Does oil impact Islamic stock markets ? evidence from MENA countries based on wavelet and markov switching approaches

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ABSTRACT

This paper combines the Wavelet and Markov switching analysis to examine the impact in the volatility of crude oil prices on the Islamic stock market returns of the Middle East and Northern African countries (MENA) over the period of July 2010 to March 2016. Result tend to show that, in all cases, the variables exhibit less coherence in the short run (first sixteen days) except in Jordan, Oman and Qatar. In general, for the entire analyzed period, the colour code shows that the co-movements between series are more persistent in the medium run (32-64 day cycles) and long run (32-64 day cycles). In the short-run, the direction of the contagion cannot be identified. The coherence is only persistent over the medium run (32-64 day cycle) from the period of 2012-2016. In case of co-movement, the Bahrain, Jordan, Saudi Arabia, and the UAE, Islamic stock indices are leading crude oil. This means that if Bahrain, Jordan, Saudi Arabia and the UAE Islamic Stock markets are bullish the oil price rises. However, over the period of 2011-2012, and 2015-2016 crude oil returns were leading the Kuwait Islamic stock index but in the period of 2014-2015, the Kuwaiti Islamic stock index led the crude oil returns. A similar case can be observed during the period of 2015-2016 where the Tunisian Islamic stock index led crude oil return but in 2016, crude oil returns led the Tunisian Islamic Index. Except for Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates over the long-run (128 day cycle), there is no coherence at that period. They move separately which implies that oil price is independent of the bullish or bearish trend of the Islamic Stock Markets of Bahrain, Jordan and Tunisia. Regarding the issue of Markov regime-switching, the results tend to reject the 'null hypothesis of no regime shifts' for the stock markets in the ASEAN countries, which means that the time-varying behaviour of these markets is better captured by the nonlinear MS-AR model.

Keywords: Islamic stock markets, oil price, wavelets, markov switching, MENA

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1.0 INTRODUCTION

The MENA region, the term used to classify countries that are located in Middle East and North Africa has 60% of the world's oil reserve (Journal of Oil and Gas, 2009) thus making it an important source of economic stability. Most of these countries heavily rely on the revenues generated from the sale of oil to plan their fiscal policies for the year and such as require the global crude oil price to be the highest it can. Over the years, global crude oil prices have experienced fluctuations, specifically from 2003 to 2008, crude oil prices rose to the highest in recorded history. However, after 2008, apparently due the global financial crisis, prices dropped. Demand for crude oil could be attributed to the growth of emerging economies of Brazil, China & India. In their paper, Jones and Kaul (1996), documented that stock price movements can be accounted for by the impact of crude oil volatility shocks on real cash-flow. Numerous studies in the past on crude oil have centered their deliberations on whether and how oil value changes sway on stock market returns. Aloui, Jammazi et al. (2008) find that adjustments in crude oil prices cause altogether the instability of the stock market returns of six developed nations utilizing univariate and multivariate methodologies (Aloui, Jammazy et al. 2008). Park and Ratti (2008) report that oil value shocks have a factually huge effect on real stock returns for the US and 13 European oil importing nations (Park & Ratti 2008). Albeit a wide range of studies have been done, there is no accord about the impact of the crude oil shocks on the conventional stock market returns and the Islamic stock market returns.

According to (Abdullah, Saiti & Masih, 2016), the underlying Islamic fund in global financial institutions is around $1.3 trillion, while the size of the Islamic financial market is estimated to be around US$230 billion, growing at a rate of 12% to 15% per year. The number of *Shariah*-compliant investment funds has increased from nine funds with a collective value of US$800 million in 1994 to approximately 126 funds in year 2006, with US$16 billion under their management. This implies that the Islamic investment funds have grown at an average annual rate in excess of 28% during this period. Within Islamic investment funds, the equity funds market is one of the fastest-growing sectors. There are approximately 100 Islamic equity funds worldwide currently. The total assets managed through these funds exceed US$5 billion, growing by 12-15% per annum (Sadeghi, 2008). Therefore, the study on Islamic stock market is important to provide Islamic investors and fund managers an idea on riskiness and potential international portfolio diversification benefits.

Some of the MENA countries (e.g. UAE & Qatar) have utilized the surplus revenues from crude oil to develop their infrastructures and economy and eight of these countries are members of the

Organization of Petroleum Exporting Countries (OPEC). Crude oil prices play an important role in the way these countries formulate policies as high prices result in surplus revenues and government can allocate such revenues to other sectors of the economy needing financing. However, low oil prices currently seen today within the global economy results in most of these countries having deficits in their budgets. This has caused the affected nations to make budget cuts and/or borrow from global institutions such as the International Monetary Fund (IMF) to sustain their budgets.

Also, Investors in Islamic stock markets would like to know the time-varying volatilities of and the dynamic correlations between crude oil and Islamic stock markets in order to obtain their diversification benefits and to mitigate risk.

The main objective of this paper is to examine the relationship that exists between crude oil price and Islamic stock markets in MENA countries. The uniqueness that this paper has over others is that in addition to Continuous Wavelet Transform (CWT) we are applying Markov Switching Autoregressive Model (MS-AR) which is used to detect the interactions between crude oil returns and Islamic Stock market in a regime switching environment.

The remainder of this study is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the methodology of Continuous Wavelets Transformation (CWT) and Markov switching model used in this study. Section 4 describes the data. Section 5 reports and discusses the results. Section 6 concludes the study.

2.0 LITERATURE REVIEW

Several studies have provided theoretical explanations on the relationship between oil price changes and the level of Islamic Stock Markets. Some studies point towards the existence of a direct statistical relationship between oil and the Islamic Stock Market while others are inverse.

A recent empirical literature devoted to assess this relationship, Abdullah et al (2015), examine the dynamic causal relationship between crude oil price and Islamic stock indices in South East Asian (SEA) countries. They found the existence of a cointegration relationship

More so, Aun & Masih (2014), examine the short term and long term correlation between oil price shocks and GCC stock market's volatility and the presence of any lead lag relationships. Their finding shows the existence of a lead lag relationship in Bahrain and Qatar, where as there is no determinable oil price impact on the investments in the Saudi, Oman, UAE and Kuwait Stock Market.

Earlier studies, Alessandro & Manera (2009), investigated oil price shocks effect on the output growth rate of a subset of developed countries (G7) by comparing alternative regime switching models. Their findings indicates that oil shocks effects tend to be asymmetric and depend on whether or not the price increases are simple corrections of past decreases. Furthermore, the economies of these developed countries are not able to affect oil market conditions

Similarly, Jammazi & Aloui (2009), combined wavelet analysis and Markov Switching Vector Autoregressive (MS-VAR) approach to explore the impact of the crude oil (CO) shocks on the stock market returns for UK, France and Japan over the period from January 1989 to December 2007. They found that the stock market variables respond negatively and temporarily to the crude oil changes during moderate (France) and expansion (UK and France) phases but not at level to plunge them into a recession phase.

Furthermore, Chun-Li Tsai (2013), use firm-level data to reexamine the issue of possibly different impacts of “informative” and “uninformative” FOMC statements on stock returns in the period from 1999 to 2007. He finds that stock returns respond significantly to surprise monetary shocks based on the informative FOMC statements; there is little evidence to show that stock returns respond to surprise monetary shocks based on uninformative statements.

In addition, Fang & You (2013) studied the dynamic interactions between oil price and stock returns utilizing a structural vector autoregressive model (SVAR) for three large NIEs, in order to understand the relationship between oil price shocks driven by demand or supply and the BRIC stock markets. They find that the impact of oil price shocks on the three large NIEs' stock prices is mixed. Firstly, when oil price is not driven by the increasing oil consumption, the oil prices have a negative impact economy. Secondly, when the oil price movement is driven by oil-specific supply shocks there are significant positive impacts on stock returns.

In line with studies mentioned earlier, Reboredo & Rivera-Castro (2013), also examined the relationship between oil and stock markets in Europe and the USA at the aggregate and sectoral levels using wavelet multi-resolution analysis. Their findings shows that oil prices changes had no effect on European and US stock markets returns and that contagion and positive interdependence between oil and stock prices is evident in Europe and the USA since the onset of the global financial crisis, at the aggregate and sectoral levels.

The studies presented thus far provide evidence that there has not been a consensus as to a definite between oil and Islamic stock markets especial in a regime switching environment. Therefore, it is of utmost importance to embark on this study.

3.0 METHODOLOGY

CONTINUOUS WAVELET TRANSFORM (CWT)

Wavelet analysis is becoming a common tool for analyzing localized variations of power within a time series. By decomposing a time series into time–frequency space, one is able to determine both the dominant modes of variability and how those modes vary in time. The wavelet transform has been used for numerous studies in geophysics, including tropical convection (Weng and Lau 1994), the El Niño–Southern Oscillation (ENSO; Gu and Philander 1995; Wang and Wang 1996), atmospheric cold fronts (Gamage and Blumen 1993), central England temperature (Baliunas et al. 1997), the dispersion of ocean waves (Meyers et al. 1993), wave growth and breaking (Liu 1994), and coherent structures in turbulent flows (Farge 1992). Wavelet analysis is relatively new in economics and finance, although the literature on wavelets is growing rapidly (In & Sangbe).

A wavelet is a small "wave packet" that grows and decays in a limited time period. It is given by a function ψ in L2(ℝ) centred at the origin (more or less), with zero average and normalized. A family of daughter wavelets ψu , s(t) can be obtained by simply scaling and translating ψ:

$$\psi_{u,s}(t) := \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right),$$

Equation 1

where s is a scaling parameter that controls the length of the wavelet, and u is a location parameter that indicates where the wavelet is centred. Given a signal x(t) inL2(ℝ), its continuous wavelet transform CWT with respect to the wavelet ψ is a function of two variables.

$$W_x(u,s) := \int_{-\infty}^{+\infty} x(t)\psi^*_{u,s}(t)\mathrm{d}t,$$

Equation 2

where $*$ denotes complex conjugation. It represents the frequency components (or details) of $x(t)$ corresponding to the scale s and time location u, providing a continuous time-frequency decomposition of $x(t)$, while the discrete wavelet transform (DWT) uses a specific subset of discrete scale and location values.

The CWT by its very nature, contains a large amount of redundant information on the original signal that makes it much easier to interpret the empirical results as it provides a more visually intuitive output. As argued by Grinsted, Moore, & Jevrejeva (2004), the CWT is better for feature extraction purposes, while the DWT is more useful for multi-resolution analysis, particularly for noise reduction and data compression. For a long time, the discrete wavelet analysis has prevailed in economic research (Gallegati, 2008, Hacker et al., 2014, Jammazi, 2012, Reboredo and Rivera-Castro, 2014a and Reboredo and Rivera-Castro, 2014b) due to its greater simplicity and more parsimonious nature. However, in recent years the continuous wavelet analysis has also become very popular in the economic-finance literature (Aguiar-Conraria and Soares, 2014, Jiang et al., 2015, Tiwari et al., 2014a and Tiwari et al., 2014b, Dewandaru et al. (2016)). One of the major benefits of the CWT is its ability to describe localized co-movement between two time series in the time-frequency space through the use of cross-wavelet tools.

Several types of wavelet families with different characteristics are available in the literature. The application presented here utilizes the Morlet wavelet because it is the most commonly used wavelet and implies a very simple inverse relationship between scale and frequency. Moreover, the Morlet wavelet is a complex wavelet that can be decomposed into real and imaginary parts. This feature allows separation of amplitude and phase of the signal under study, providing more information about synchronization and delays between two time series. The Morlet wavelet was introduced by Goupillaud, Grossman, & Morlet (1984) and can be defined as $\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}$, where ω_0 denotes the central frequency of the wavelet. We set $\omega_0 = 6$ since this choice provides a good balance between time and frequency localization and it is very often employed in economic and financial applications (Aguiar-Conraria & Soares, 2014).

In order to detect and quantify relationships between time series, two cross-wavelet tools, introduced by Torrence & Compo (1998) within the framework of the CWT, can be used, namely the wavelet coherence and wavelet phase-difference. According to Torrence & Webster (1999), the wavelet coherence between two time series $x(t)$ and $y(t)$ is defined by.

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S(s^{-1}|W_x(u,s)|^2)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)},$$

Equation 3

where Wxy(u, s) : = Wx(u, s)Wy∗(u, s) is the cross-wavelet spectrum (∗ indicates the complex conjugate), and S is a smoothing operator in both time and frequency. The wavelet coherence (3) ranges from 0 (no correlation) to 1 (perfect correlation) and is analogous to the squared correlation coefficient in linear regression. This concept is particularly useful for determining the regions in the time-frequency domain where two time series have a significant co-movement or interdependence.

In spite of its usefulness for measuring the strength of the linkage between any two time series in the time-frequency space, the wavelet coherence is able neither to determine the sign of this link nor to identify lead–lag relations between the two series. This problem can be solved by using the wavelet phase-difference, which characterizes possible delays in the oscillations between the two series, providing information on lead–lag effects as well as the sign of the association. Following Torrence & Webster (1999), the phase-difference is defined by

$$\phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}{\Re\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}\right),$$

Equation 4

where $\Re$ and $\Im$ represent the real and imaginary parts, respectively.

The phase information is graphically displayed on the same figure that the wavelet coherence by plotting arrows inside the regions characterized by high coherence. A phase-difference of zero indicates that the two time series move together at the specified frequency. Arrows point to the right (left) when the two time series are in phase (anti-phase). When the two series are in phase, they move in the same direction. Anti-phase means that the two series move in the opposite direction. Arrows pointing up suggest that the first time series leads the second one, while arrows pointing down indicate that the second series leads the first one.

The Markov switching models

Recently regime switching models have become a popular framework for capturing the non-linear behavior seen in these time series. These models are based on the idea that the parameters of the time series, such as the mean and variance, assume different values within different time periods or "regimes". The time series switches between these different regimes in accordance with a probability law. First introduced by Hamilton (1989) to explain business cycles, regime switching models have since been applied to a great number of phenomena including interest rates (Gray, 1996), exchange rates (Engle, 1994), inflation (Simon, 1996), the volatility of equity returns (Dueker, 1997) and more recently merger and acquisitions activity (Town, 1992)

Following Hamilton (1989), a time-series variable yt can be modelled by a Markov switching autoregressive of order p (MS-AR) with regime shifts in mean and variance as follows

$$y_t = \mu(s_t) + \left[\sum_{i=1}^{P} \phi\,(y_t = \mu(s_{t-i}))\right] + \sigma(s_t)\varepsilon_t$$

Equation 5

where ϕi are the autoregressive coefficients. μ and σ are the mean and standard deviation depending on the regime St at time t. yt represents the Islamic stock market returns of the MENA countries. This MS-AR framework allows us to not only detect potential regime shifts in the stock market returns, but also investigate the impact of crises on the stock market volatility.

$$e_t = \beta_1 + \sum_{k=1}^{l} \beta_{2j}\,(s_t)e_{t-k} + \sum_{k=1}^{l} \beta_{3j}\,(s_t)r_{t-k} + v(s_t)u_{e,t}$$

Equation 6

where rt and et denote the stock market and exchange rate returns for each country, respectively. ut is the innovation process with a variance v(st) depending on regime St which is assumed to follow an irreducible ergodic two-state Markov process, defined by the transition probabilities pij between states as follows:

where

$$\begin{cases} P_{11} = P(S_t = 1|S_{t-1} = 1) \\ P_{12} = 1 - P_{11} = P(S_t = 1|S_{t-1} = 2) \\ P_{21} = 1 - P_{11} = P(S_t = 2|S_{t-1} = 1) \\ P_{22} = P(S_t = 2|S_{t-1} = 2) \end{cases}$$

Equation 8

4.0 DATA

Our dataset consists of weekly stock prices returns for eight Middle East and North Africa (MENA) countries (Bahrain, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Tunisia, and the United Arab Emirates) and crude oil price returns. The sample period spans from 14th July 2010 to 23rd March 2016, yielding a total of 298 observations. The data for crude oil returns and Islamic stock indices returns were extracted from Thompson Reuters DataStream International and are expressed in United States Dollars. Daily returns were calculated from the Islamic Stock indices prices and crude oil prices by first making the variables in level form followed by the first difference in logarithm.

	BAH	JOR	KUW	OIL	OMA	QAT	SAU	TUN	UAE
Mean	33.03004	874.0720	52.22408	89.82800	137.5012	180.8350	156.9652	358.8677	103.8907
Median	31.12400	959.3840	55.26800	103.8670	140.5170	164.9100	152.6840	339.7710	100.2780
Maximum	50.01800	1206.544	62.54000	123.7820	183.8180	256.5920	215.9580	545.6080	167.7020
Minimum	22.12400	605.4920	29.60600	24.06000	91.23000	115.6260	105.9380	236.5880	60.62400
Std. Dev.	7.026653	170.3378	8.448513	26.36102	27.88888	36.17149	20.91286	79.46133	31.95256
Skewness	0.620240	-0.148258	-1.126672	-1.001803	0.037113	0.478367	0.591363	0.446680	0.315817
Kurtosis	2.238665	1.413035	3.029005	2.628217	1.534396	2.120825	3.142265	2.182613	1.717330
Jarque-Bera	26.30372	32.36255	63.05676	51.56222	26.73936	20.96294	17.62025	18.20548	25.38217
Probability	0.000002	0.000000	0.000000	0.000000	0.000002	0.000028	0.000149	0.000111	0.000003
Sum	9842.953	260473.5	15562.78	26768.74	40975.36	53888.83	46775.62	106942.6	30959.43
Sum Sq. Dev.	14664.03	8617449.	21199.08	206386.3	231003.5	388587.8	129892.3	1875289.	303226.9
Observations	298	298	298	298	298	298	298	298	298

Table 1: Descriptive statistics

Table 1 reports summary statistics for the series. On average, with the exception of Tunisia has the highest stock market returns whereas, Bahrain has the lowest returns. In terms of volatility, Jordan is most volatile while Bahrain is least volatile as indicated by the associated standard deviations.

5.0 RESULTS

5.1 OIL AND MENA ISLAMIC STOCK MARKET: WAVLET ANALYSIS

Wavelets provide a unique decomposition of time series observations that enable one to deconstruct the data in ways that are potentially revealing (Ramsey, 2002). It is used to decompose non-stationary time series into different time scales and it provides useful information for the interpretation of the series structure and the analysis of its history (Jammazi & Aloui, 2010).

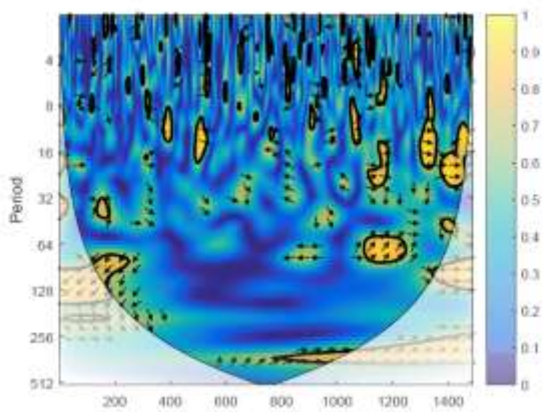
As pointed out by Dewandaru et al. (2015), when interpreting the result of wavelet coherence and phase-difference in the field of finance and economics, we should be aware that the leading role of one market over another market does not necessarily mean that there is a specific causality between the two. We should interpret with caution that the two markets, in fact, co-move with one market taking a leading role over another. To explore further whether it implies any causation, we commonly need to investigate several channels of transmission, according to the documented theoretical and empirical studies, and are estimated using Granger causality in a multivariate framework. Since we focus on measuring market co-movements in a bivariate framework, this is therefore beyond the scope of our study, which may be a subject for future research.

Figure 1 represents wavelet squared coherency and wavelet phase-difference between changes in crude oil returns and Islamic stocks returns for each of the eight MENA countries. Following standard practice in the literature, the wavelet coherence is presented by using contour plots as it involves three dimensions: frequency, time and wavelet coherence power. Frequency and time are represented on the y (vertical) and x (horizontal) axes, respectively. With the aim of easing interpretation, the frequency is converted into time units (years) and it ranges from the highest frequency of one week (top of the plot) to the lowest frequency of 512 days (1 and half years) at the bottom of the plot. The wavelet coherence is depicted by colour ranging from blue (low power) to Gold Yellow (high power). The Gold Yellow colour simply means that the two series have high common power. Intuitively, the two series experience the same high volatility regime.

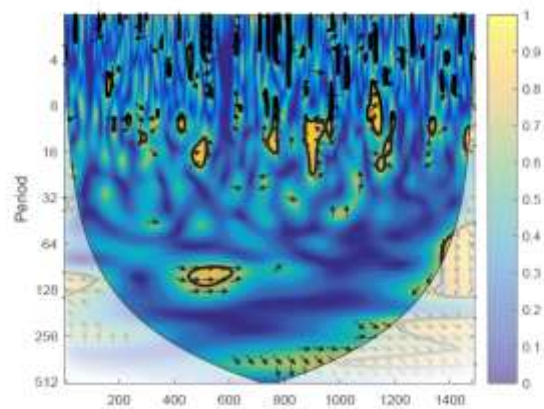
The thin black line represents the cone of influence below which edge effects become important. Hence, values outside the cone of influence should be interpreted very carefully. The thick black line isolates regions where the wavelet coherence is significant at the 5% level estimated from the Monte Carlo simulations.

Cross Wavelet Transform

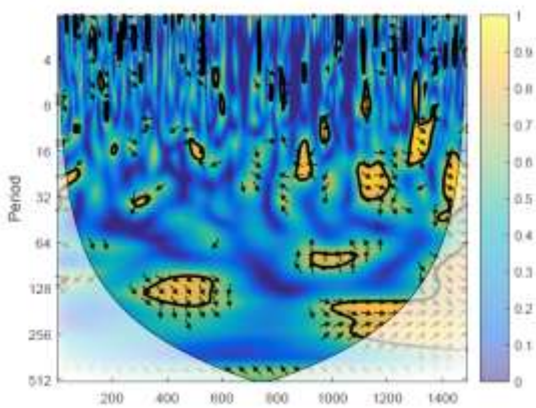
Oil vs Bahrain



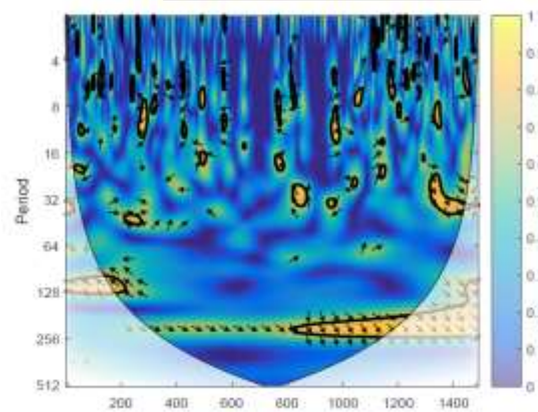
Oil vs Jordan



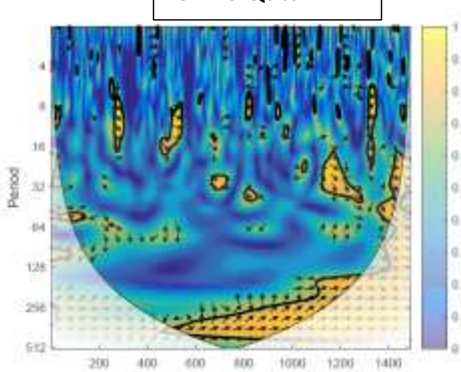
Oil vs Kuwait



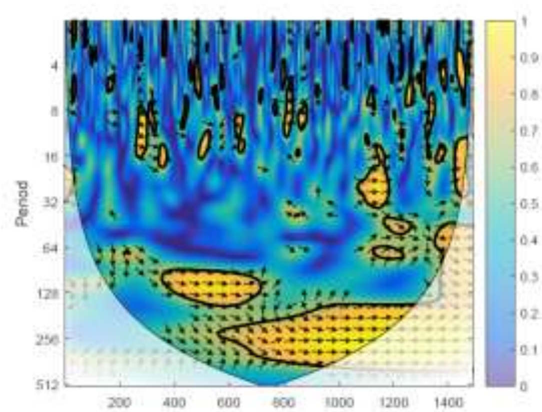
Oil vs Oman



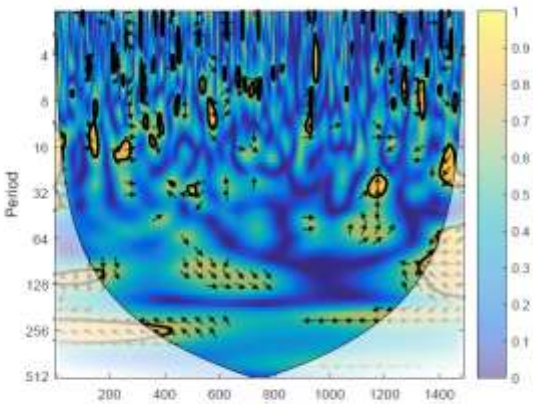
Oil vs Qatar



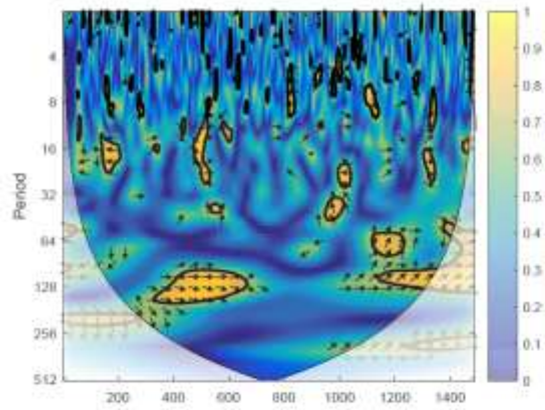
Oil vs Saudi Arabia



Oil vs Tunisia



Oil vs UAE



The 5% significance level against red noise is shown as a thick contour. The relative phase relationship is shown as pointing arrows: Right: in-phase, positively correlated; Left: anti-phase, negatively correlated; Down: crude oil leading Country’s Islamic stock index by 90°; Up: Country’s Islamic Stock Index leading crude oil by 90°. The yellow-Gold colour denotes high power spectrum.

Result shows that, in all cases, the variables exhibit less coherence in the short run (first sixteen days) except in Jordan, Oman and Qatar. In general, for the entire analyzed period, the colour code shows that the co-movements between series are more persistent in the medium run (32-64 day cycles) and long run (32-64 day cycles). In the short-run, the direction of the contagion cannot be identified.

The coherence is only persistent over the medium run (32-64 day cycle) from the period of 2012-2016. In case of co-movement, the Bahrain, Jordan, Saudi Arabia, and the UAE, Islamic stock indices are leading crude oil. This means that if Bahrain Jordan Saudi Arabia and the UAE Islamic Stock markets are bullish the oil price rises. However, over the period of 2011-2012, and 2015-2016 crude oil returns was leading the Kuwait Islamic stock index but in the period of 2014-2015, the Kuwaiti Islamic stock index let crude oil returns. A similar case can be observed during the period of 2015-2016 where the Tunisian Islamic stock index led crude oil return but in 2016, crude oil returns led the Tunisian Islamic Index. Except for Kuwait, Oman, Qatar, Saudi Arabia, and the

United Arab Emirates over the long-run (128 day cycle), there is no coherence at that period. They move separately which implies that oil price is independent of the bullish or bearish trend of the Islamic Stock Markets of Bahrain Jordan and Tunisia. Implication? However, both markets are in anti-phase most of the medium and long-run. Implication?

5.2 REGIME SHIFTS IN THE ISLAMIC STOCK MARKETS OF MENA COUNTRIES

In examining the relationships between crude oil returns and Islamic Stock Markets, in a regime-switching environment, the first step in our empirical investigation consists of verifying whether stock returns of sample markets exhibit regime-switching behaviour. For this purpose, we proceed to test the null hypothesis of no regime shifts (i.e., the dynamics of stock returns is better reproduced by a linear autoregressive model) against the alternative of regime switching model which corresponds to a MS-AR model. Formally, the likelihood ratio test (LR) developed by Garcia and Perron (1996) is used to make final choice of suitable modelling approaches. This test is computed as follows

$$LR = 2 \times |lnL_{MS-AR} - lnL_{AR}$$

where lnL is the log likelihood of the competing models. The best-suited model is selected on the basis of Davies (1987) critical values. As shown in Table 2, the LR test statistics are significant in all cases at the 1% level. These results lead us to reject the null hypothesis of no regime shifts for the stock markets in the ASEAN countries, which means that the time-varying behaviour of these markets is better described by the nonlinear MS-AR model. Past studies, including, among others, Kanas (2005), Wang and Theobald (2008), Chkili et al. (2012), Chkili and Nguyen (2011), Chkili and Nguyen (2014), and find similar results for other emerging markets. From a theoretical point of view, this behaviour is expected and can be explained by the changing economic structure in these markets owing to structural economic reform policies (financial liberalization, tax system adjustments, competition policy) as well as the occurrence of successive economic and financial crises at both regional and international levels.

Variables	lnL:MSAR	lnL:AR	LR
BAH	1359.853	1312.804	94.098++
JOR	1417.855	1385.182	65.346++
KUW	1477.503	1455.678	43.65++
OIL	1059.937	1004.802	110.27++
OMA	1490.686	1401.8	177.772++
QAT	1417.965	1350.913	134.104++
SAU	1423.654	1356.974	133.36++
TUN	1451.082	1412.702	76.76++
UAE	1340.099	1289.965	100.268++

Notes: ++ denote the null hypothesis of no regime shift is rejected at the 1% significance level

The MS-AR models are then estimated for oil and each of the sample stock markets following which the estimation results are reported in Table 2. The standard deviations of oil and Islamic stock markets indicate that they are highly significant and that their values clearly indicate the existence of two different regimes. The first regime, referred to as regime 1, is characterized by a high volatility level and the second regime (regime 2) displays a low volatility level. Among the MENA Islamic stock markets, Saudi Arabia has the highest volatility in both the low and high volatility regimes. Table 2 also indicates that the probability of being in regime 1 is higher than the probability of staying in regime 2, regardless of the markets. Indeed, the probability of being in the high volatility regime 1 ranges from 1.80 (Jordan) to 3.96 (Tunisia), while the probability of being in low volatility regime is comprised between -0.628 (Kuwait) and -3.39 (Qatar). The size of these probabilities (P11 and P22) suggests that the high volatility regime is more persistent than the low volatility one, or in other words, the Islamic stock markets of MENA countries stay longer in regime 1 than in regime 2. This finding is fully confirmed by the average duration in weeks for each regime (d1 and d2). The results show that the high volatility regime lasts, on average, between 53.5 weeks in Tunisia and 7.06 weeks in Jordan. On the other hand, the average duration of the low volatility regime is 30.9 weeks in Qatar, followed by 2.87 weeks in Kuwait, 30.59 weeks in Jordan, 16.55 weeks in Saudi Arabia, 12.7 weeks in Oman, 8.89 weeks in Tunisia, 7.45 weeks in Bahrain, 2.92 weeks in the UAE and weeks in Kuwait.

Estimation results for the MS-AR model

	Bahrain	Jordan	Kuwait	Oman	Qatar	Saudi Arabia	Tunisia	UAE	Oil
C(1)	-0.000437** (0.000122)	-0.000032* (0.000125)	- 0.0000475* (0.000137)	0.000224** (0.0000673)	0.000283* (0.000366)	0.000224** (0.0000955)	-0.000139* (0.0000889)	-0.00013* (0.000173)	- 0.003019* (0.002183)
C(2)	0.000331* (0.000407)	-0.000156* (0.0000939)	-0.000657* (0.000673)	-0.000171* (0.000464)	0.0000576* (0.0000897)	-0.00071* (0.000451)	-0.000489* (0.000564)	0.000576* (0.000647)	0.000131* (0.000681)
AR1	0.033959* (0.053604)	-0.142297** (0.060915)	0.131181** (0.06275)	0.028265* (0.055669)	-0.045732* (0.06671)	-0.01351* (0.07585)	-0.084044* (0.060086)	- 0.053016* (0.049718)	0.147790* (0.060627)
LS1	6.66226*** (0.091054)	- 5.534511*** (0.125757)	- 6.70799*** (0.108528)	- 6.940756*** (0.063719)	-5.579229 *** (0.085997)	- 6.658242 *** (0.066674)	-6.566042 *** (0.059523)	-6.431554 *** (0.178809)	- - 4.385043 *** (0.119298)
LS2	- 5.497344*** (0.084672)	- 6.501951*** (0.061332)	-5.790083 *** (0.199578)	- 5.618822*** (0.090166)	-6.770705 *** (0.064354)	- 5.533036 *** (0.094907)	-5.548500 *** (0.145206)	-5.239186 *** (0.177192)	- 5.413422 *** (0.092724)
P11	2.294919	1.802529	2.477198	3.455673	2.816931	3.653394	3.9609	2.044356	2.973967
P22	-1.86423	-3.387735	-0.628014	-2.460632	-3.398053	-2.744212	-2.066177	-0.656946	-3.643464
d1	10.92363	7.064966	12.90785	32.67961	17.72544	39.60548	53.50457	8.724181	20.56939
d2	7.450966	30.59884	2.873886	12.71221	30.90581	16.55235	8.894585	2.928892	39.22403
logL	1359.853	1417.855	1477.503	1490.686	1417.965	1423.654	1451.082	1340.099	1059.937

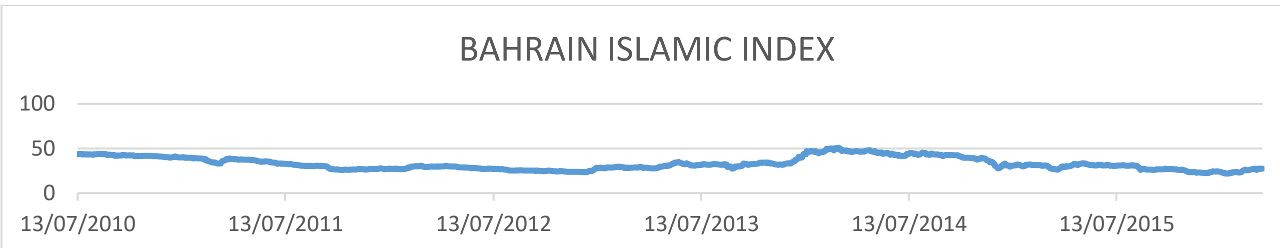
Notes: standard deviations are highlighted in bold. d1 and d2 are the average durations for the stock market to be in regime 1 and in regime 2, respectively. ***, **, * indicate that the estimated coefficients are significant at the 1%, 5% and 10% levels, respectively.

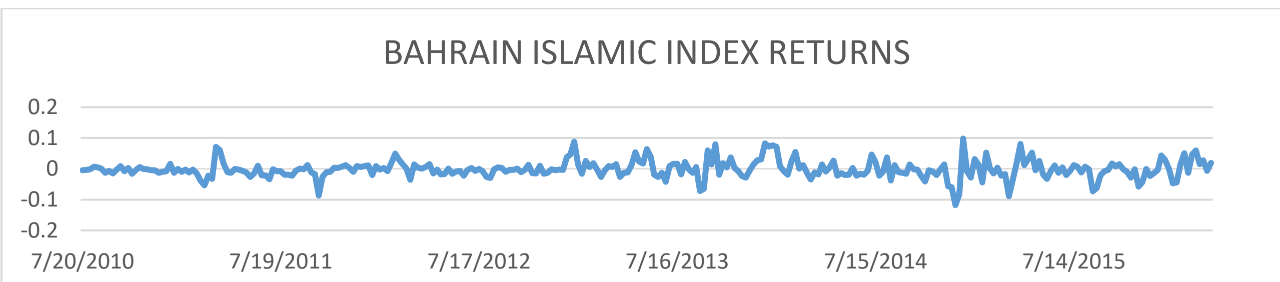
Table: 2

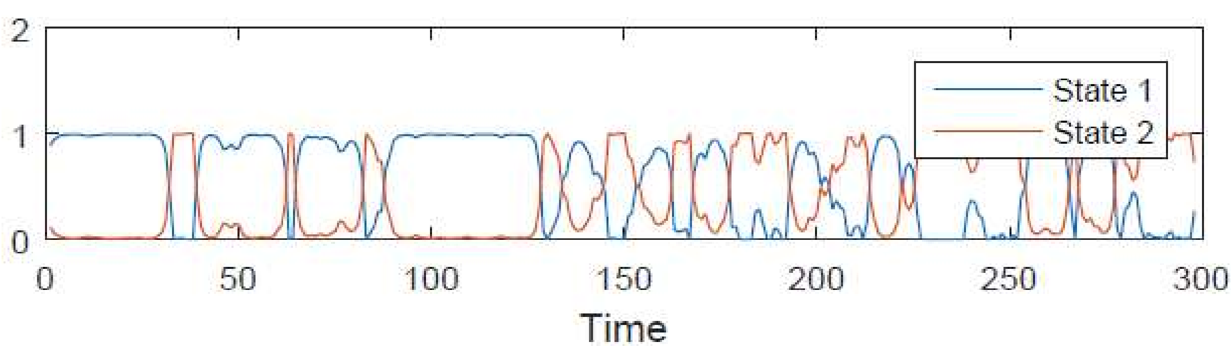
The following figures below, show the stock market index, stock market returns and the smoothed probability of being in regime 2 for the eight countries. The upper graphs show that the stock markets in the eight MENA countries

More specifically,

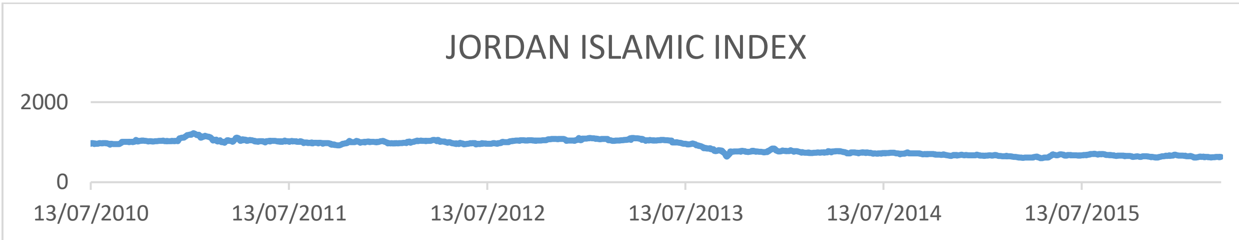
a. Bahrain

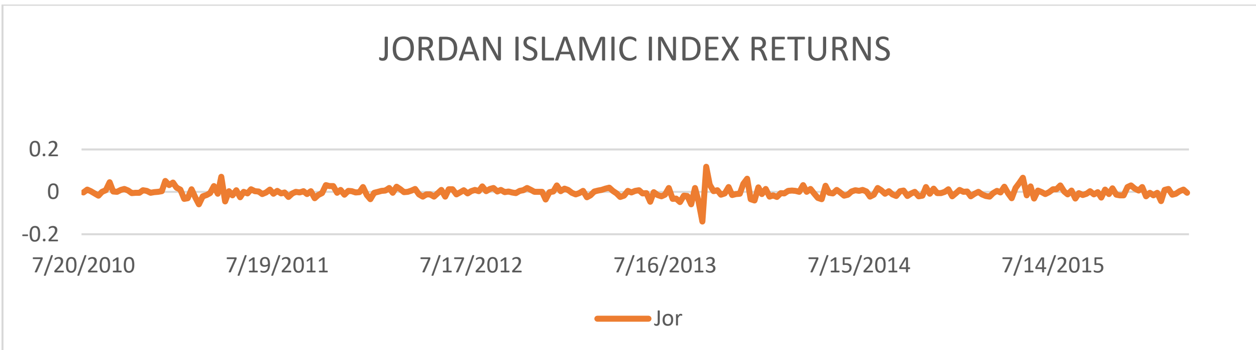


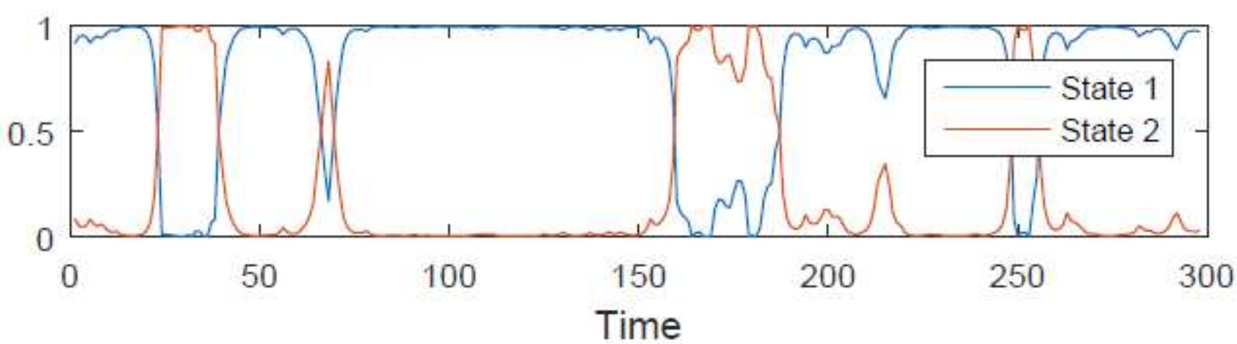




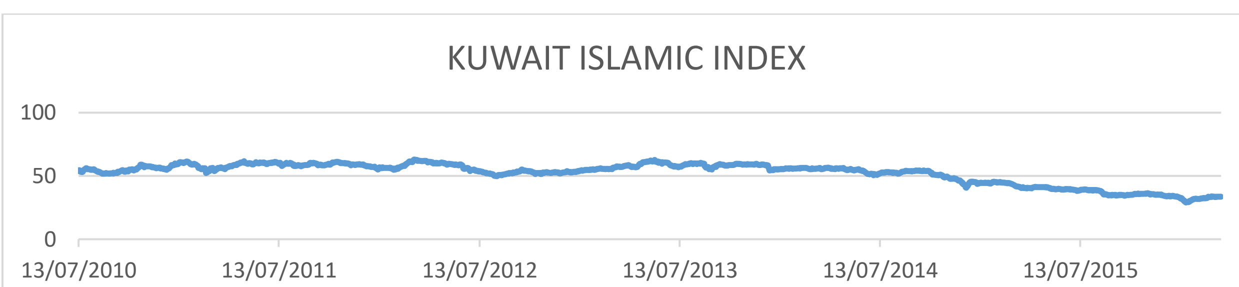
b. Jordan

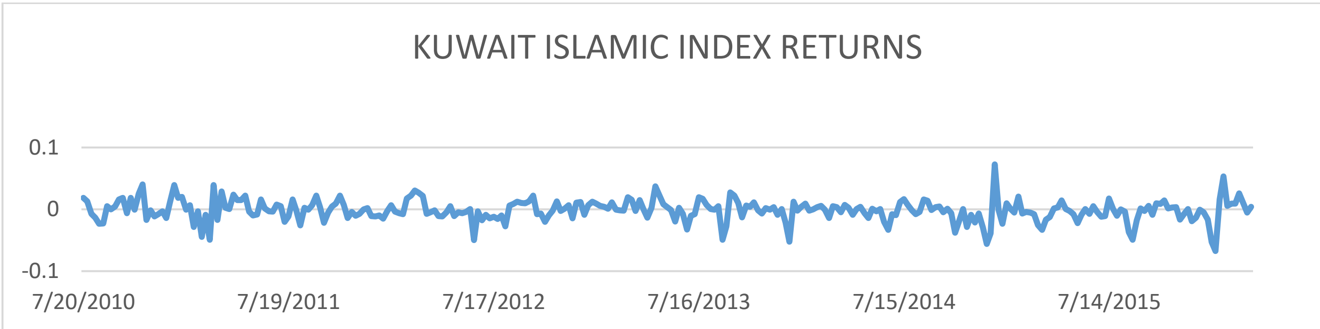


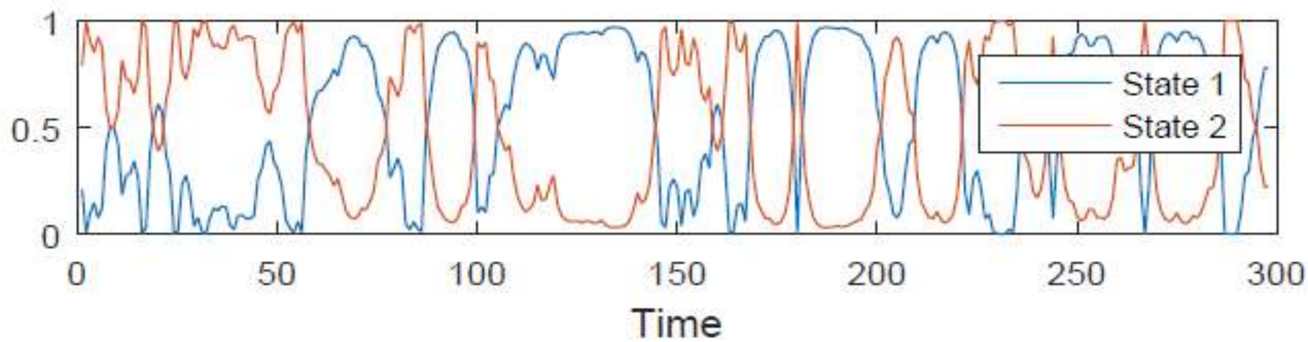




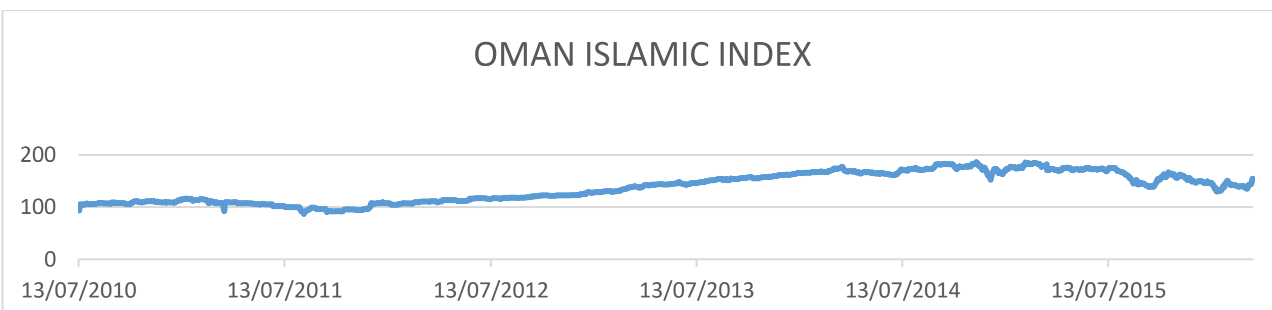
c. Kuwait

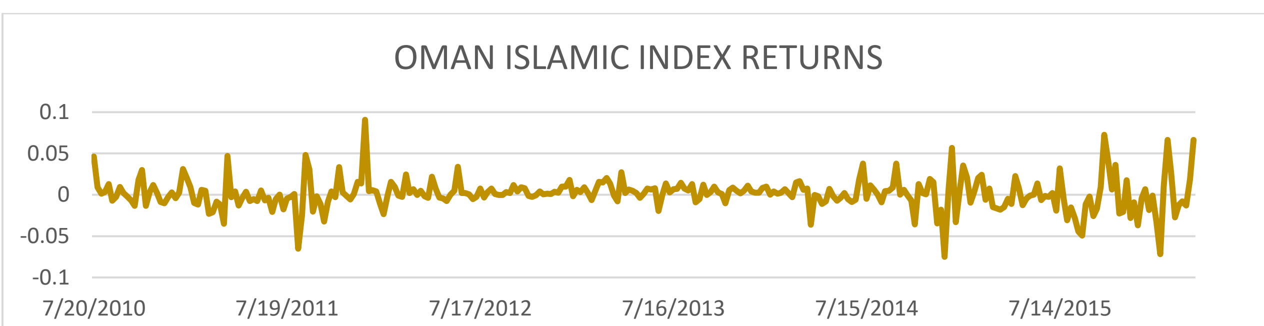


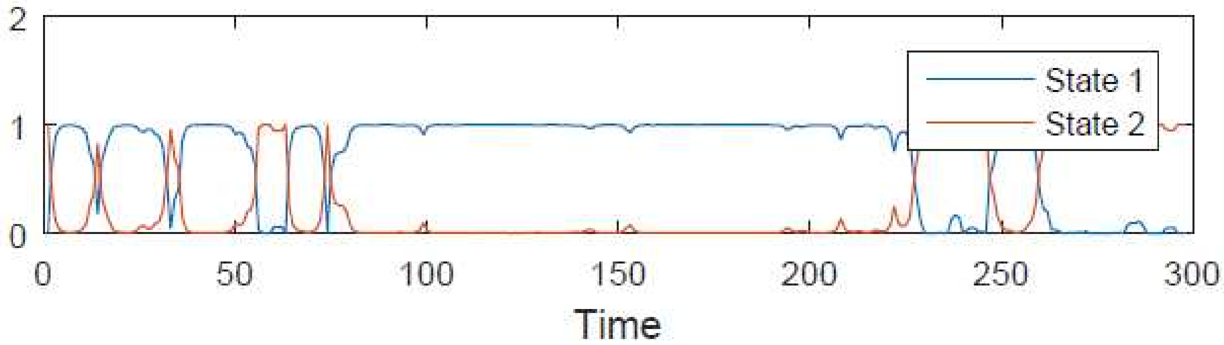

KUWAIT ISLAMIC INDEX RETURNS
0.1
0
-0.1
7/20/2010
7/19/2011
7/17/2012
7/16/2013
7/15/2014
7/14/2015


1
0.5
0
0
50
100
150
200
250
300
Time
State 1
State 2

d. Oman

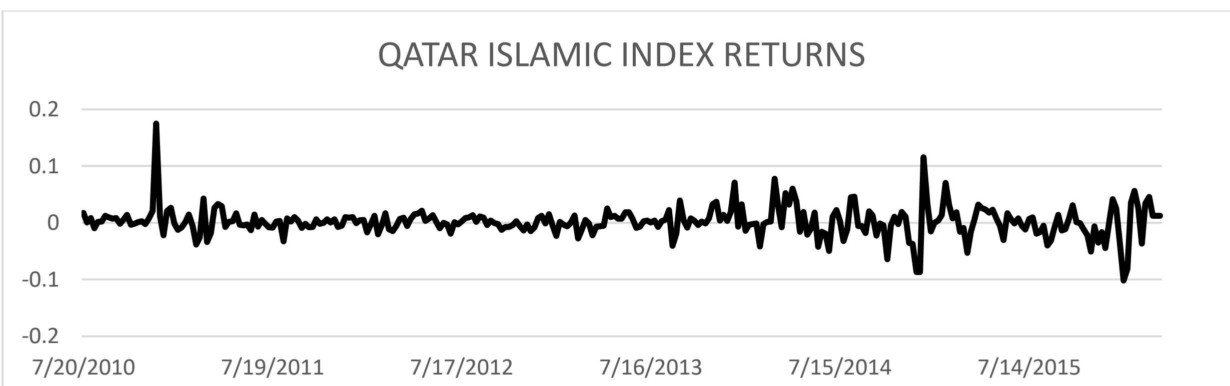

OMAN ISLAMIC INDEX
200
100
0
13/07/2010
13/07/2011
13/07/2012
13/07/2013
13/07/2014
13/07/2015

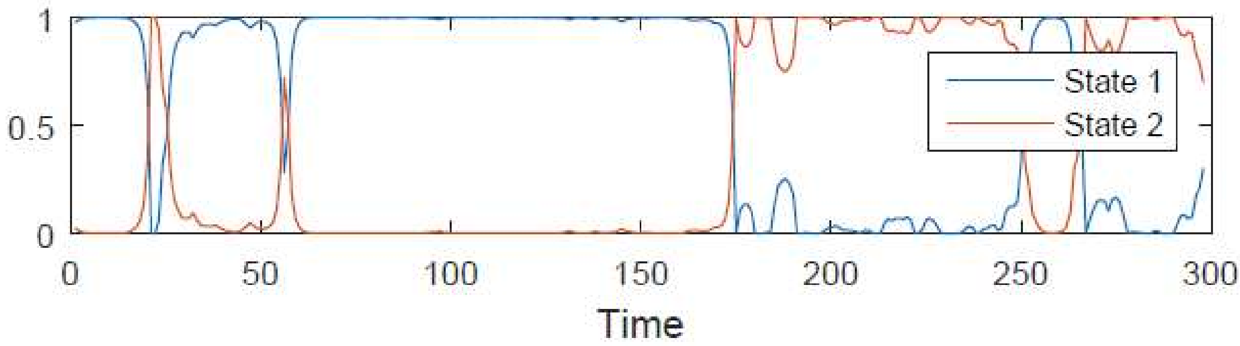

OMAN ISLAMIC INDEX RETURNS
0.1
0.05
0
-0.05
-0.1
7/20/2010
7/19/2011
7/17/2012
7/16/2013
7/15/2014
7/14/2015


State 1
State 2
Time
0
50
100
150
200
250
300
0
1
2

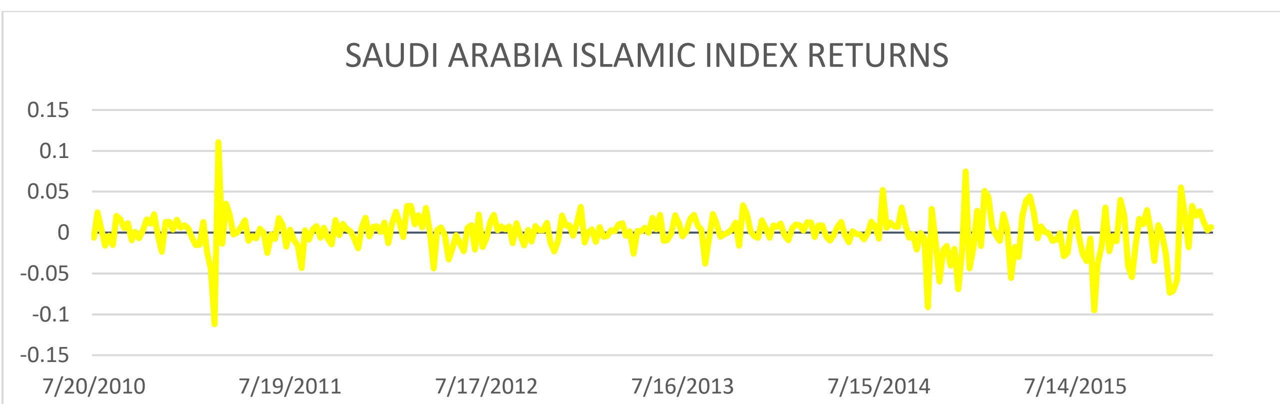
e. Qatar

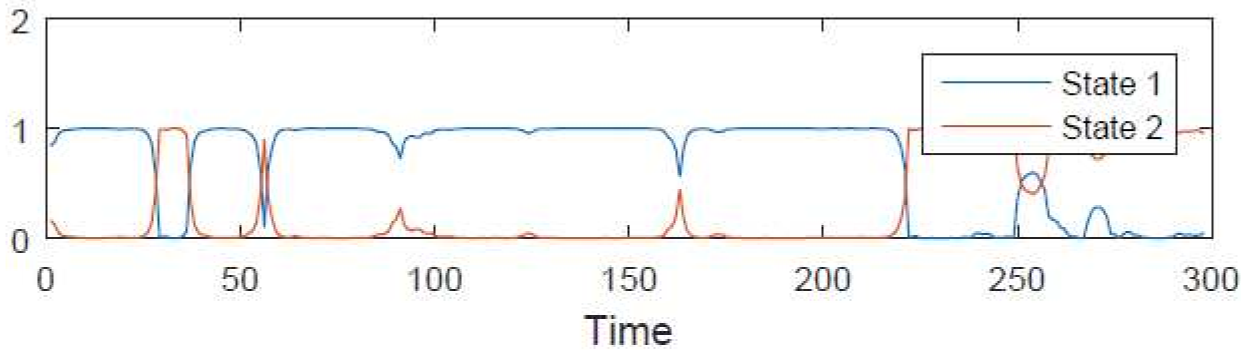

QATAR ISLAMIC INDEX
400
200
0
13/07/2010
13/07/2011
13/07/2012
13/07/2013
13/07/2014
13/07/2015


QATAR ISLAMIC INDEX RETURNS
0.2
0.1
0
-0.1
-0.2
7/20/2010
7/19/2011
7/17/2012
7/16/2013
7/15/2014
7/14/2015



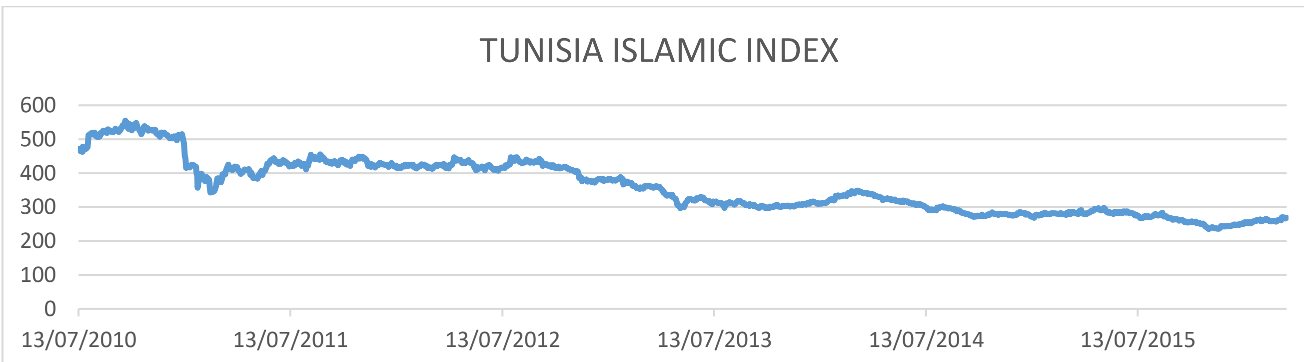
f. Saudi Arabia



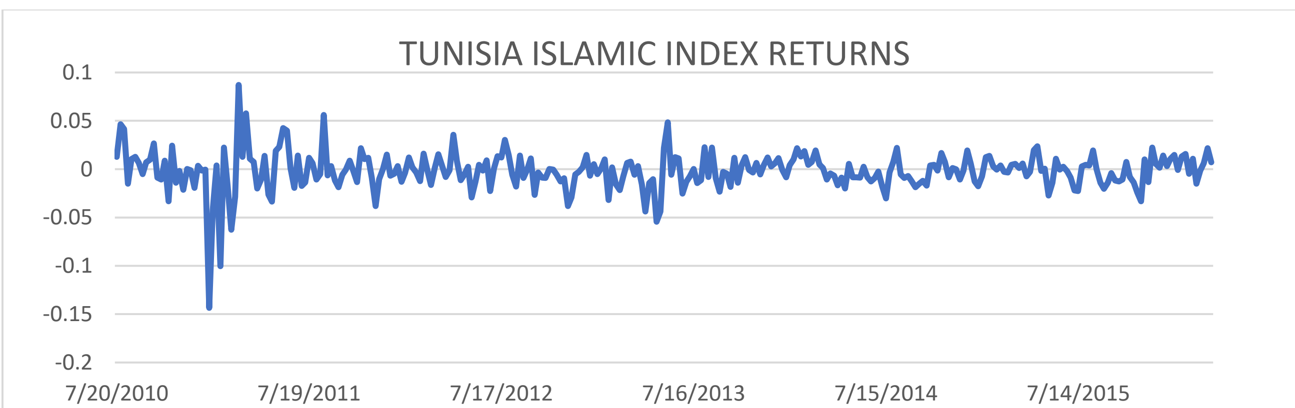


2
1
0
0
50
100
150
200
250
300
Time
State 1
State 2

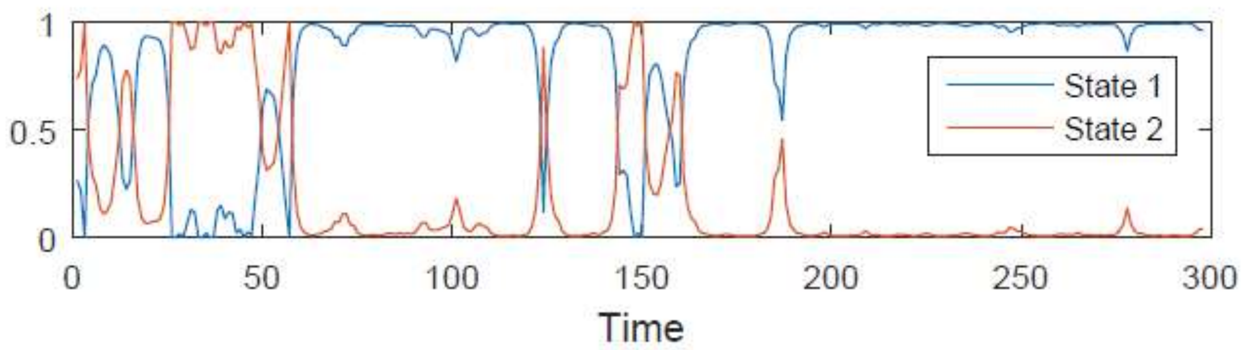
g. Tunisia



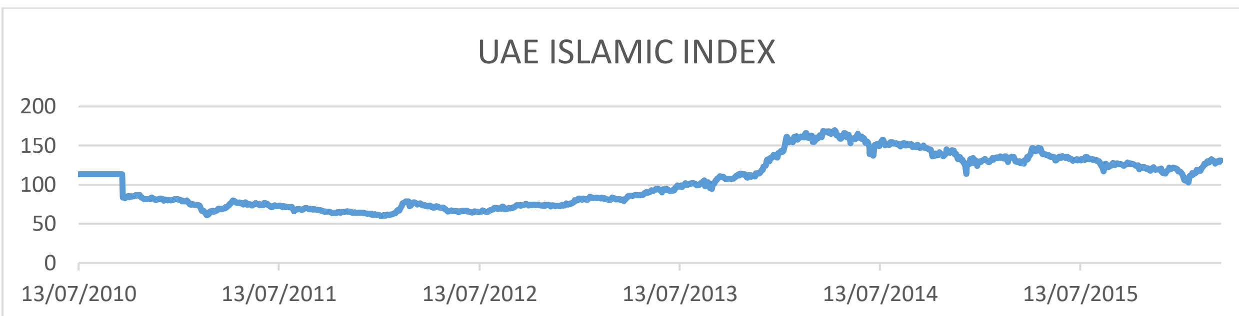
TUNISIA ISLAMIC INDEX
600
500
400
300
200
100
0
13/07/2010
13/07/2011
13/07/2012
13/07/2013
13/07/2014
13/07/2015

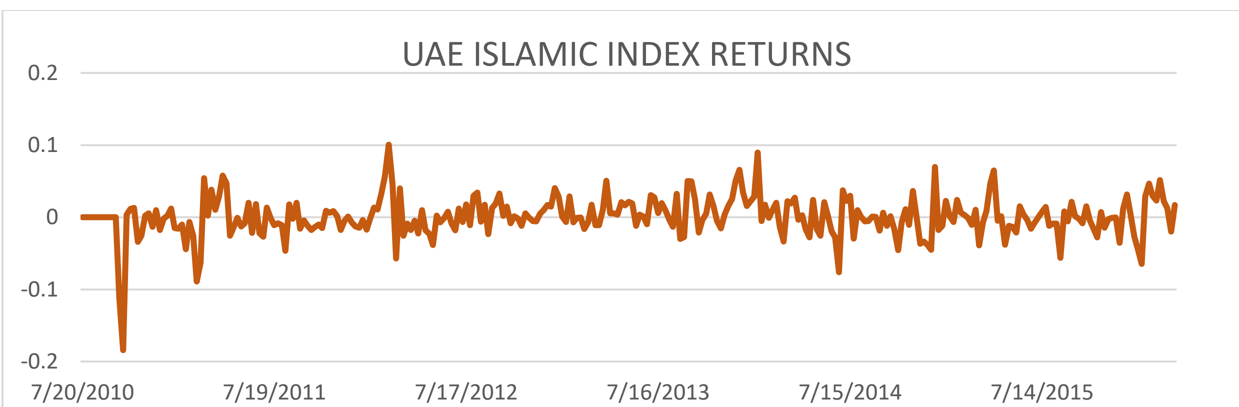


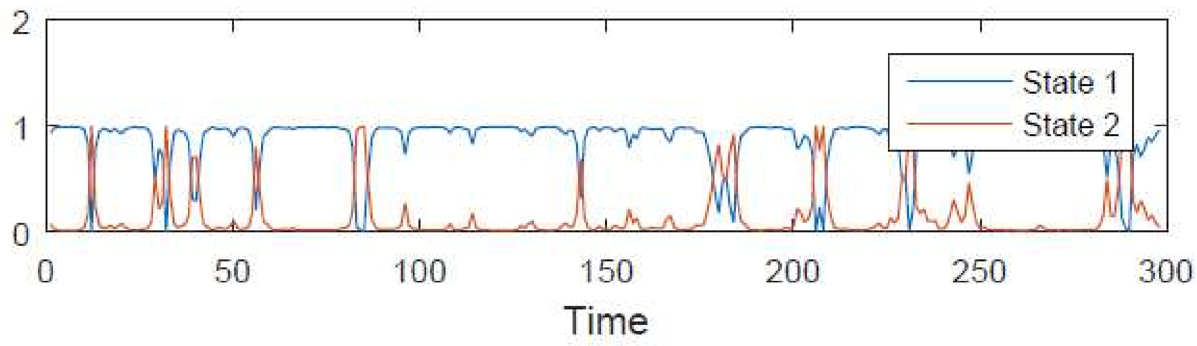
TUNISIA ISLAMIC INDEX RETURNS
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
7/20/2010
7/19/2011
7/17/2012
7/16/2013
7/15/2014
7/14/2015



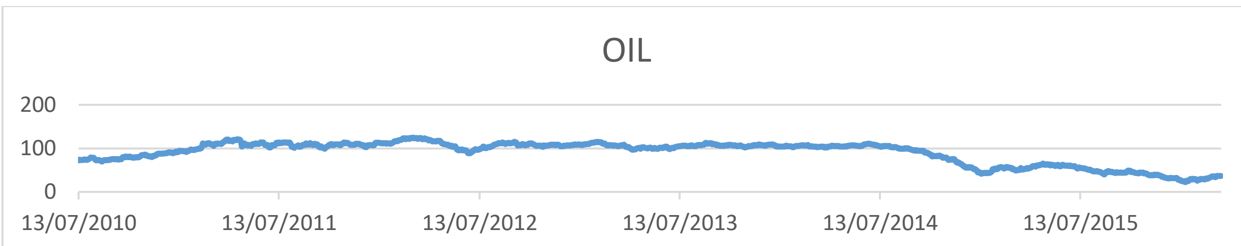
h. United Arab Emirates

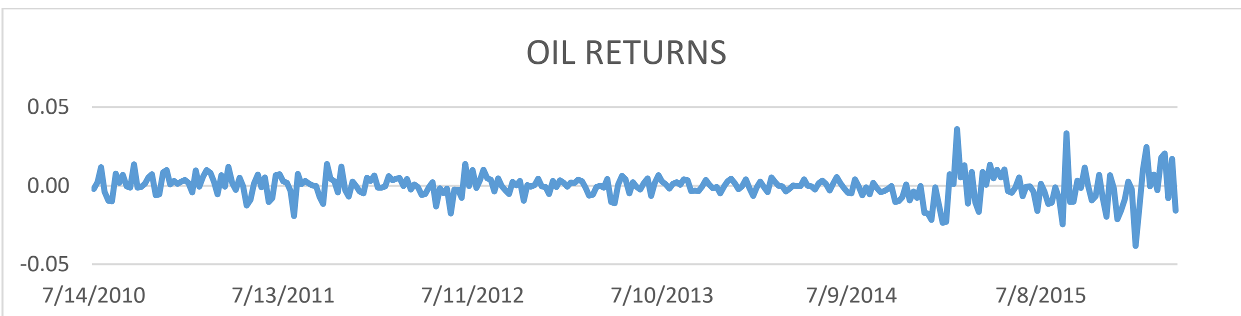


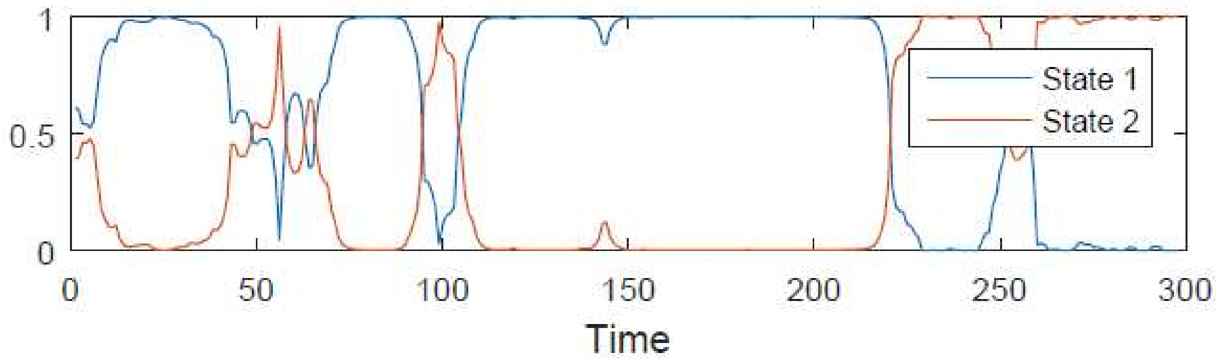



State 1
State 2
Time

i. Oil


OIL
200
100
0
13/07/2010
13/07/2011
13/07/2012
13/07/2013
13/07/2014
13/07/2015


OIL RETURNS
0.05
0.00
-0.05
7/14/2010
7/13/2011
7/11/2012
7/10/2013
7/9/2014
7/8/2015



6.0 CONCLUDING REMARKS

Though studies have been conducted to investigate weather crude oil has an impact on conventional stock market, to the best of my knowledge, not many have been conducted to see the same impact on the Islamic stock market. The main objective of this paper is to examine the relationship that exists between crude oil price and Islamic stock markets in MENA countries using Markov switching and Wavelet analysis. Our results tend to indicate that there is a lead lag relationship between crude oil and the Islamic Stock Market but whether negative or positive is not known. In terms of policy implications, when crude oil prices increase, investors should invest in the respective stock markets. However, when crude oil prices are low, investors should not invest. Instead they should invest in other commodities such as gold. One of the limitations of this paper is that not enough information was available for all the MENA countries in order to conduct an extensive research which may be pursued in the future.

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