Eastern Mediterranean University

Department of Economics

Discussion Paper Series

The links between crude oil prices and GCC stock markets: Evidence from time-varying Granger causality tests

Mehmet Balcılar[a], İsmail H. Genç[b], Rangan Gupta[c]

Discussion Paper 15-30

October 2016

Department of Economics

Eastern Mediterranean University

Famagusta, North Cyprus

The links between crude oil prices and GCC stock markets: Evidence from time-varying Granger causality tests

Mehmet Balcılar[a], İsmail H. Genç[b] and Rangan Gupta[c]

[a] Department of Economics, Eastern Mediterranean University, Famagusta, via Mersin 10, Northern Cyprus, Turkey and Department of Economics, University of Pretoria, Pretoria, 0002, South Africa; IPAG Business School, Paris, France. E-mail: mehmet@mbalcilar.net.

[b] Department of Economics, School of Business and Management, American University of Sharjah, P.O. Box 26666, Sharjah, United Arab Emirates. E-mail: igenc@aus.edu.

[c] Corresponding authors. Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.

Abstract

This paper investigates the impact of crude oil price movements on the stock markets of Gulf Corporation Council (GCC) countries using weekly data for the period of February 2, 1994-February 26, 2010. The causal link between oil and stock markets are modeled using a Markov switching vector autoregressive (MS-VAR) model in order to reflect changes in Granger causality over time. The MS-VAR model allows testing for both conditional Granger causality and regime predicting causality. The parameter instability tests indicate that causal links between crude oil prices and stock market indexes are highly time-varying. The full sample conditional Granger causality tests based on the MS-VAR model, which identifies four regimes each corresponding to causal relationships, rejects both the causal impact of lagged stock market prices on oil prices and the causal impact from crude oil spot prices to stock market indexes in the full sample. However, regime prediction causality from oil prices to GCC stock markets is not rejected for all countries we consider, indicating that oil prices have predictive content for the regime of GCC stock markets. These results encompass the previous findings and offer new insights into the nature of causal relationships between oil price and stock markets in GCC countries.

JEL classifications: E44; Q43; C32

Key words: Oil Price; Stock Market; Gulf Corporation Council (GCC) countries; Markov-Switching Model; Time-Varying Granger-causality

1. Introduction

The very important part oil has retained in the political and economic conjecture of the modern world cannot be underestimated. The modern history has witnessed a portion of this prominent part during the international crisis of 1991, September 11, 2001 attack, and 2003 second Iraq war. This being the case, the study of oil price and its relation to such macro-economic variables as economic growth, economic stability and current account deficits attracted a great deal of interest. On this, Hamilton (1983) finds out that the higher the oil prices, the lower the real GNP. In their study Gilbert and Mork (1984) attempt to form a model of the macro effects of oil supply disruption and investigate alternative policies to closely deal with the problem. Loungani (1986), Burbridge and Harrison (1984), Mork (1989) and Lee *et al*. (1995) also reach similar results, using different data and statistical approaches. Mork *et al*. (1994), using data from six industrialized countries, namely Germany, France, the United Kingdom, Norway, Canada and Japan, show that oil price shocks affect the GDP in all of these countries, but that the effects are stronger in the United States, Japan, and Norway. Considering this important role oil has in the economies of developed countries, in particular the US, as put by Hamilton (1983); Gilbert and Mork (1984); Mork *et al.* (1994), and others, it will not be wrong to assume that oil prices and stock prices are somehow correlated[1]. If we hold that oil prices have impact on macroeconomic variables, then there should be a contemporaneous correlation between stock prices and oil prices owing to the swift reaction of markets to flow information about oil prices and the nature of investor expectations. Efficient markets are thought to be sensitive to new information, and a contemporaneous relationship among the markets is what is expected in general. Market frictions, inefficiencies, transactions costs, etc., may however result in delayed response and a lead-lag relationship between the oil prices and stock markets may be observed. This study sets out to examine the causal links between the stock market and oil prices using weekly data over the February 2, 1994-February 26, 2010 sample period. Particularly, the causal links between the West Texas Intermediate (WTI) crude oil spot price and the stock price indexes of six GCC countries, Bahrain, Oman, Saudi Arabia, Kuwait, Qatar, and the United Arab Emirates (UAE) are investigated.

Early studies on the impact of oil prices concentrated on the macroeconomic effects of oil price shocks in developed economies. One of the channels through which oil prices affect

[1] Recent studies, such as Cunado and Perez de Garcia (2005), Balaz and Londarev (2006), Gronwald (2008), Cologni and Manera (2008), and Kilian (2008), have also established that oil price changes have significant impact on economic activity in several developed and emerging economies.

stock markets is their impact on macroeconomic variables. This is the most studied channel in the literature. Value of a stock is equal to the discounted sum of future cash flows, which depends significantly on the macroeconomic events. Two studies with macro-economic focus, namely, Kaul and Jones (1996) using quarterly data and Sadorsky (1999) using monthly data, find that oil price movements do affect U.S. stock returns. Huang *et al*. (1996) investigate the impact of oil price shocks on the U.S. equity market from a financial market perspective. Using a vector autoregression (VAR) model, they examine interrelations between daily oil futures and stock returns. They find evidence for significant Granger causality from oil futures to stocks of individual oil companies; but they detect no impact on the S&P 500. They conclude that the much-touted influence of oil price shocks on the stock market is more of a myth than reality. Moreover, Papapetrou (2001) attempts to shed light on the dynamic relationship among oil prices, real stock prices, interest rates, real economic activity and employment for Greece, utilizing a VAR model. The results of Papapetrou's (2001) study indicate that oil prices are important in explaining stock price movements. El-Sharif *et al*. (2005) investigates the relationship between the price of crude oil and equity values in the oil and gas sector for the UK, indicating that the relationship is always positive and often highly significant, reflecting the direct impact of volatility in the price of crude oil on share values within the sector. Recently, Nandha and Faff (2008) examine whether the adverse effect of oil price shocks impact stock market returns and if so and to what extent, using the 35 global sectors for the April 1983 to September 2005 period. Their findings underline that oil price rises have a negative impact on equity returns for all sectors with the exception of mining, and oil and gas industries, and are consistent with economic theory and evidence provided by previous empirical studies. The most striking finding of the study by Nandha and Faff (2008) is that little evidence of any asymmetry is found in the oil price sensitivities.

Most studies on the relationship between oil prices and stock markets focused on developed economies with a few recent study on emerging markets (see, e.g., Basher and Sadorsky, 2006; Nandha and Faff, 2006). Even less work has been done on GCC countries. No one doubts the dependence of GCC economies on revenues from oil exports. Therefore, a significant impact from oil prices movements to stock markets of these countries is expected. A few studies examined the causal links between crude oil prices and stock market indexes of GCC countries and the evidence to date is mixed, some finding bidirectional causality while others finding causality from oil prices to stock market indexes. Studying the link between oil prices and stock markets in GCC countries is interesting at least for three reasons. First, the

GCC countries are major suppliers of oil in the world energy markets, thus their economies and stock markets are likely to be susceptible to change in oil prices. Second, the GCC countries are largely segmented from the international markets and overly sensitive to regional and political events. Therefore, they do differ from the developed and emerging markets significantly. The sensitivity of the stock markets in the GCC economies is of interest to international investors since these markets look promising for regional and world portfolio diversification.

A few number of studies examined the relationship between oil prices and stock markets in the GCC countries. Hammoudeh and Eleisa (2004) examined the links between oil futures prices and stock market indices of five members of the GCC—excluding Qatar—using daily data for the period 15 February 1994-25 December 2001. The analysis is based on vector error correction (VEC) models and suggests a bidirectional linkage between Saudi stock market and oil prices, while other GCC stock markets seem to be not linked to the oil price. Zarour (2006) also investigated the effect of oil prices on stock market returns of the five GCC countries using daily data from 25 May, 2001 to 24 May, 2005. He estimated VAR models and, based on impulse response functions, indicated that the predictive power of oil prices for the stock marker indices have increased after the rise in oil prices, Saudi and Omani markets have predictive power oil prices, and the impact of oil prices on the Saudi stock market is stronger compared to other countries. Hammoudeh and Choi (2006) estimated VEC model between weekly stock market returns of the GCC countries and the oil price using data from February 15, 1994 to December 28, 2004. Based on the impulse response estimates they concluded that oil price shocks have significant impact on stock markets of the most GCC countries. Nevertheless, the variance decomposition indicated that the domestic factors account for the largest proportion of the stock market indices. Their estimates showed that the oil price accounts for 30 percent 19 percent of the total equity price variations in Oman and Saudi Arabia, respectively. Onour (2008) examined the links between daily stock market price indices if the GCC countries and Brent oil price using data from May 3, 2004 to September 2, 2006. Based on the volatility spillover estimates, he concluded that for most of the GCC markets both speculative factors and oil price uncertainty account for the equity return volatility in the short-run, but only oil price changes remain as the significant factor in the long-run. Arouri and Rault (2010) used panel data estimations with weekly and monthly data sets covering from June 7, 2005 to October 21, 2008, and from January 1996 to December 2007, respectively, to investigate the causal relationship between GCC stock market indices and oil prices. They found strong evidence that the causal relationship is bidirectional for Saudi Arabia and is from oil prices to stock markets in other countries. Two studies, Arouri and Fouquau (2009) and Arouri *et al*. (2010) found evidence that contemporaneous and dynamic links between the GCC stock market and oil prices are nonlinear and statistical evidence in favor of the significant interaction is stronger when nonlinearity is taken into account. Arouri and Julien Fouquau (2009) used using nonlinear (kernel) regression and weekly data from the first week of June 2005 to the third week of October 2008 to examine short-run relationships between oil prices and GCC stock markets. They found significant links between the two variables in Qatar, Oman, and UAE. Nevertheless, the evidence indicated that oil price changes do not affect stock market returns for Bahrain, Kuwait, and Saudi Arabia. Arouri *et al*. (2010) used threshold regression and weekly data from June 7, 2005 to October 21, 2008 and found that stock markets of Qatar, Oman, Saudi Arabia and UAE showed strong response to oil price changes. They further argued that the relationship is of the switching type and the switch depends on the level of the oil price.

The mixed evidence obtained in the previous studies on the direction and significance of the relationship between oil price and stock markets may be because the tests they use are not powerful enough to detect nonlinear linkages. Indeed, a number of authors, such as Mork (1989), Mork *et al*. (1994), Hamilton (1996, 2003), Balke *et al*. (1999), Lardic and Mignon (2006, 2008), Zhang (2008), Cologni and Manera (2009) argue that the relationship between oil and the economy is nonlinear. These studies show that oil price hikes are much more influential than oil price decreases and so create an asymmetric relationship between oil prices and the economic output, suggesting that nonlinear linkages between oil prices and the stock market could be uncovered. Ciner (2001) extends the relationship between oil prices and the stock market by testing for both nonlinear and linear linkages. Ciner (2001) uses the modified Baek and Brock (1992) test, developed by Hiemstra and Jones (1994), to examine nonlinear linkages and finds significant nonlinear Granger causality from crude oil futures returns to S&P 500 index returns. He finds evidence that stock index returns affect crude oil futures, suggesting a feedback relation. Overwhelmingly, results obtained in these studies about the causal link appear to be sensitive with respect to the countries analyzed, sample period and methodology employed.

There is also evidence of nonlinear and asymmetric relationship between crude oil prices and stock market indexes of GCC countries due to different impacts of oil price decreases than oil price increases in magnitude and speed (Arouri and Fouquau 2009, Arouri *et al*., 2010). Since oil price decreases and increases alternated in the past, this should cause a time-varying temporal relationship between oil prices and stock price indexes. In order to overcome the difficulties arising from nonlinearity and time variation, we propose a method that allows time-varying Granger causality. The method, which is based on the MS-VAR, models parameter time-variation so as to reflect changes in Granger causality. The MS-VAR model allows identification of four possible causality relationships at each point in time and allows testing for both the conditional Granger causality (lead-lag relationship) and regime predicting causality between oil price and GCC markets. We use weekly West Texas Intermediate (WTI) crude oil spot prices and stock price indexes of six GCC countries, namely (Bahrain, Oman, Saudi Arabia, Kuwait, Qatar, and the United Arab Emirates (UAE), from February 2, 1994 to February 26, 2010 to test for nonlinear causalities between the oil price and stock market indices. The full sample conditional Granger causality tests based on the MS-VAR model, which identify four regimes each corresponding to causal relationships, reject both the causal impact of lagged stock market prices on oil prices and the causal impact from crude oil spot prices to stock market indexes in the full sample. However, regime prediction causality from oil prices to GCC stock markets is not rejected for all countries we consider, indicating that oil prices have predictive content for the regime of GCC stock markets. These results encompass the previous findings and offer new insights into the nature of causal relationships between oil price and stock markets in GCC countries.

The rest of the paper is organized as follows. The next section presents the methodology. Section 3 estimates and evaluates the empirical results. The fourth and the final section conclude.

2. Methodology

2.1. Markov switching VAR model

The starting point in this paper is not to assume a permanent causal relation between oil and stock markets, but rather adopt a notion of "temporary" Granger causality, that is causality that holds during some periods but not in others. Previous researchers have noted that results from Granger causality tests tend to be sensitive with respect to changes in the sample period[2]. They have also observed that direction of causality is sensitive to the choice of the sample period and also there are periods where no causality found along with periods where

[2] Aloui and Rania (2009) and Miller and Ratti (2009) content that the dynamic links between oil prices and stock markets indices are instable and test results are sensitive to sample period.

bidirectional causality between the oil futures and stock market prices exists. Based on these findings, we adopt a testing approach based on a VAR model with time-varying parameters where, given our objectives, parameter time-variation directly reflects changes in causality. In this approach changes in causality are treated as random events governed by an exogenous Markov process, leading to the MS-VAR model. In the MS-VAR model, inferences about changes in the causality can be made on the basis of the estimated probability that each observation in the sample comes from a particular regime of causality.

To be concrete, let F_t and R_t weekly oil price changes and stock market returns[3], respectively, and let the time series of these variables up to and including period t be given by $\mathcal{F}_t \equiv \{F_\tau : \tau = t, t-1, \ldots, 1-p\}$ and $\mathcal{R}_t \equiv \{R_\tau : \tau = t, t-1, \ldots, 1-p\}$, where p is a nonnegative integer. Define the vector of time series of X_t up to and including period t as $X_t = [R_t', F_t']'$ and let $\mathcal{X}_t \equiv \{\mathcal{F}_t, \mathcal{R}_t\}$, correspondingly.

The MS-VAR model, used for weekly oil price changes and stock returns, is nested within the class of autoregressive models studied in Hamilton (1990) and Krishnamurthy and Rydén (1998), and allows asymmetric (regime dependent) inference for causality. The structure of the MS-VAR model we use is analogous to one used in Warne (2000), but our model is more general and allows inference on all types of causality relationships[4]. Our analysis is based on the following MS-VAR model:

$$X_t = \mu_{S_t} D_t + \sum_{k=1}^{p} \Phi_{S_t}^{(k)} X_{t-k} + \varepsilon_t \tag{1}$$

where p is the order of the MS-VAR model, $\varepsilon_t | S_t \sim N(0, \Omega_{S_t})$ and Ω_{S_t} is positive definite. The vector D_t is d dimensional and deterministic, e.g. a constant, cantered seasonal dummies, and other dummies corresponding to outliers. The random state or regime variable S_t, conditional on S_{t-1}, is unobserved, independent of past X, and assumed to follow a q-state Markov

[3] Oil prices and stock market indices we use are all nonstationary time series as shown by the unit root tests given in Section 3. Variables in an MS-VAR model should be stationary, and therefore, the MS-VAR model is specified in terms of log differences of the oil price, and stock market returns. Stationarity of the individual series is not sufficient for stationarity of MS-VAR models. As long as the autoregressive parameters depend on the regime process, the stationarity conditions valid for a linear VAR model do not apply to MS-VAR models and hence unit root tests may be redundant. Conditions given in Karlsen (1990) do also apply to MS-VAR models as sufficient conditions for second order stationarity.

[4] Warne's (2000) model is a restriction version of our model and allows testing for conditional Granger causality assuming that the regime is given. Therefore, Warne tests whether a variable does not Granger cause another variable conditional on the known regime. Our model allows Granger causality test without conditioning on a known regime for a variable, although it is possible to restrict the model on a given regime and obtain the tests in Warne (2000).

process. In other words, $\Pr[S_t = j | S_{t-1} = i, S_{t-2} = h_2, ..., \Lambda_{t-1}] = p_{ij}$, for all t and h_l, regimes i,j = 1, 2, ..., q, and $l \geq 2$. In our particular application, the maintained hypothesis is that q=4, that is four states or regimes for each variable are sufficient to describe the all possible causality relationships between oil and stock market prices. For instance, in the first state one variable (say oil price) may be causal for the other variable (stock price). Analogously, in the second state the second variable is not causal for the first variable, etc. When q=4, i.e., S_t is a 4-state Markov process for both variables, the MS-VAR model does indeed allow four regimes in terms of causality classification[5]. That is, the 4-state MS-VAR defined in equation (1) accommodates four causality results, that F_t Granger causing R_t $(F_t \Rightarrow R_t)$, R_t Granger causing F_t $(R_t \Rightarrow F_t)$, F_t and R_t both Granger causing each other (a feedback system or bidirectional causality) $(F_t \Leftrightarrow R_t)$, and no Granger causality between F_t and R_t $(F_t <\neq> R_t)$. How these four regimes are inferred will be explained below.

We assume that two subsystems, one in which F_t Granger causing R_t and the other in which R_t Granger causing F_t, of the Granger causality regimes are independent. This implies that coefficients in two subsystems of equation (1) are allowed to vary with the regime, while, at the same time, be independent. A Markov chain that splits into two independent processes each with two regimes will have this property. Let $S_{1,t}$ and $S_{2,t}$ be a $q_1 = 2$ and a $q_2 = 2$ state Markov processes, respectively, with $q = q_1 q_2$=4 and independent, i.e., $p_{ij} = p^{(1)}_{i_1 j_1} p^{(2)}_{i_2 j_2}$ where $\Pr[S_{l,t} = j_l | S_{l,t-1} = i_l] = p^{(l)}_{i_l j_l}$ and $\sum_{j_l=1}^{q_l} p^{(l)}_{i_l j_l} = 1$ for i_l=1,…, q_l . Collecting the probabilities of two states into $P^{(1)}$ and $P^{(2)}$ and defining $S_t = S_{2,t} + q_2(S_{1,t} - 1)$ for the pair ($S_{1,t}$, $S_{2,t}$), we have that $P = (P^{(1)} \otimes P^{(2)})$. Thus, $S_{1,t}$ and $S_{2,t}$ are latent random variables that reflect the state or regime of the system at date t and take their values in the set {1,2}. Two independent subsystems do indeed define four alternative states of the nature[6], which are conveniently indexed by S_t as

[5] An MS-VAR model in which each of two variables following two independent states has a total of 4 inferred states. Such an MS-VAR model can be reformulated in terms of a latent state variable with 4 states defined on two distinct state variables, where each variable follows a separate and independent 2-state Markov process. This 4-state classification allows an intuitive interpretation of the four possible causality regimes. We later reformulate the MS-VAR model in a 4-sate form using two independent Markov processes for a clear representation of the causal classification between oil futures and stock prices.

[6] These four states correspond to four types of causality regimes relating to our model defined in equation (1). Defining these regimes in terms of two independent states gives us the flexibility of fixing one of the variables in a particular state while allowing the other variable to follow two states for a richer analysis of regime dependent causality.

$$S_t = \begin{cases} 1, & \text{if } S_{1,t} = 1 \text{ and } S_{2,t} = 1 \\ 2, & \text{if } S_{1,t} = 2 \text{ and } S_{2,t} = 1 \\ 3, & \text{if } S_{1,t} = 1 \text{ and } S_{2,t} = 2 \\ 4, & \text{if } S_{1,t} = 2 \text{ and } S_{2,t} = 2 \end{cases} \tag{3}$$

Using the above definition of the MS-VAR model we can link inference about the Markov regime with Granger causality. Consider the MS-VAR in equation (1) for $X_t = [R_t', F_t']'$:

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{1,S_t} \\ \mu_{2,S_t} \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \phi_{11,S_t}^{(k)} & \phi_{12,S_t}^{(k)} \\ \phi_{21,S_t}^{(k)} & \phi_{22,S_t}^{(k)} \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{4}$$

Here $\varepsilon_t = [\varepsilon_{1,t}', \varepsilon_{2,t}']'$ is a white noise process, independent of S_t with mean zero and covariance matrix Ω_{S_t}, partitioned conformably with $\varepsilon_{i,t}$, i.e., $\Omega_{ij,S_t} = E[\varepsilon_{i,t}' \varepsilon_{j,t} | S_t]$.

2.2. Testing for causality in the MS-VAR model

In the MS-VAR model, there are two channels in which oil prices Granger cause the stock prices. The first channel leads to the regime-prediction Granger causality test, which investigates whether the shocks in the oil prices is helpful in predicting the regime of the stock market prices (an indirect prediction channel). In this case, oil prices become useful in predicting the regime of stock market prices. The second channel leads to the conditional Granger causality test, which investigates the lead–lag relationship assuming the regime is known. This test is conditional on the known regime and, therefore, it is a test of whether the oil prices help improving the one step ahead forecast of the stock market prices. For instance, if the regime is known and oil prices cannot help to improve the one step ahead prediction of the stock prices, then oil market does not Granger cause the stock market conditional on the given regime. This test is analogous to the traditional Granger causality test; conditional on the assumption that regime is known. If either of the conditional or regime-prediction Granger non-causality is rejected, the null hypothesis of Granger non-causality will similarly be rejected.

Conditions for Granger non-causality in equation (4) are not straightforward, because there are two channels through which the oil market, for example, can be informative about the regime of the stock market[7]. Therefore, no unique set of parameter restrictions can be specified for testing the non-causality of oil prices for the stock market prices, and *vice versa*. However, there is a finite number of cases and if one of these cases is true, then the oil prices, for example, is Granger non-causal (in mean-variance) for the stock market prices.[8]

We now give the conditions under which Granger non-causality holds within the context of the bivariate MS-VAR model in equation (4). The oil price shocks are non-causal for stock market returns, i.e., the regime forecasts $S_{1,t+1}$ and $S_{2,t+1}$ are independent and there is no information in $\acute{A}_t$ for predicting $S_{1,t+1}$, if and only if for all t

$$\mu_{i,S_t} = \mu_{i,S_i,t}, \phi_{ij,S_t}^{(k)} = \phi_{ij,S_i,t}^{(k)}, \Omega_{ii,S_t} = \Omega_{ii,S_i,t}, \Omega_{12,S_t} = 0, \text{ and } P = (P^{(1)} \otimes P^{(2)}) \tag{5}$$

for all i,j=1,2, k=1,…,p, and S_t = 1,…,4; and

$$\phi_{12,S_{1,t}}^{(k)} = 0 \tag{6}$$

for k=1,…,p, and $S_{1,t}$ = {1,2} (see Warne, 2000)[9]. The condition given in equation (6) is straightforward to interpret. For expositional purpose let us assume that all regimes are known. Then, the necessary and sufficient condition for oil market not to Granger cause stock market (in mean-variance, and also in distribution[10]) is that $\phi_{12,S_{1,t}}^{(k)}$ in equation (4) is equal to zero for all k and t. Indeed, this is the conditional Granger causality case explained as the second channel above. When the regimes are unknown then the additional restrictions in (5) should also hold for non-causality of oil market for regime-prediction Granger non-causality. Under this case, then, oil market is conditionally (that $\phi_{12,S_{1,t}}^{(k)} = 0$) uninformative about the

[7] The Granger non-causality cannot be directly tested by imposing straightforward zero restrictions on equation (4) and one needs to derive the conditions that must be imposed on the parameters of the model. In an MS-VAR model implied restrictions involve lag parameters in equation (4) as well as the restrictions on the covariance matrix Ω_{S_t} and transition probabilities P.

[8] In a related context, Jacobson *et al*. (2002) consider a 2-state MS-VAR model with 3 variables and list four conditions for a variable to be Granger non-causal.

[9] Warne (2000) proposes conditions under which one variable is not Granger causal for the other in a 2-state MS-VAR model. The conditions given here are specified for a 4-state MS-VAR model where all possible causality classifications are allowed. In a 2-state MS-VAR model one can only test for Granger causality by allowing two regimes and discarding the possibility of other types of causal relationships, which is valid only when the regime for one of the variables is known. The cases given in Warne (2000) corresponds to H_0^2, H_0^3, H_0^6, and H_0^7 given in Table 1. Compared to Warne's model our specification allows for complete regime inference, that is inferred probability can be computed for each of the four regimes and full sample causality tests can be performed without assuming that the regime is known.

[10] If the error term e_t in equation (1) is conditionally normal and that the matrix P has either the full rank or equal to one, Warne (2000) shows that the Granger causality in mean-variance implies Granger causality in distribution.

regime. These non-causality conditions are given as the null hypothesis H_0^1 in Table 1. This 4-state MS-VAR specification with conditions in equations (5) and (6) is the most general case and allows separation of four types of regime classifications relating to all possible causal relationship between oil and stock prices. In this general case, in order for the oil market to be non-causal for the stock market all coefficients in the stock returns equation must be constant, while the coefficients on lags of the oil futures returns are all zero; and additionally all error variances should be constant and covariance across the error terms should be zero. Note also that all restrictions in equations (5) and (6) are linear. If we change the restrictions in equation (6) to $\phi_{21,S_{2,t}}^{(k)} = 0$, then there is no information in $\Re_t$ for predicting $S_{2,t+1}$. This case corresponds to the non-causality of stock market returns for the oil futures returns and given as the hypothesis H_0^5 in Table 1.

It is also possible to consider two sub-cases of the Granger non-causality conditions given in equations (5) and (6). First case arises when R_t follows a single-regime while F_t follows a two-regime process (q_1=1 and q_2=2). In this case, R_t does not directly depend on the regime, other than probably via residual covariances and F_t will be conditionally non-causal for R_t, if it fails to have effect through second channel, i.e., conditional causality. That is, F_t is non-causal for R_t, if it fails to improve the one-step ahead prediction of R_t. Similarly, R_t is conditionally non-causal for F_t when F_t does not directly depend on the regime and the regime for R_t is unknown (q_1=2 and q_2=1), if it fails to improve the one-step ahead prediction of F_t. This type of conditional Granger non-causality is specified under the null hypothesis of H_0^2 for non-causality of oil prices and H_0^6 for non-causality of stock prices. The second case occurs when R_t follows a two-regime while F_t follows a single-regime process (q_1=2 and q_2=1). Under this case, the regime of R_t should not be predictable using Á_t in addition to failure of F_t to improve the one-step ahead prediction of R_t. Therefore, oil market may have impact on stock market via both channels and both regime-prediction and conditional Granger non-causality can be tested in this case. This case is given as the hypothesis H_0^3 for the regime-prediction non-causality of oil prices for stock prices and H_0^7 for the regime-prediction non-causality of stock prices for oil prices. In this case, the conditional, i.e., the known regime, Granger non-causality restrictions are $\phi_{12,S_{1,t}}^{(k)} = 0$, $S_{1,t} = \{1,2\}$, $k = 1,2,\ldots,p$ and $\phi_{21,S_{2,t}}^{(k)} = 0$, $S_{2,t} = \{1,2\}$, $k = 1,2,\ldots,p$, respectively.

Finally, as the last case, oil price changes F_t can be non-causal for stock market returns R_t under conditions of the hypothesis H_0^4 given in Table 1. In this case, F_t is conditionally uninformative about the regime and non-causal for R_t. Analogously, H_0^8 gives the analogous conditions for R_t to be conditionally uninformative about the regime and non-causal for F_t.

< insert Table 1 around here >

Under the assumption that the maximum likelihood (ML) estimator of the parameters of the MS-VAR model is asymptotically normal with a positive definite covariance matrix, the limiting distributions of the Wald (W), Lagrange multiplier (LM), and likelihood ratio (LR) statistics for testing the restrictions given in Table 1 are known when *P* has full rank. When *P* has full rank the limiting distribution of the Wald statistics is χ^2 with *m* degrees of freedom and that of the *F* statistics is approximated by the *F* distribution with numerator degrees of freedom *m* and denominator degrees of freedom *T* minus the average number of parameters per equation (see Lütkepohl, 1991; Warne, 1997).

2.2. Representation of causality regimes

The restrictions given in Table 1 allow us to test for regime prediction causality. In order to test for conditional causality, we reparametrize the model in equation (1) with four states defined in equation (3) as follows:

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{11} - \mu_{12}(1 - S_{1,t}) \\ \mu_{21} - \mu_{22}(1 - S_{2,t}) \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \alpha_{11}^{(k)} - \alpha_{12}^{(k)}(1 - S_{1,t}) & -\alpha_{1}^{(k)}(1 - S_{1,t}) \\ -\alpha_{2}^{(k)}(1 - S_{2,t}) & \alpha_{21}^{(k)} - \alpha_{22}^{(k)}(1 - S_{2,t}) \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \tag{7}$$

for $S_{1,t}, S_{2,t} \in \{1,2\}$ and $t = 1, 2, \ldots, T$. Using the four cases given in equation (3) we can write the equations corresponding to each regime as follows:

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{11} \\ \mu_{21} \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \alpha_{11}^{(k)} & 0 \\ 0 & \alpha_{21}^{(k)} \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 1 \tag{8a}$$

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{11} + \mu_{12} \\ \mu_{21} \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \alpha_{11}^{(k)} + \alpha_{12}^{(k)} & \alpha_{1}^{(k)} \\ 0 & \alpha_{21}^{(k)} \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 2 \tag{8b}$$

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{11} \\ \mu_{21} + \mu_{22} \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \alpha_{11}^{(k)} & 0 \\ \alpha_{2}^{(k)} & \alpha_{21}^{(k)} + \alpha_{22}^{(k)} \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 3 \tag{8c}$$

$$\begin{bmatrix} R_t \\ F_t \end{bmatrix} = \begin{bmatrix} \mu_{11} + \mu_{12} \\ \mu_{21} + \mu_{22} \end{bmatrix} D_t + \sum_{k=1}^{p} \begin{bmatrix} \alpha_{11}^{(k)} + \alpha_{12}^{(k)} & \alpha_{1}^{(k)} \\ \alpha_{2}^{(k)} & \alpha_{21}^{(k)} + \alpha_{22}^{(k)} \end{bmatrix} \begin{bmatrix} R_{t-k} \\ F_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 4 \tag{8d}$$

These four equations allow us to estimate four regimes for each time period t. Regime inference may be based on four estimated states of the causal relationships. From this representation, it is easily seen that the regime indicators $S_{1,t}$ and $S_{2,t}$, and therefore S_t, determine the causal links in the model. Specifically, $S_{1,t}$ determines whether F_t is Granger-causal for R_t while $S_{2,t}$ determines whether R_t is Granger causal for F_t. Given that all of the parameters $\alpha_1^{(k)}$, k=1,2,…,p, are zero, F_t does not, conditional on the known regime, Granger-cause R_t for the entire sample when $S_{1,t}$=1 (S_t=1 or S_t=3). Equivalently, F_t conditionally Granger-cause R_t when $S_{1,t}$=2 (S_t=2 or S_t=4). Analogously, given that all of the parameters $\alpha_2^{(k)}$, k=1,2,…,p, are zero, R_t does not, conditional on the known regime, Granger cause F_t for the entire sample when $S_{2,t}$=1 (S_t=1 or S_t=2) or that R_t conditionally Granger cause F_t when $S_{2,t}$=2 (S_t=3 or S_t=4). Both variables are causal for each other when $S_{1,t}$=2 and $S_{2,t}$=2 (S_t=4). Likewise both variables are non-causal for each other when $S_{1,t}$=1 and $S_{2,t}$=1 (S_t=1), if not all $\alpha_1^{(k)}$ are zero and not all $\alpha_2^{(k)}$ are zero, respectively. As an example, the case H_0^1 in Table 1 can be intuitively illustrated using the reparameterized model. The hypothesis H_0^1, that the F_t dos not Granger cause R_t for the whole period implies $\alpha_1^{(1)} = \cdots = \alpha_1^{(p)} = 0$ simultaneously in regimes S_t=2 and S_t=4. Likewise the hypothesis that that the R_t does not Granger cause F_t for the whole period, H_0^5, implies $\alpha_2^{(1)} = \cdots = \alpha_2^{(p)} = 0$ simultaneously in regimes S_t=3 and S_t=4. It should be noted that the restrictions $\alpha_1^{(1)} = \cdots = \alpha_1^{(p)} = 0$ and $\alpha_2^{(1)} = \cdots = \alpha_2^{(p)} = 0$ are not sufficient for testing regime-prediction Granger non-causality for the whole period and the additional restrictions given in Table 1 should also be imposed. The rejection of the restriction $\alpha_1^{(1)} = \cdots = \alpha_1^{(p)} = 0$ implies oil market conditionally Granger causes stock market. Analogously, conditional causality of stock market can be tested via the restriction $\alpha_2^{(1)} = \cdots = \alpha_2^{(p)} = 0$.

3. Data and Empirical Results

3.1. The data

The data consist of weekly oil prices and stock price indexes of six GCC countries, which are Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates (UAE). Weekly data is more appropriate since it avoids time differences with the rest of the World. The equity markets in the GCC countries are generally closed on Thursdays and Fridays, while they are closed on Saturdays and Sundays in other countries. In order to avoid issue of time synchronization across markets, we use closing price of Tuesdays for all markets, which is in the middle of the three common trading days. All stock market data are obtained from Datastream. For the oil price we use crude oil spot price of the West Texas Intermediate (WTI), published by the Energy Information Administration (www.eia.doe.gov), which is a type of crude oil used as a benchmark in oil pricing and the underlying commodity of NYMEX oil futures contracts. All prices are in US dollars. The sample period varies across countries, see Table 1, due to data availability. Table 2 reports descriptive statistics for both log levels and log differences of all series. Figure 1 plots log levels and log returns of all series. From visual inspection of Figure 1, several regime shifts can be detected clearly across time in all series. This feature can be verified by the plots of weekly return series on the right column. As seen in Figure 1, right panel, there are frequent large positive and negative returns over the sample period. This aspect shows occurrence of regime shifts during the period. A perusal of Figure 1 also reveals characteristics of spot oil prices and stock market indices of the GCC countries. First and foremost, Figure 1 demonstrates short-term fluctuations in oil prices and stock market indices due to various incidents that surfaced during the last three decades. The price series suggest that crude oil stock price series can be characterized by several structural breaks and a large number of jumps. Additionally, both the duration and the length of jumps changed over the whole sample period. Second, volatility clustering is easily detected from the log return series from the right panels of Figure 1, where large (small) price changes tend to be followed by large (small) price changes over consecutive days. The clustering in the returns are substantial, and hence also in the corresponding volatilities. All the series show similar characteristics in regard to the presence of extreme observations or outliers corresponding to various incidents. An important feature of the data is the association of oil price collapses with stock market crashes in all countries. Also, the upward trend in the oil price series is matched by a similar upward trend in stock marked indices for all GCC countries.

< insert Table 2 around here >

< insert Figure 1 around here >

3.2. Unit roots

We first apply the Augmented Dickey-Fuller (henceforth ADF) of Said and Dickey (1984) and Kwiatkowski *et al*. (1992) (henceforth KPSS) unit root test to the oil spot and stock price series to determine whether they are stationary or not. For the ADF tests, we select the lag length, *k*, using the Bayesian Information Criterion (BIC), with the maximum lag length set to 16, while for the KPSS tests the lag truncation is automatically selected using Newey and West (1994) automatic selection procedure with Bartlett kernel. The results are presented in Table 3. The critical values of the ADF test have been calculated using Monte-Carlo simulations calibrated for 20,000 replications with sample size *T*. The results reported in Table 3 for the ADF tests indicate that the null hypothesis of a unit root can not be rejected at 1%, 5% and 10% levels for price series, regardless of whether a constant and linear trend or only a constant is included in the deterministic component. Similarly, the results obtained for the KPSS test rejects the stationarity hypothesis at conventional significance levels, regardless of the specification for the deterministic component. Furthermore, both the ADF and KPSS tests results reported in Table 3 show that the first differences of the logarithm crude oil spot and stock prices (log returns) are stationary, except the stock price series of Bahrain, Kuwait, Qatar, and Saudi Arabia for which the KPSS test indicates I(2) at 1 percent significance level. Therefore, the combined results from all the ADF and KPSS tests suggest that all the series under consideration appear to be I(1) processes.

< insert Table 3 around here >

3.3. Cointegration

All crude oil and stock price series are found to be integrated of order one. This implies that we need to test for the presence of cointegration between pairs of stock price and oil price series for each country. The non-stationary series that are I(1) may have a stable long-run (equilibrium) relationship, i.e., they may be cointegrated. To test for cointegration, we use the Johansen cointegration rank test (Johansen, 1988; Johansen & Juselius, 1990). In order to implement the Johansen test, consider the following bivariate VAR:

$$X_t = \mu + \sum_{k=1}^{p} \Phi_k X_{t-k} + \varepsilon_t, \qquad t = 1, 2, \ldots, T \tag{9}$$

where $X_t = [R_t, F_t]'$, p is the order of the VAR model, Φ_k are (2×2) coefficient matrices, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a vector of disturbances. The Johansen test is based on the vector error correction model (VEC) representation of equation (9), which is expressed as

$$\Delta X_t = \mu + \sum_{k=1}^{p-1} \Gamma_k X_{t-k} + \Pi X_{t-1} + \varepsilon_t, \qquad t = 1, 2, \ldots, T \tag{10}$$

where $\Gamma_k = -\Phi_{k+1} - \Phi_{k+2} - \cdots - \Phi_p$ for $k = 1, 2, \ldots, p-1$ and $\Pi = -I + \Phi_1 + \Phi_2 + \cdots + \Phi_p$. To test for cointegration between the pairs of stock price and oil price series for each country, we first determine the optimal lag length of the bivariate linear VAR model in (9). To find out the optimal lag length of model, we use the BIC with the maximum lag length set equal to 16. These lag lengths as well as the Johansen's trace (λ_{trace}) and maximum eigenvalue ($\lambda_{\max}$) test statistics of cointegration are given in Table 4. The lag lengths suggested by the BIC for the pairs $[R_t, F_{it}]$, are 5, 5, 4, 8, 2, and 6 for Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE, respectively. Because the means of the log returns are different from zero (see Table I, Panel B), the cointegration tests are run assuming the presence of an intercept (representing the non zero growth) in each cointegrating equation. The estimated λ_{trace} and and $\lambda_{\max}$ statistics, in Table 4, both indicate that a cointegrating relationships between the pairs of stock and oil prices does not exists for all GCC countries. Therefore, we take the first difference to analyze the dynamic linkages between the series in the VAR and MS-VAR models estimated.

< insert Table 4 around here >

3.4. Granger causality

The tests results in the previous subsection showed that there is no co-integration between the oil and stock price series. Therefore, as an initial analysis of the linkages between the oil price changes and stock market returns, we consider conventional full-sample tests for Granger non-causality between the series based on linear VAR model of the form

$$\begin{bmatrix} F_t \\ R_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{21}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} F_t \\ R_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{11}$$

where $\phi_{ij}(L) = \sum_{k=1}^{p} \phi_{ij,k} L^k$, $i, j = 1, 2$, L is the lag operator defined as $L^k x_t = x_{t-k}$, p is the order of the VAR model and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are uncorrelated disturbance terms with zero means and finite variances. F_t and R_t denote spot oil returns and stock market returns, respectively. As an alternative method for testing causality between cointegrated series, we employ Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) methodology. This technique is applicable irrespective of the integration and cointegration properties of the system. The method involves using a Modified Wald statistic for testing the joint significance of the parameters on first p lags after estimating a VAR(p+$d_{\max}$), where $d_{\max}$ is maximum order of integration in the model. The method guarantees the asymptotic χ^2 distribution of the Wald statistic. The results of pair-wise Granger non-causality tests between the series are given in Table 5. The results of Granger causality tests indicate unidirectional causality from oil prices to stock market for Bahrain and Saudi Arabia at 5 percent level and Oman at 10 percent level. On the other hand, a unidirectional causality is found from stock market to oil prices for UEA at 5 percent level, while a bidirectional causality is found for Kuwait and no causality is found for Qatar. Thus, the results of Granger causality tests are quite heterogeneous across the countries. Interestingly, the Toda-Yamamoto test agrees with the standard causality test only for Oman, Saudi Arabia and UEA. The Toda-Yamamoto test indicates no causality for Bahrain, unidirectional causality from oil prices to stock markets for Kuwait and Qatar. Thus, the causality test results vary largely across countries when the full sample is considered.

< insert Table 5 around here >

3.5. Parameter stability

Linear Granger causality tests reported above may be misleading, if the parameters of the VAR model are temporally unstable. Structural changes may create shifts in the parameters and the pattern of the causal relationship may change over time. If the parameters of the VAR model are not stable, then the results of the Granger causality tests will show sensitivity to sample period used and order of the VAR model. Therefore, studies using different sample periods and different VAR specification will find conflicting results for the causal links between oil and stock market prices. Salman and Shukur (2004) show that when the assumption of parameter constancy is violated, due to structural changes or regime shifts, Granger causality tests lead to misleading inference about the underlying causality relationship. Various tests are used in practice to examine the temporal stability of VAR models (see Hansen 1990, 1992; Andrews 1993; Andrews and Ploberger, 1994). We use the Sup-LM, Mean-LM and Exp-LM tests developed by Andrews (1993) and Andrews and Ploberger (1994) to investigate the stability of the parameters of the VAR model. These tests investigate the presence of one or more unknown structural breakpoints in the sample for a specified equation. The idea behind these tests is that a single Chow breakpoint test is performed at every observation τ between two dates, or observations, $t_1 = aT$ and $t_2 = (1- a)T$, where α is a trimming parameter and T is total number of observations in the sample. Let LM(τ) be LM statistic of the parameter stability for the date τ. The Sup-LM, Mean-LM, and Exp-LM tests are defined as

$$\text{Sup-LM} = \sup_{\tau_1 \le \tau \le \tau_2} \text{LM}(\tau),$$

$$\text{Mean-LM} = \frac{1}{\tau_2 - \tau_1 + 1} \sum_{\tau=\tau_1}^{\tau_2} \text{LM}(\tau),$$

$$\text{Exp-LM} = \ln\left(\frac{1}{\tau_2 - \tau_1 + 1}\right) \sum_{\tau=\tau_1}^{\tau_2} \exp\left(\frac{1}{2}\text{LM}(\tau)\right)$$

These tests are based on the sequence of LM(τ) statistics which test the null hypothesis of parameter stability against the alternative of a one-time structural change at each possible time in the sample. We also report the parameter stability test that is put forward by Nyblom (1989) for I(0) series and extended to I(1) series by Hansen (1993). This test is denoted as L_c. The L_c test is computed as an LM test for randomly time-varying parameters against the alternative hypothesis that the coefficients follow a random walk. Following Andrews (1993), we implement the tests with 15 percent trimming from both ends of the sample, i.e., we set $a = 0.15$.

These tests are used to examine the constancy of the coefficients in the VAR model formed by oil price change and stock market return series for each country. The analysis is based on the VAR models estimated both in levels and first differences using the specifications reported in Table 4. The LM tests are computed for each equation separately and for the VAR system as well. Figure 2 plots the sequence of the LM statistics for the level VAR with 5 percent critical value of the Mean-LM test. For Bahrain, Kuwait, Qatar, Saudi Arabia, and UEA the test values exceeds critical value around 2004-2005 period and stay above the critical value afterwards, indicating a regime shift after the period the oil prices started rising in early 2002. For Oman, computed test statistics exceed the 5 percent critical value for the whole period. Figure 3 plots the system LM statistics for the VAR models in first differences along with the 5 percent critical value for the Mean-LM test. Interestingly, the LM parameter stability tests for the first differenced VAR are analogous to level VAR test results, except for Saudi Arabia for which the first differenced VAR is found to be stable on average. The Sup-LM test for the VAR in first differences does however reject the parameter stability for Saudi Arabia.

In Table 6, the outcome of the parameter stability tests for oil price equation, stock price equation, and VAR system along with the associated *p*-values are reported. These *p*-values are obtained from a bootstrap approximation to the null distribution of the test statistics, constructed by means of Monte Carlo simulation using 2,000 artificial samples generated from a VAR model with constant parameters. The results reported in Table 6 indicate a strong rejection of the null hypothesis of parameter constancy in both individual equations and the system VAR when the Sup-LM test is used, except the individual equation test for Saudi Arabia. The first differenced VAR models seem to display average parameter stability when the tests are performed on each equation separately. When the system VAR tests are considered, average parameter stability of the first differenced VAR is rejected for all countries except Saudi Arabia. Parameter stability for the VAR models in levels are almost uniformly rejected by all tests. The evidence of parameter instability implies that the linear VAR models are not suitable for modeling lead-lag relationship between oil and stock markets. Any inference on the causal linkages, based on VAR models estimated assuming parameter constancy, between these markets may also be misleading. However, these tests of parameter instability are not designed to be optimal against MS type parameter changes, or any specific form of time variation, in parameters and may not be particularly powerful in the presence of MS type time-varying parameters (see Carrasco, 2002).

< insert Table 6 around here >

3.6. MS-VAR model estimates and time-varying causality

We estimate the parameters of Markov switching model via the expectation maximization (EM) algorithm (Lindgren 1978; Hamilton 1990, 1994) assuming that the conditional distribution of X_t given $\{\Omega_t, S_t, S_{t-1}, \ldots, S_0; \theta'\}$ is normal. The likelihood function is numerically approximated using the EM algorithm and the ML estimates are found by the Broyden–Fletcher–Goldfarb–Shano (BFGS) optimization algorithm. The order of the MS-VAR model for each pair of oil price and stock index series is selected by the SIC and 4 for Bahrain, Kuwait, Oman, and UEA; 5 for Qatar; and 2 for Saudi Arabia. We impose the restrictions given in Table 1 to test for regime prediction causality. Conditional Granger causality tests are straightforward since they involve restrictions only on the lags.

The F statistics for conditional Granger causality are given in Table 7. In the case of, say, the hypothesis that oil price changes do not Granger stock returns, i.e., $\alpha_1^{(k)} = 0$ or $\phi_{12,S_t}^{(k)} = 0,$ a common feature of the four sufficient conditions (under the hypotheses $H_0^1,$ $H_0^2,$ $H_0^3,$ and H_0^4) is that, conditional on the regime and the past values of R, F does not help to predict the next period value of R. This means that $\phi_{12,S_t}^{(k)} = 0$ for all regimes, $S_t = \{1,2,3,4\}$, when the regimes are not identified by the causality directions. If we further assume that, conditional on the given regime and the regimes are identified by the causality direction, i.e., as expressed in equations (8a)-(8d), it means that $\alpha_1^{(k)} = 0$. Analogous restrictions apply to the hypothesis that stock returns do not Granger cause oil price change. These restrictions represent the second prediction channel that was explained in Section 2.

In Table 7, we report the F statistics and corresponding p-values from testing the hypothesis that $F_t \neq> R_t$ ($\alpha_1^{(k)} = 0$ and $\phi_{12,S_t}^{(k)} = 0$, $S_t = \{1,2,3,4\}$) and that $R_t \neq> F_t$ ($\alpha_2^{(k)} = 0$ and $\phi_{21,S_t}^{(k)} = 0$, $S_t = \{1,2,3,4\}$). For testing $R_t \neq> F_t$, the evidence here, obtained from the F statistics shows that the hypothesis that the coefficients on the lagged stock returns are all zero in the oil price equation cannot be rejected at 10 percent level for all GCC countries, irrespective of whether the regimes are identified by causality direction or unidentified. The same holds when either of the variables is restricted to follow a single known regime. The F statistics for testing $F_t \neq> R_t$ ($\alpha_1^{(k)} = 0$ and $\phi_{12,S_t}^{(k)} = 0$, $S_t = \{1,2,3,4\}$) are all insignificant at 10 percent significance level except for Kuwait and Saudi Arabia for which the tests for $\phi_{12,S_t}^{(k)} = 0$ are significant when both series follow two regimes and the regimes are not identified. Contrary to results obtained from a linear VAR model, the evidence obtained here implies that the past values of oil prices, conditional on the given regime and independent of whether the regimes are identified by causality direction or not, does not help to predict the next period value of stock market returns in the GCC countries. Analogous result holds for impact from lagged stock returns to oil price changes. In summary, we do not obtain any evidence to support the conditional Granger causality in any direction, i.e., no lead–lag relationship is found between oil price and stock market prices for all six GCC economies.

< insert Table 7 around here >

Table 8 presents the estimation results of the regime-prediction Granger causality tests. With regard to the non-causality of oil price shock for the stock market, $F_t \neq> R_t$, the relevant four sufficiency restrictions are H_0^1, H_0^2, H_0^3, and H_0^4, which are given in Table 1. In this case, the regime-predication non-causality hypothesis implies that at least one of the four sets of restrictions, under H_0^1, H_0^2, H_0^3, and H_0^4, must be satisfied; the specific parameter restrictions are given in Table 1. For the case when we wish to test the hypothesis that oil prices are Granger non-causal in mean-variance for stock market prices, the restrictions H_0^1, H_0^3, and H_0^4 imply that oil market is conditionally uninformative about the regime, while H_0^2 implies that stock market returns do not directly depend on the regime (other than via the residual covariances). In addition, restrictions under the hypotheses H_0^1 and H_0^3 allow the Markov process to be serially correlated, while the restrictions relating to H_0^4 do not. Analogously, in regard to the non-causality of stock market for the oil prices, $R_t \neq> F_t$, the relevant four restrictions are H_0^5, H_0^6, H_0^7, and H_0^8, which are also given in Table 1. For the hypothesis $R_t \neq> F_t$ to hold, one of the regime-prediction non-causality restrictions given for each of the hypotheses H_0^5, H_0^6, H_0^7, and H_0^8 must be satisfied. Restrictions that hold under these hypotheses do have the same properties as the restrictions relating to hypothesis $F_t \neq> R_t$. With regard to the hypothesis $F_t \neq> R_t$, the four set of restrictions relating to H_0^1, H_0^2, H_0^3, and H_0^4 are strongly rejected for all countries by the *F* tests with *p*-values mostly less than 5 percent, except two cases where the *p*-value is less than 10 percent. Recall that such overall rejections suggest the existence of regime-prediction Granger causality. Thus, the oil market shocks help to predict the regime of stock markets in the GCC countries, i.e., the oil market price process contains unique information for predicting the regime process. This indicates that the oil price changes are informative about the regime process. The restriction(s) that is (are) inconsistent with the data will determine exactly how this matters.

< insert Table 8 around here >

For testing the regime-prediction non-causality of stock market for the oil market the hypotheses H_0^5, H_0^6, and H_0^7,, are strongly rejected with *p*-values less then 5 percent, except for two cases where the *p*-value for H_0^7 is less than 10 percent for Bahrain and Kuwait.

However, the hypothesis H_0^8 is not rejected at conventional significance levels for Bahrain, Qatar and UEA and rejected only at 10 percent for Kuwait, Oman and Saudi Arabia. Therefore, one of the sufficiency conditions does not hold and regime-prediction Granger non-causality of stock market for oil market is not rejected for three countries. Interestingly enough, the only restriction that cannot be rejected for testing $R_t \neq> F_t$ is H_0^8, while the other sets of restrictions are always rejected. This means both variables are useful for making inference about the regime process and that the evidence on causality is primarily found in the equation describing the stock market index.

4. Conclusion

The present study, using VAR model with time-varying parameters to carry out Granger causality analysis in situations where causality is non-permanent, examines the causal relationship between oil prices and the equity markets of the GCC countries for the February 2, 1994-February 26, 2010 period. The results from a linear VAR model suggest that the evidence for the predictive power between oil prices and stock price indices of the GCC countries is mixed, if not confusing. The previous studies obtained significant evidence of nonlinear and asymmetric relationship between crude oil prices and stock market indexes of due to different impacts oil price decreases than oil price increases in magnitude and speed. Since oil price decreases and increases alternated in the past, this should cause a time-varying temporal relationship between oil prices and stock price indexes. Additionally, we show that the parameters of the VAR model formed by oil price and equity index for each of the GCC countries are temporally not stable. In order to overcome the difficulties arising from nonlinearity and time variation, we propose a method that allows time-varying Granger causality. The method, which is based on the MS-VAR, models parameter time-variation so as to reflect changes in Granger causality. The MS-VAR model allows the identification of four possible causality relationships at each point in time. The model allows us to test for both the lead-lag (conditional Granger) causality and regime predicting causality. We obtain strong evidence against the existence of lead-lag relationships for all countries. However, the regime-predication Granger causality tests obtain overwhelming evidence that both oil and stock markets are informative about the regime of the other and the full sample causality evidence from oil market to stock market is stronger. The results of the study point to two directions, one of which is that as far as the changes in the oil market and the developments in financial sector in the GCC countries are considered, the findings on the time-varying nature of the predictive power of financial variables are not unexpected. The second one is that the causal relationship between oil prices and the stock markets implies predictive power for regime in both markets. The economic implications of causal relationship with regime predictive content should be put under close investigation for efficient markets.

References

Aloui, C., and Jammazi, R. (2009). The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach *Energy Economics* 31 789-799.

Andrews, D.W.K. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica* 61, 821-856.

Andrews, D.W.K. and Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica* 62, 1383-1414.

Arouri. M.E.H., and Fouquau, J. (2009). On the short-term influence of oil price changes on stock markets in GCC countries: linear and nonlinear analyses. Working Paper.

Arouri. M.E.H., and Rault, C. (2010). Oil Prices and Stock Markets: What Drives what in the Gulf Corporation Council Countries? CESifo Working Paper Series 2934, CESifo Group Munich.

Arouri, M.E.H., Lahiani, A., and Bellalah, M. (2010). Oil Price Shocks and Stock Market Returns in Oil-Exporting Countries: The Case of GCC Countries. *International Journal of Economics and Finance* 2, 132-139.

Baek, E. and Brock, W. A. (1992). General Test for Non-linear Granger Causality: Bivariate Model, Working Paper, Iowa State University and University of Wisconsin, Madison, WI.

Balke, N.S., Brown, S.P.A., and Yucel, M. (1999). Oil price shocks and the US economy: Where does the asymmetry originate?, Working paper. Dallas: Federal Reserve Bank of Dallas.

Balkowski, J. (2003). Modelling returns of stock indices for Western and Central European stock exchange-Markov switching approaches. *Southeast European Journal of Economic* 2, 81-100.

Burbridge, J. and Harrison, A. (1984). Testing for the effects of monetary policy shocks: Evidence from the flow of funds. *International Economic Review* 25, 459-484.

Carrasco, M. (2002). Misspecified structural change, threshold, and Markov-switching models. *Journal of Econometrics* 109, 239-273.

Ciner, C. (2001). Energy Shocks and Financial Markets: Nonlinear Linkages. *Studies in Nonlinear Dynamics* & *Econometrics* 5, 203-212.

Cologni, A., and Manera M. (2009). The Asymmetric Effects of Oil Shocks on Output Growth: A Markov-Switching Analysis for the G-7 Countries. *Economic Modelling* 26, 1-29.

El-Sharif, I., Brown, D., Burton, B., Nixon, B. and Russell, A. (2005). Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. *Energy Economics* 27, 819-830.

George, H. and Evangelia, P., (2005). Stock returns and inflation in Greece. A Markov switching approach. *Review of Financial Economics* 15, 76-94.

Gilbert, R.J. and Mork, K.A. (1984). Will Oil Markets Tighten Again? A Survey of Policies to Manage Possible Oil Supply Disruptions. *Journal of Policy Modeling* 6, 111-142.

Granger, C.W.J., Engle, R.F. and Robins, R.P. (1986). Wholesale and retail prices: Bivariate time series modelling with forecastable error variances. In D. Belsley andE. Kuh, eds., Model Reliability, MIT Press, Cambridge, MA, 1-17.

Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross spectral methods. *Econometrica* 37, 424-438.

Hamilton, J.D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy* 88, 829-853.

Hamilton, J. D. (1990). Analysis of Time Series Subject to Changes in Regime. *Journal of Econometrics* 45, 39-70.

Hamilton, J. D. (1994). *Time Series Analysis,* Princeton, NJ: Princeton University Press.

Hamilton, J.D. and Raul, S. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics* 64, 307-333.

Hamilton, J.D. (1996). This is what happened to the oil price–macroeconomy relationship. *Journal of Monetary Economics*, 38, 215-220.

Hamilton, J.D. (2001). A parametric approach to flexible nonlinear inference. *Econometrica* 69, 537-573.

Hamilton, J.D. (2003). What is an oil shock? *Journal of Econometrics* 113, 363–398.

Hammoudeh, S. and Li, H. (2004). The impact of the Asian crisis on the behavior of US and international petroleum prices. *Energy Economics* 26, 135-160.

Hammoudeh, S. and Elesia, E. (2004), Dynamic relationships among GCC Stock Markets and NYMEX Oil Futures. *Contemporary Economic Policy* 22, 250-269.

Hammoudeh S., and Choi, K. (2006). Behavior of GCC stock markets and impacts of US oil and financial markets. *Research in International Business and Finance* 20: 22–44.

Hansen, B.E. (1990). Lagrange multiplier tests of parameter instability in non-linear models. Unpublished manuscript, Department of Economics, University of Rochester.

Hansen, B.E. (1992). Tests for parameter instability in regressions with I(1) processes. *Journal of Business and Economic Statistics* 10, 321-336.

Hiemstra, C. and Jones, J.D. (1994). Testing for linear and non-linear Granger causality in the stock price–volume relation. *Journal of Finance* 5, 1639-1664.

Huang, R.D., Masulis, R.W. and Stoll, H.R. (1996). Energy shocks and financial markets. *Journal of Futures Markets* 16, 1-27.

Jacobson, T., Lindh, T. and Warne, A. (2002). Growth, saving, financial markets, and Markov-Switching regimes. *Studies in Nonlinear Dynamics and Econometrics* 5, 241-259.

Karlsen, H. (1990). A Class of Non-Linear Time Series Models. PhD Thesis, Department of Mathematics, University of Bergen, Norway.

Kaul, G. and Jones, C.M. (1996). Oil and the stock markets. *Journal of Finance* 51, 463-491.

Krishnamurthy, V. and Rydén, T. (1998). Consistent estimation of linear and non-linear autoregressive models with Markov regime. *Journal of Time Series Analysis* 19, 291-307.

Kuswanto, H., Salamah, M. (2009). Regime Switching Long Memory Model for German Stock Returns. *European Journal of Economics* 15, 7-17.

Lardic S. and Mignon V. (2006). The impact of oil prices on GDP in European countries: An empirical investigation based on asymmetric cointegration. *Energy Policy* 34, 3910-3915.

Lardic S. and Mignon V. (2008). Oil prices and economic activity: An asymmetric cointegration approach. *Energy Economics* 30, 847-855

Lee, K., Ni, S. and Ratti, R.A. (1995). Oil shocks and the macroeconomy: The role of price variability. *Energy Journal* 16, 39-56.

Lindgren, G. (1978). Markov Regime Models for Mixed Distributions and Switching Regressions. *Scandinavian Journal of Statistics* 5, 81-91.

Loungani, P. (1986). Oil price shocks and the dispersion hypothesis. *Review of Economics and Statistics* 68, 536-539.

Lütkepohl, H. (1991). *Introduction to Multiple Time Series Analysis*, Berlin: Springer-Verlag.

Miller, J.I., and Ratti, R.A., (2009). Crude oil and stock markets: Stability, instability, and bubbles. *Energy Economics* 31, 559-568.

Mork, K.A. (1989). Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results. *Journal of Political Economy* 91, 740-744.

Mork, K.A., Olsen, O. and Mysen, H.T. (1994). Macroeconomic responses to oil price increases and decreases in seven OECD countries. *Energy Journal* 15, 19-35.

Newey, W., West, K., (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies* 61: 631-653.

Nandha, M. and Faff, R. (2008). Does oil move equity prices? A global view. *Energy Economics* 30, 986-997.

Onour, I.A. (2008). What drives short-term GCC stock market returns? Empirical evidence from fat-tailed distribution, *Afro-Asian Journal of Finance and Accounting* 1, 17-25.

Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. *Energy Economics* 23, 511-532.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics* 21, 449-469.

Salman, A.K. and Shukur, G. (2004). Testing for Granger causality between industrial output and CPI in the presence of regime shift. *Journal of Economic Studies* 31, 492-499.

Silvapulle, P. and Moosa, I. (1999). The relationship between spot and futures prices: evidence from the crude oil market. *Journal of Futures Markets* 19, 175-193.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics* 66, 225-250.

Warne, A. (2000). Causality and Regime Inference in a Markov Switching VAR, Working Paper Series 118, Sveriges Riksbank (Central Bank of Sweden).

Zarour, B.A. (2006). Wild oil prices, but brave stock markets! The case of GCC stock markets, *Operational Research* 6, 145-162.

Zhang, D., (2008) Oil shock and economic growth in Japan: A nonlinear approach. *Energy Economics* 30, 2374-2390.

Table 1. Non-causality and conditional regime independence restrictions in 2-state and 4-state MS-VAR(p) models with $X_t = [R_t' \; F_t']'$

Hypothesis		Restrictions	# restrictions
H_0^1	F_t dos not Granger cause R_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	$\mu_{1,S_t} = \mu_{1,S_{1,t}}, \mu_{2,S_2,t} = \mu_{2,S_{2,t}}, \phi_{11,S_t}^{(k)} = \phi_{11,S_{1,t}}^{(k)},$ $\phi_{12,S_t}^{(k)} = \phi_{12,S_{1,t}}^{(k)}, \phi_{22,S_t}^{(k)} = \phi_{22,S_{2,t}}^{(k)}, \phi_{21,S_t}^{(k)} = \phi_{21,S_{2,t}}^{(k)},$ $\Omega_{11,S_t} = \Omega_{11,S_{1,t}}, \Omega_{22,S_t} = \Omega_{22,S_{2,t}},$ $\Omega_{12,S_t} = 0, \phi_{12,S_{1,t}}^{(k)} = 0,$	m=8p+12
H_0^2	F_t dos not Granger cause R_t with q_1=1 and q_2=2 (S_t =1,3)	$\mu_{1,S_t} = \mu_1, \quad \phi_{11,S_t}^{(k)} = \phi_{11}^{(k)}, \quad \phi_{12,S_t}^{(k)} = 0,$ $\Omega_{11,S_t} = \Omega_{11}, \quad \Omega_{12,S_t} = 0$	m=3p+4
H_0^3	F_t dos not Granger cause R_t with q_1=2 and q_2=1 (S_t = 1,2)	$\mu_{2,S_t} = \mu_2, \quad \phi_{21,S_t}^{(k)} = \phi_{21}^{(k)}, \quad \phi_{22,S_t}^{(k)} = \phi_{22}^{(k)},$ $\Omega_{22,S_t} = \Omega_{22}, \quad \Omega_{12,S_t} = 0, \quad \phi_{12,S_t}^{(k)} = 0,$	m=4p+4
H_0^4	F_t dos not Granger cause R_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	$p_{11}^{(1)} = p_{21}^{(1)}, \quad p_{11}^{(2)} = p_{21}^{(2)}, \quad \phi_{12,S_t}^{(k)} = \phi_{12,S_{1,t}}^{(k)} = 0$	m=2p+2
H_0^5	R_t dos not Granger cause F_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	$\mu_{1,S_t} = \mu_{1,S_{1,t}}, \mu_{2,S_2,t} = \mu_{2,S_{2,t}}, \phi_{11,S_t}^{(k)} = \phi_{11,S_{1,t}}^{(k)},$ $\phi_{12,S_t}^{(k)} = \phi_{12,S_{1,t}}^{(k)}, \phi_{22,S_t}^{(k)} = \phi_{22,S_{2,t}}^{(k)}, \phi_{21,S_t}^{(k)} = \phi_{21,S_{2,t}}^{(k)},$ $\Omega_{11,S_t} = \Omega_{11,S_{1,t}}, \Omega_{22,S_t} = \Omega_{22,S_{2,t}},$ $\Omega_{21,S_t} = 0, \phi_{21,S_{2,t}}^{(k)} = 0,$	m=8p+12
H_0^6	R_t dos not Granger cause F_t with q_1=1 and q_2=2 (S_t =1,3)	$\mu_{1,S_t} = \mu_1, \phi_{11,S_t}^{(k)} = \phi_{11}^{(k)}, \phi_{12,S_t}^{(k)} = \phi_{12}^{(k)}$ $\Omega_{11,S_t} = \Omega_{11}, \Omega_{21,S_t} = 0, \phi_{21,S_t}^{(k)} = 0$	m=4p+4
H_0^7	R_t dos not Granger cause F_t with q_1=2 and q_2=1 (S_t = 1,2)	$\mu_{2,S_t} = \mu_2, \phi_{22,S_t}^{(k)} = \phi_{22}^{(k)}, \phi_{21,S_t}^{(k)} = 0,$ $\Omega_{22,S_t} = \Omega_{22}, \Omega_{21,S_t} = 0$	m=3p+4
H_0^8	R_t dos not Granger cause F_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	$p_{21}^{(1)} = p_{22}^{(1)}, \quad p_{21}^{(2)} = p_{22}^{(2)}, \quad \phi_{21,S_t}^{(k)} = \phi_{21,S_{2,t}}^{(k)} = 0$	m=2p+2

Table 2. Descriptive statistics for weekly GCC stock index and WTI crude oil spot price series

Panel A: log levels	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE	WTI
Mean	8.492	7.239	9.120	6.950	6.792	6.563	3.504
Median	8.576	7.313	9.071	7.281	6.515	6.634	3.372
Maximum	8.945	8.323	10.347	8.172	8.585	7.430	4.952
Minimum	7.886	6.091	8.243	5.775	5.717	5.609	2.394
Std. Dev.	0.281	0.619	0.533	0.822	0.796	0.493	0.600
Skewness	-0.343	-0.211	0.279	-0.220	0.432	-0.182	0.384
Kurtosis	2.272	1.924	2.046	1.448	1.828	1.885	2.062
JB	16.155	29.282	36.226	66.951	75.393	26.785	52.254
p-value for JB	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sample period	1/7/2003-6/8/2010	5/16/2000-6/8/2010	10/22/1996-6/8/2010	8/11/1998-6/8/2010	2/8/1994-6/8/2010	7/3/2001-6/8/2010	2/8/1994-6/8/2010
Observations	388	526	712	618	853	467	853
Panel B: log returns (percent)							
Mean	0.078	0.233	0.167	0.265	0.146	0.195	0.183
Median	0.144	0.352	0.054	0.118	0.432	0.175	0.614
Maximum	6.054	11.724	13.941	14.315	13.706	16.666	21.397
Minimum	-9.069	-15.490	-21.055	-24.028	-23.245	-15.303	-24.005
Std. Dev.	1.649	3.031	3.017	3.884	3.377	3.358	5.099
Skewness	-0.524	-0.907	-0.830	-0.869	-1.410	-0.332	-0.410
Kurtosis	6.603	7.798	10.526	9.290	10.420	7.517	4.630
JB	227.033	575.488	1759.737	1094.900	2237.110	404.639	118.226
p-value for JB	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: JB is the Jarqua-Berra test of normality, which is distributed as $\chi^2(2)$, and *p*-value JB is the associated *p*-value

Table 3. Unit root test results for weekly GCC stock index and WTI crude oil spot price series

	Level				First Differences			
	H_0: I(1)		H_0: I(0)		H_0: I(1)		H_0: I(0)	
Series	ADF_{μ}[a]	ADF_{τ}[b]	$KPSS_{\mu}$[c]	$KPSS_{\tau}$[d]	ADF_{μ}[a]	ADF_{τ}[b]	$KPSS_{\mu}$[c]	$KPSS_{\tau}$[d]
Bahrain	-1.246	-0.913	0.828*	0.494*	-10.174*	-10.749*	0.717**	0.060
Kuwait	-2.083	-0.400	2.271*	0.497*	-10.482*	-10.769*	0.399***	0.103
Oman	-0.734	-1.791	2.302*	0.560*	-11.544*	-11.563*	0.093	0.097
Qatar	-1.282	-0.561	2.874*	0.505*	-15.319*	-15.355*	0.200	0.138***
Saudi Arabia	-1.062	-0.886	3.511*	0.350*	-19.248*	-19.257*	0.160	0.159**
UAE	-1.605	-0.692	1.525*	0.489*	-9.540*	-9.688*	0.315	0.060
WTI	-1.095	-2.601	3.576*	0.326*	-21.524*	-21.511*	0.034	0.034

Notes: *, ** and *** denote 1, 5 and 10 percent levels of significance respectively.

[a]Test allows for a constant; one-sided test of the null hypothesis that the variable has a unit root; 10, 5, 1 percent significance critical value equals -2.57, -2.87, -3.44, respectively.

[b]Test allows for a constant and a linear trend; one-sided test of the null hypothesis that the variable has a unit root; 10, 5, 1 percent critical value equals -3.13, -3.42, -3.98, respectively.

[c]Test allows for a constant; one-sided test of the null hypothesis that the variable is stationary; 10, 5, 1 percent critical values equals 0.347, 0.463, 0.739, respectively.

[d]Test allows for a constant and a linear trend; one-sided test of the null hypothesis that the variable is stationary; 10, 5, 1 percent critical values equals 0.119, 0.146, 0.216, respectively.

Table 4. Johansen test for cointegration between stock index and WTI oil price series

Statistics / Series	H_0	H_1	*Bahrain*	*Kuwait*	*Oman*	*Qatar*	*Saudi A*	*UAE*
Eigenvalues (λ)								
$\hat{\lambda}_1$			0.025	0.020	0.007	0.013	0.011	0.017
$\hat{\lambda}_2$			0.005	0.010	0.003	0.003	0.002	0.010
Trace statistics (λ_{trace})								
	$r=0$	$r \le 1$	11.482	15.493	7.021	9.638	11.443	12.485
	$r=1$	$r \le 2$	1.809	5.185*	1.826	1.671	1.668	4.466*
Maximal eigenvalue statistics $(\lambda_{\max})$								
	$r=0$	$r=1$	9.673	10.308	5.196	7.968	9.775	8.019
	$r=1$	$r=2$	1.809	5.185*	1.826	1.671	1.668	4.466*
Five percent critical values for λ_{trace}								
	$r=0$	$r \le 1$	15.495	15.495	15.495	15.495	15.495	15.495
	$r=1$	$r \le 2$	3.841	3.841	3.841	3.841	3.841	3.841
Five percent critical values for $\lambda_{\max}$								
	$r=0$	$r=1$	14.265	14.265	14.265	14.265	14.265	14.265
	$r=1$	$r=2$	3.841	3.841	3.841	3.841	3.841	3.841
p			5	5	4	8	2	4

Notes: * denotes significance at the 5 percent level. The critical values for the Johansen tests are based on MacKinnon *et al*. (1999). *r* represents the number of cointegrating vectors. $\lambda_{\max} = -T(1-\hat{\lambda}_{r+1})$ and $\lambda_{\text{trace}} = -T\sum_{k=r+1}^{n}(1-\hat{\lambda}_i)$ where $\hat{\lambda}_i$ are the estimated eigenvalues of the Π matrix in equation (9).

Table 5. Granger causality test between stock index and WTI oil price series

	Short-run Granger causality test in first differenced VAR(p-1)		Toda-Yamamoto causality test in VAR(p+1)	
Bahrain				
$R \neq> F$	$\chi^2(4) = 3.847$	[0.427]	$\chi^2(5) = 4.590$	[0.468]
$F \neq> R$	$\chi^2(4) = 8.809^{**}$	[0.066]	$\chi^2(5) = 8.867$	[0.115]
Kuwait				
$R \neq> F$	$\chi^2(4) = 7.795^{***}$	[0.099]	$\chi^2(5) = 8.902$	[0.113]
$F \neq> R$	$\chi^2(4) = 13.109^{**}$	[0.011]	$\chi^2(5) = 14.152^{**}$	[0.015]
Oman				
$R \neq> F$	$\chi^2(3) = 1.065$	[0.786]	$\chi^2(4) = 1.832$	[0.767]
$F \neq> R$	$\chi^2(3) = 22.721^{*}$	[0.000]	$\chi^2(4) = 23.355^{*}$	[0.000]
Qatar				
$R \neq> F$	$\chi^2(7) = 6.183$	[0.289]	$\chi^2(8) = 12.763$	[0.120]
$F \neq> R$	$\chi^2(7) = 8.329$	[0.139]	$\chi^2(8) = 16.818^{**}$	[0.032]
Saudi Arabia				
$R \neq> F$	$\chi^2(1) = 1.154$	[0.283]	$\chi^2(2) = 1.908$	[0.167]
$F \neq> R$	$\chi^2(1) = 4.948^{**}$	[0.026]	$\chi^2(2) = 5.573^{***}$	[0.062]
UAE				
$R \neq> F$	$\chi^2(3) = 9.896^{**}$	[0.020]	$\chi^2(4) = 9.939^{**}$	[0.042]
$F \neq> R$	$\chi^2(3) = 0.081$	[0.994]	$\chi^2(4) = 0.092$	[0.999]

Notes: $\neq>$ represents "does not Granger cause". *, ** and *** denote 1, 5 and 10 percent levels of significance respectively. Figures in brackets are p-values. $\chi^2(m)$ represents a Wald statistic distributed as Chi-square with m degrees of freedom, m being the number of zero restrictions.

Table 6. Parameter stability tests in VAR models

Statistic	VAR(p) in levels: Stock index equation	VAR(p) in levels: WTI oil price equation	VAR(p) in levels: VAR(p) system	VAR(p-1) in first differences: Stock index equation	VAR(p-1) in first differences: WTI oil price equation	VAR(p-1) in first differences: VAR(p-1) system
Bahrain						
Sup-LM	34.0942* [0.0097]	60.4406* [0.0000]	80.2742* [0.0000]	29.5623** [0.0122]	25.6873** [0.0443]	57.3647* [0.0002]
Ave-LM	22.4619* [0.0024]	28.5539* [0.0001]	44.0657* [0.0001]	19.7970* [0.0023]	12.9719*** [0.0893]	33.7568* [0.0011]
Exp-LM	13.4232* [0.0084]	25.1838* [0.0000]	35.5552* [0.0000]	11.8224* [0.0080]	9.6591** [0.0407]	25.4973* [0.0001]
L_c	1.5846 [0.4302]	2.0251 [0.2717]	9.1744* [0.0061]	1.7843 [0.2271]	1.1477 [0.5028]	7.1775* [0.0050]
Kuwait						
Sup-LM	53.2778* [0.0000]	37.6653 * [0.0029]	114.9729* [0.0000]	36.4809* [0.0009]	19.5429 [0.2471]	66.7660* [0.0000]
Ave-LM	22.8407* [0.0019]	10.6808 [0.4899]	34.8546* [0.0056]	16.3798** [0.0159]	8.8196 [0.4661]	30.2219* [0.0058]
Exp-LM	21.5957* [0.0000]	13.4327* [0.0083]	51.5889* [0.0000]	13.8338* [0.0016]	6.7993 [0.2563]	29.7933* [0.0000]
L_c	2.2027 [0.2079]	1.5578 [0.4398]	7.2370v [0.0061]	1.9714 [0.1444]	1.1926 [0.4834]	6.5279* [0.0086]
Oman						
Sup-LM	43.3591* [0.0001]	40.1106* [0.0002]	120.6392* [0.0000]	29.3844* [0.0033]	20.2341*** [0.0849]	95.1949* [0.0000]
Ave-LM	22.3640* [0.0005]	21.7710* [0.0007]	72.6225* [0.0000]	17.3049* [0.0018]	14.3349** [0.0110]	54.7377* [0.0000]
Exp-LM	17.1712* [0.0001]	14.4947* [0.0009]	54.8381* [0.0000]	11.2867* [0.0027]	8.0716** [0.0388]	43.8533* [0.0000]
L_c	1.6474 [0.2864]	2.8884* [0.0085]	13.5931* [0.0000]	1.4198 [0.2235]	1.9126** [0.0486]	12.3151* [0.0035]
Qatar						
Sup-LM	71.0784* [0.0000]	50.2756* [0.0012]	120.4661* [0.0000]	37.2701** [0.0267]	45.5849* [0.0020]	70.0552* [0.0016]
Ave-LM	33.8264* [0.0004]	22.4292*** [0.0887]	50.3470* [0.0055]	19.4306 [0.1131]	18.5000 [0.1588]	36.7508*** [0.0986]
Exp-LM	31.9401* [0.0000]	22.1622* [0.0006]	54.5353* [0.0000]	15.3126** [0.0202]	18.9796* [0.0016]	31.6664* [0.0010]
L_c	3.3148 [0.2019]	2.3114 [0.4435]	10.1358* [0.0001]	1.9649 [0.4690]	1.9499 [0.4731]	8.9302* [0.0057]
Saudi Arabia						
Sup-LM	27.3008* [0.0014]	21.1609** [0.0165]	65.0941* [0.0000]	9.9180 [0.2187]	8.7329 [0.3209]	18.7193*** [0.0773]
Ave-LM	13.8607* [0.0019]	7.1050 [0.1476]	20.5153* [0.0036]	4.2258 [0.1852]	3.0930 [0.3808]	7.3748 [0.2335]
Exp-LM	9.1031* [0.0033]	6.9990** [0.0222]	26.5978* [0.0000]	2.7596 [0.1980]	2.1496 [0.3404]	5.9596 [0.1062]
L_c	1.5567** [0.0353]	0.5927 [0.5589]	3.8319 [0.2415]	0.5176 [0.3865]	0.4010 [0.5246]	1.4411 [0.1164]
UAE						
Sup-LM	23.9430*** [0.0755]	49.8163* [0.0000]	70.0048* [0.0000]	20.0900*** [0.0890]	37.1122* [0.0001]	59.3692* [0.0000]
Ave-LM	12.6887 [0.1019]	26.4592* [0.0000]	40.3989* [0.0000]	9.8615 [0.1263]	18.9005* [0.0006]	31.5601* [0.0002]
Exp-LM	8.0624 [0.1203]	20.8620* [0.0000]	29.8941* [0.0000]	6.4115 [0.1316]	15.4972* [0.0001]	25.4152* [0.0000]
L_c	1.6453 [0.2873]	2.3429** [0.0492]	7.8513* [0.0068]	1.2064 [0.3402]	1.8788*** [0.0546]	6.2101* [0.0086]

Notes: *, ** and *** denote 1, 5 and 10 percent levels of significance respectively. Bootstrap p-values are given in brackets.

Table 7. Conditional Granger non-causality in 2-state and 4-state the MS-VAR(4) model of oil and stock market prices[a]

Hypothesis	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
q_1=2, q_2=2						
$\alpha_1^{(k)} = 0$	1.439 [0.220]	1.206 [0.307]	1.525 [0.193]	1.611 [0.170]	1.414 [0.228]	1.132 [0.341
$\alpha_2^{(k)} = 0$	1.768 [0.135]	1.227 [0.298]	1.027 [0.392]	1.147 [0.333]	0.904 [0.461]	1.324 [0.260]
q_1=1, q_2=2						
$\alpha_1^{(k)} = 0$	1.102 [0.355]	1.530 [0.192]	0.948 [0.436]	1.394 [0.234]	1.823 [0.122]	1.485 [0.206]
$\alpha_2^{(k)} = 0$	1.454 [0.216]	0.903 [0.462]	1.634 [0.164]	2.107† [0.078]	1.438 [0.220]	1.804 [0.127]
q_1=2, q_2=1						
$\alpha_1^{(k)} = 0$	1.471 [0.210]	0.914 [0.455]	0.977 [0.481]	1.002 [0.406]	1.478 [0.207]	0.992 [0.411]
$\alpha_2^{(k)} = 0$	1.195 [0.266]	1.443 [0.219]	0.931 [0.445]	1.744 [0.139]	1.619 [0.167]	1.415 [0.228]
q_1=2, q_2=2						
$f_{12,S_t}^{(k)} = 0$[b]	1.003 [0.452]	2.041† [0.087]	1.086 [0.364]	1.199 [0.264]	2.041† [0.087]	0.980 [0.477]
$f_{21,S_t}^{(k)} = 0$[c]	0.932 [0.532]	1.287 [0.200]	1.075 [0.376]	1.054 [0.397]	1.039 [0.412]	1.340 [0.169]

[a] For the F statistic the reference distribution is $F(m, T-s)$ and the F statistic is computed from $F=((T-s)/(mT))W$, where W is the Wald statistic computed for, T is the number of observations, s is the closest integer to the average number of free parameters per equation under H_0, i.e., s=int[$(k-m)/2$], where k is the total number of parameters estimated.

[b] Test of the null hypothesis that oil prices do not Granger cause stock prices in an unrestricted MS-VAR(4) model with 4 states.

[c] Test of the null hypothesis that stock prices do not Granger cause oil prices in an unrestricted MS-VAR(4) model with 4 states.

†, *, and ** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively. p-values are given in brackets.

Table 8. Regime prediction Granger non-causality tests in 2-state and 4-state MS-VAR(4) model of oil and stock market prices[a]

Hypothesis		Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
H_0^1	F_t dos not Granger cause R_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	2.834* [0.024]	3.225* [0.013]	2.687* [0.030]	3.548** [0.007]	3.868** [0.004]	2.468* [0.044]
H_0^2	F_t dos not Granger cause R_t with q_1=1 and q_2=2 (S_t =1,3)	3.273* [0.012]	2.569* [0.037]	2.499* [0.041]	2.369† [0.051]	2.785* [0.026]	2.524* [0.040]
H_0^3	F_t dos not Granger cause R_t with q_1=2 and q_2=1 (S_t = 1,2)	2.335† [0.055]	2.526* [0.040]	2.712* [0.029]	2.774* [0.026]	2.335† [0.054]	2.832* [0.024]
H_0^4	F_t dos not Granger cause R_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	2.542* [0.039]	2.705* [0.030]	2.435* [0.046]	2.843* [0.024]	3.429** [0.009]	2.748* [0.028]
H_0^5	R_t dos not Granger cause F_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	2.431* [0.047]	3.202* [0.013]	2.846* [0.023]	4.065** [0.003]	2.725* [0.028]	2.603* [0.035]
H_0^6	R_t dos not Granger cause F_t with q_1=1 and q_2=2 (S_t =1,3)	2.654* [0.033]	2.940* [0.020]	2.548* [0.038]	2.680* [0.031]	2.403* [0.048]	2.761* [0.027]
H_0^7	R_t dos not Granger cause F_t with q_1=2 and q_2=1 (S_t = 1,2)	1.576† [0.073]	1.556† [0.077]	1.707* [0.041]	1.583† [0.068]	1.756* [0.033]	1.954* [0.015]
H_0^8	R_t dos not Granger cause F_t with q_1=2 and q_2=2 (S_t = 1,2,3,4)	1.402 [0.138]	1.541† [0.081]	1.509† [0.090]	1.475 [0.103]	1.608† [0.061]	1.400 [0.137]

[a] For the F statistic the reference distribution is $F(m, T- s)$ and the F statistic is computed from $F=((T-s)/(mT))W$, where W is the Wald statistic, T is the number of observations, s is the closest integer to the average number of free parameters per equation under H_0, i.e., s=int[$(k-m)/2$], where k is the total number of parameters estimated.

†, *, and ** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively. p-values are given in brackets.

Figure 1. GCC Equity Price Indices and WTI Crude Oil Price

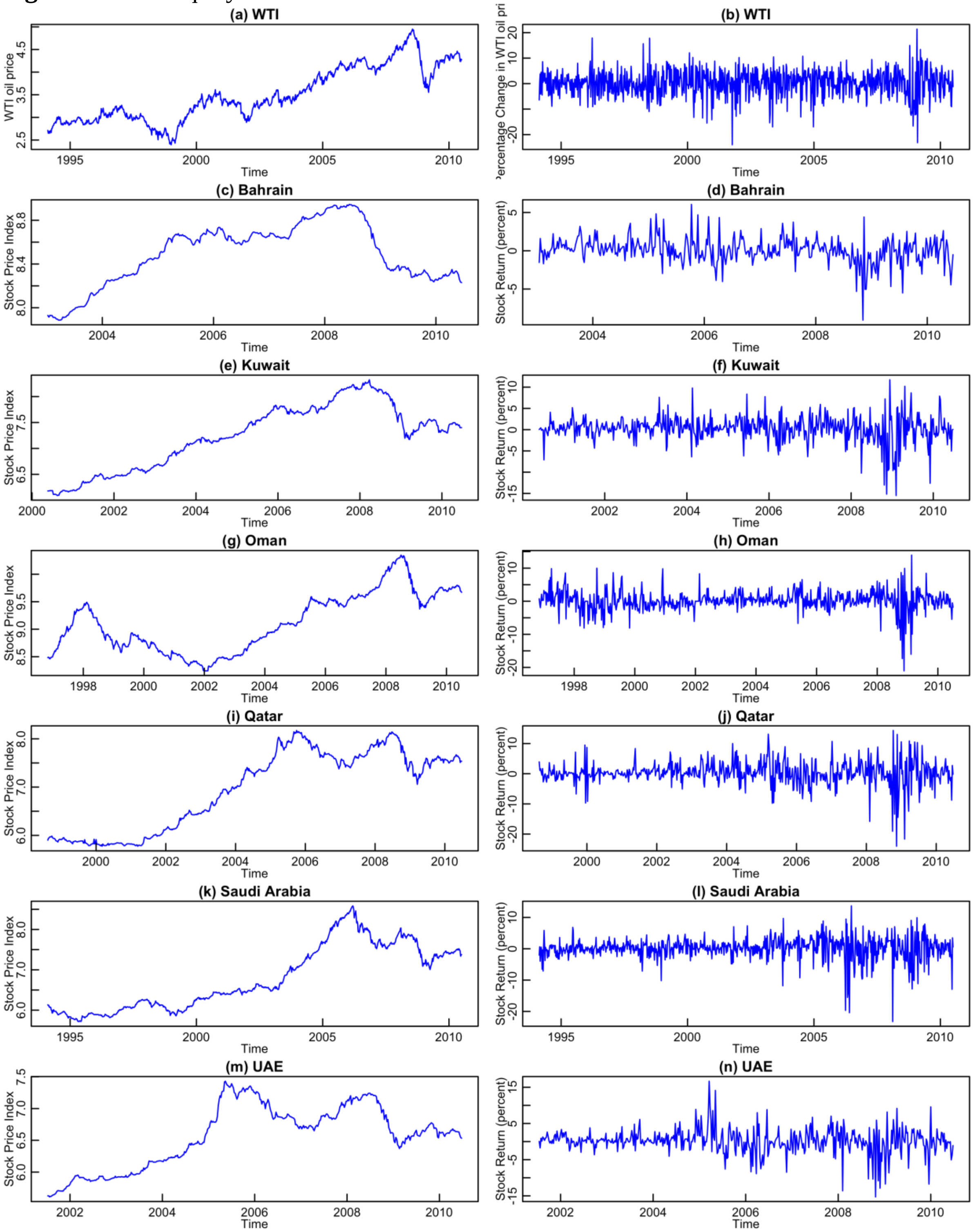

Figure 2. Parameter Stability Test for the VAR(p) in Levels

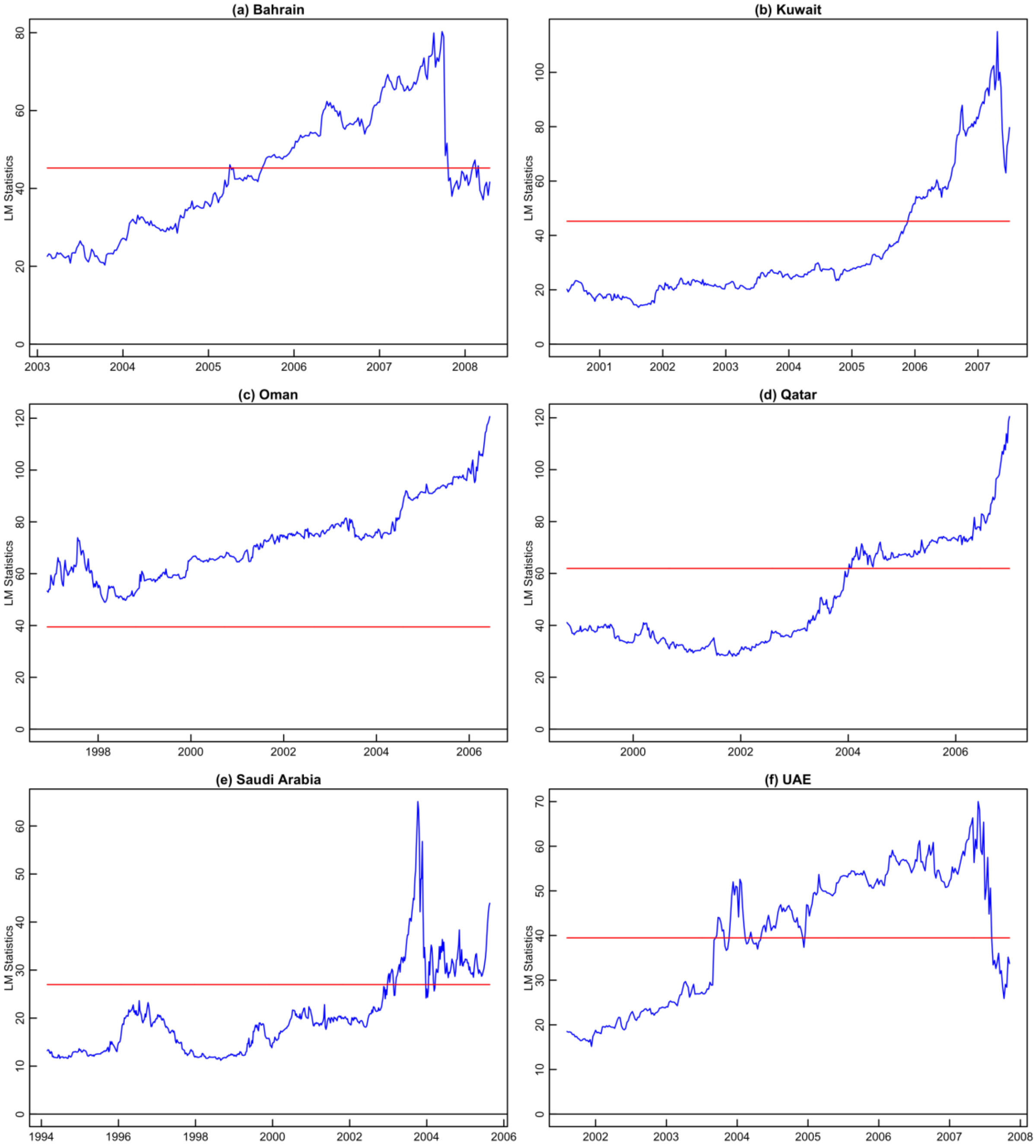

Figure 3. Parameter Stability Test for the VAR(p) in First Differences