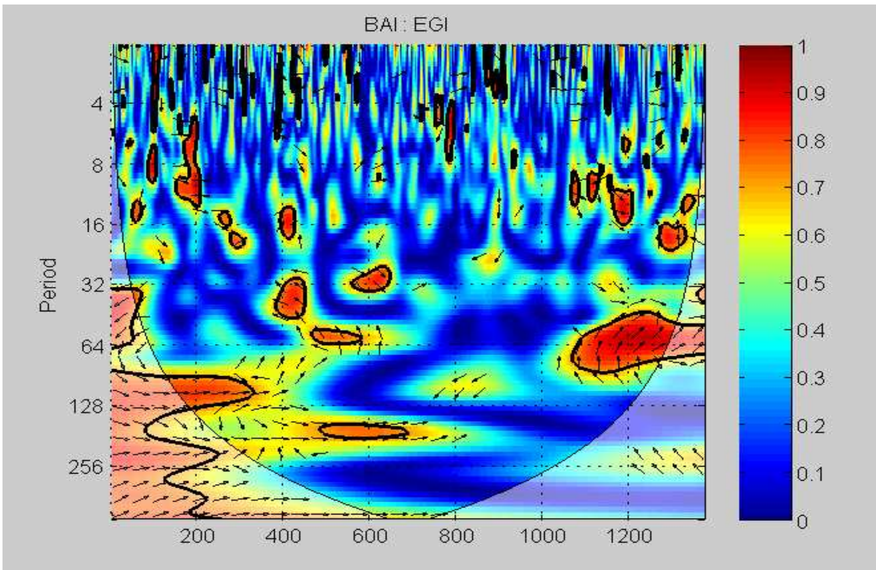
From the analysis of the wavelet coherence. We can disclose some interesting results.

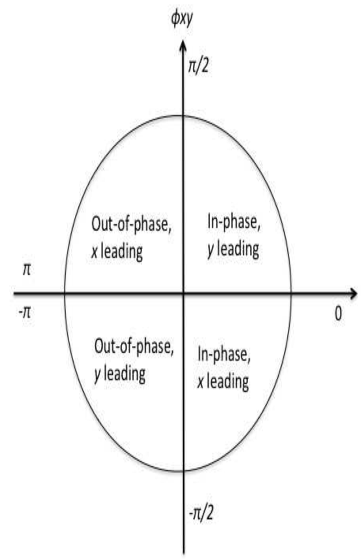
First of all, we can easily observe that the dynamics of the interactive relationship between the selected MENA stock market is changing rapidly in time, we can also note that the dynamic change in frequency as well. All our 28 figures depicting the possible bares of our 8 markets , all figures have 8 intervals (8 holding stock periods, starting from two days to 4 days (4-8, 8-16, 16-32,32-64,64-128, finally from 128 days to 256 which is indicate one year). A first layman glance here instantly confirms the lower levels of correlations between two stock indices in the short period, especially in the third level, which is 16 days. We can see how blue the area indicating a weak form of correlation this is a good opportunity for investors to take advantage of that and act accordingly (**offering effective portfolio diversification opportunities).**

[12] In the same study, the authors computed the VaR for different time-scales. They showed that risk tends to concentrate more at higher frequencies for the GCC stock Markets.

Table equivalent data observed from Excel to match the date in wavelet results

0 to 200	200-400	400-600	600-800	800-1000	1000-1200	1200-1400
2008-2009	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014

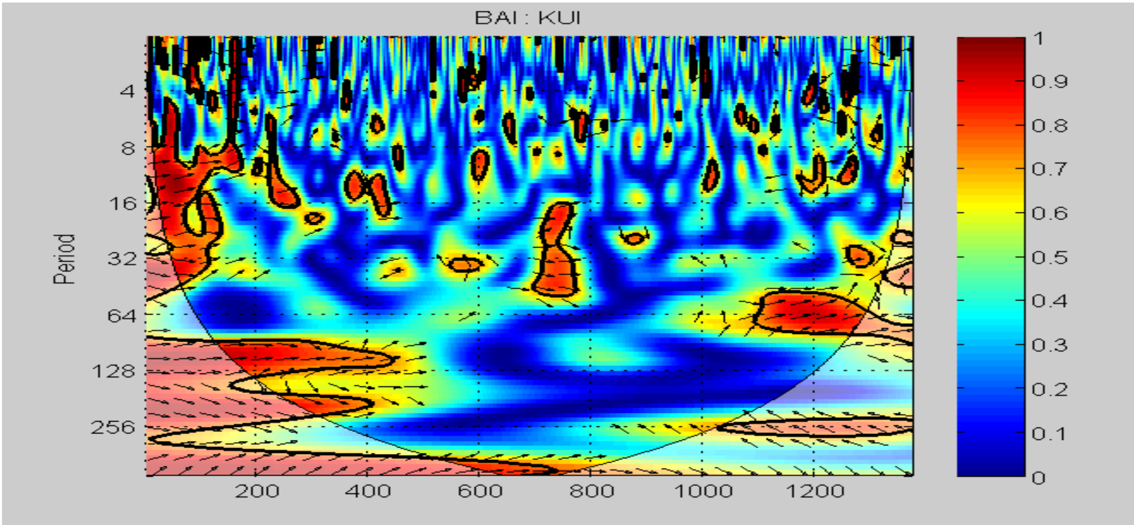


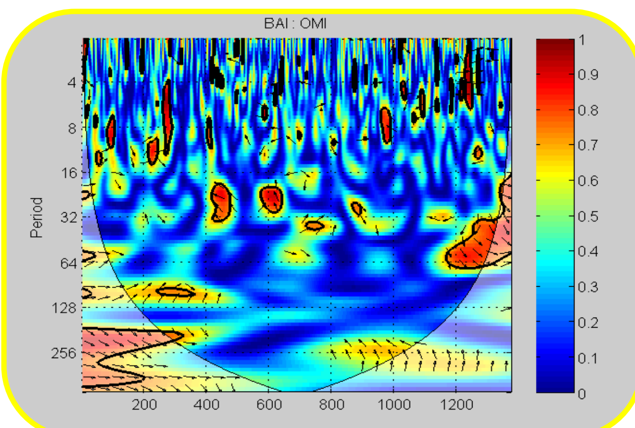


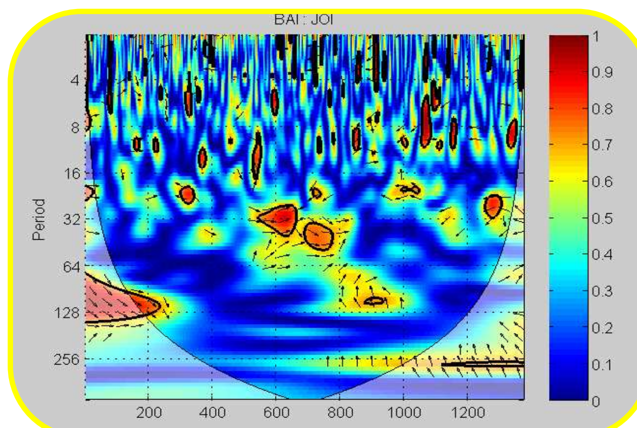
[13]

For example, when considering the co-movement between Bahrain and Eygept which shows weak co-movement for an investment horizon of several months between 2010-2012 as the color in that area is blue which indicate no correlation in the crystal of 32-64 days .,the short term dependence seems to be very low during the period under consideration . This result corroborates some previous findings by By Chaker Aloui ,Besma Hkiri(2013), Masih et al. (2010). We can see the highest increase in the year 2013 in the period of 64-128 days as the correlation is strong and the arrows indicate in phase to up left which means Bahrain leading.

[13] This shape from Burhan Saiti PHD reaserch under the title of "Testomg the Contagion Between Conventional ans Sharia'ah-Compliant Stock Indexes:A Multi Country Study Using Wavelet Analysis.







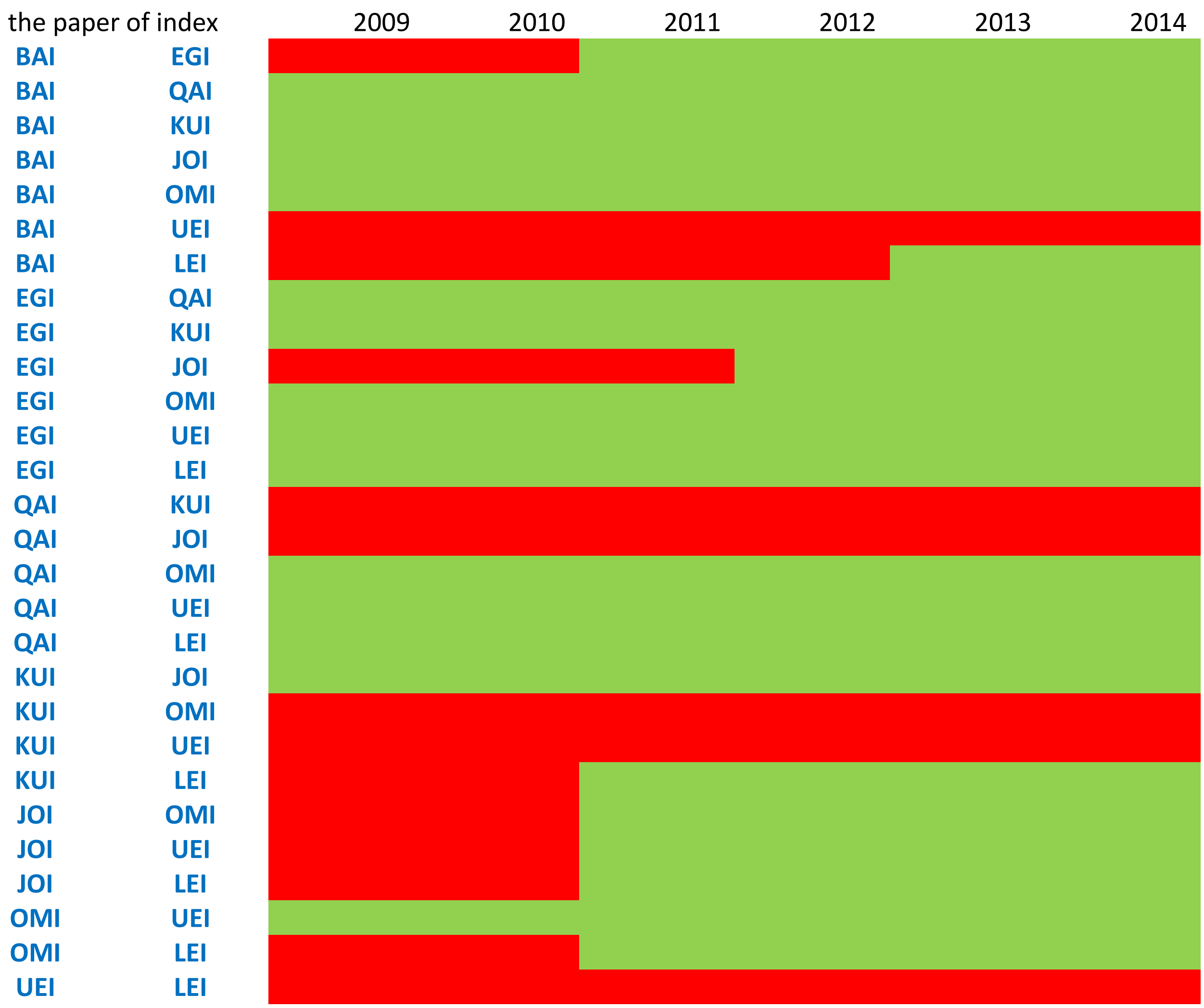
The same rules applied here as in the first two Phase correlation in weak between markets (BAI: OMI and BAI:JOi)

But for the period 64 days to 128 of the years 2011-2013 the graph tells something else as the changes in the year 2011 indicate there is more correlation between the two markets in Phase. Arrows to upright indicate JOI leading.

By scanning throw the 28 figures (Attached as an appendix). We can con get some ideas how the countries of the MENA region connecting to each other, the schedule below summarize the relationship just on the holding period of 64 to 128 days, also 128 to 256 day (one whole business year),(six months holding period and one year holding period . The red color indicates strong correlation, while the green color indicates low correlation .For further research I will investigate more and have a clear explanation of this shape.

Table equivalent data observed from Excel to match the date in wavelet results

0 to 200	**200-400**	**400-600**	**600-800**	**800-1000**	**1000-1200**	**1200-1400**
2008-2009	2008-2009	2009-2010	2010-2011	2011-2012	2012 2013	2013-2014



We can notice some facts as well .The first one most of the figures indicate low correlation this inconsistent with previous studies for Masih et.al (2010). The argument was interesting to explain why most those markets in the GCC area have not correlated as they mentioned the region driven by other financial sector. It seemed real economy has been driven by banks sectors, not by stock market sectors. Second in term of technical machinery the region is behind , also the difficulty of moving capitals among markets and lack of transparency and unreliable matter all these reasons make the market co -integration in its lowest level. The other clear Idea we can spot it through the figures. They are in two different categories, one for the country has uprising incidence in their counties such Egypt, Bahrain, Jorden, and Lebanon and the other is the market indices, on the GCC (Qatar, Kuwait, Oman, UAE) with the other shape.

From the financial view, the increasing of MENA region stock market correlation comovement during the revolutionary period, especially at low and high frequencies corroborate the "contagion Hypothesis" during these periods. That's going in parallel with previous studies, (Forbs and Rigobon, 2002) have clearly differentiated between stock market interdependence and the contagion effect.

From an empirical outlook, the time-varying behavior of the correlation coefficients could result in structural breaks in the asset price series when significant external shocks occurred. But from a practical side, our results clearly indicate the changing pattern of co-movement among the major MENA stock markets. The instability in various aspects of the MENA stock markets, co-movement may provide several implications for portfolio managers, international investors, as well as for hedge fund operators.

CONCLUSION

In this paper, we examined the effects of political uprisings on the volatility and integration of major stock markets across the MENA region. Our results indicate that the Arab Spring (and the associated political turbulence) contributed to the volatility of MENA stock markets, particularly as it is illustrated in Islamic indices. This supports previous studies, including O'Sullivan et al. 2012; World Bank, 2011 and Frankie and Wand, 2014. Our results are, as expected, similar to some parts of previous studies, but present interestingly different features on other parts.

Previous political uncertainties, such as the United States' Black Monday of October 1987, the Asian financial crisis of 1997-1998, the dot.com tech bubble, the September 11 terrorists attack on the World Trade Center in New York, and the global financial crisis of 2008, all contributed to financial volatility. This suggests that financial asset price movement is driven, in part, by political events as well as common financial and economic factors (Gilpin, 2001).

Overall, our findings complement previous studies in an increasing corpus of literature on the relationship between political risk and asset prices, giving investors sufficient information to make informed business decisions in times of political turmoil. We also identify the best holding period, which depends on the categories of investment interest – daily, weekly, monthly , quarterly, semi annually or one year periods. This was obtained by employing the sophisticated technique of CWT wavelet. These results represent very important contribution to the current discussion about the role of political risk and asset price.

This study can be expanded by adding the conventional sector and comparing the effects of the Arab Spring on both the conventional financial market and Islamic financial market. This will present a complete picture to investors, policy makers and market regulators. Another important recommendation for further study of this topic is employing the Markov Regime switching technique on the same data to test market conditions under old and new political regimes. This permits a coherent analysis of economic conditions under different pre and post revolution regimes and the sustainability of economic growth under post revolution regimes.

The core goal of this research has been to underline the importance of market stability and economic growth for political stability and prosperity. It is imperative for any new governments to restore business stability in order to gain investors' confidence and secure a progressive move towards a better future.

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