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VOLATILITY SPILLOVER, INTERDEPENDENCE, COMOVEMENTS ACROSS GCC, OIL AND U.S. MARKETS AND PORTFOLIO MANAGEMENT STRATEGIES IN A REGIME-CHANGING ENVIRONMENT

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Volatility Spillover, Interdependence, Comovements across GCC, Oil and U.S. Markets and Portfolio Management Strategies in a Regime-Changing Environment

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Abstract

This study examines the volatility transmissions across the Gulf Arab states (GCC) stock markets and the linkages between these markets and the United States stock and oil markets, using the Multi-chain Markov Switching model. This approach enables the distinction between different transmission types including volatility spillover, interdependence, comovements and independence. The results demonstrate the presence of different transmissions between the markets and that the type of transmission is highly sensitive to the state of the economy characterized by turbulence or tranquility. They support strong interdependence between the oil price, the U.S. S&P 500 index, Saudi Arabia and Abu Dhabi. There is also a strong spillover from the U.S. S&P 500 index to Oman and Kuwait, but interdependence with Dubai. There are also different diversification opportunities between the GCC markets. Policy implications on portfolio strategies under different states are also discussed.

Keywords: GCC markets; S&P 500, Oil price, Multi-chain MS model, Volatility Transmissions.
JEL Classifications: C32, G11, G15.

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1 Introduction

Information flows across the Gulf Cooperation Council stock markets -Saudi Arabia, Kuwait, UAE (Dubai and Abu-Dhabi), Oman, and Qatar- (GCC hereafter) are major determinants of cross patterns among those markets. Information may flow through macroeconomic linkages that include cross-country trade and customs relationships, direct investment flows, interrelated portfolios, exchange rate regime coordination, and monetary and fiscal policy arrangements. While these macroeconomic relationships among the GCC countries have been strengthening over time, they however make them more vulnerable to shocks during crisis than during tranquility periods. In addition to these macroeconomic linkages, there are regional and international macroeconomic announcements that bring shocks to these countries, thus directly affecting the volatility of their stock markets. Within this macroeconomic framework, volatility in the GCC stock markets behaves differently during normal and crisis periods. However, those markets as a group often behave similarly but to varying degrees over the same periods.[1]

Moreover, changes in the oil price can be an underlying cause or source of volatility in the oil-based GCC markets. Therefore, the oil price volatility can have a great impact on the market interdependence or spillover across the GCC stock markets. This impact may be different over oil booms and busts, but again the GCC stock markets as a region behave in a similar way in each of these cycles.

Within this context, this paper will focus on measuring volatility transmission across the six GCC stock markets indicated earlier. The volatility transmission can be defined as a significant increase in cross-market linkages after a shock or a change in regime. Changes in the across market linkages can be measured by changes in an integration array, ranging from correlations in asset returns to the probability of a speculative attack and to the transmission of shocks or volatility (Forbes and Rigobon, 2004). But how are shocks transmitted across the GCC markets? We investigate this question through estimating volatility transmission across the GCC markets, oil and U.S. (S&P 500) markets.

In the contagion literature, there are two possible spillover mechanisms that can be related to the GCC stock markets. The first mechanism is the multiple equilibria or the shifting from good to bad equilibrium for a disrupted economy, thereby causing a crash in the second economy (Paul, 1998). The second mechanism is the endogenous liquidity (or lack thereof) where a crisis in one country can reduce the liquidity of market participants in that country. The reduced liquidity can in turn force the investors to rebalance their portfolios and sell assets in other countries in order to continue operating in the troubled market to meet regulatory requirements or to satisfy margin calls (Valdés, 1996).

To investigate the volatility transmissions and mechanisms of linkages across the GCC stock markets and other markets, this study will follow the Multi Chain Markov Switching model (MCMS, hereafter), which is introduced by Otranto (2005). This approach aims at distinguishing between different concepts of volatility transmissions across stock markets and has been applied by Gallo and Otranto (2007) to estimate volatility transmission

[1] Bahrain is excluded because of lack of adequate data at the cross-sectional level.

across the Asian stock markets. The MCMS model will be employed to comprehensively document the different volatility transmission mechanisms (spillover, interdependence, comovements and independence) across the GCC stock markets, oil market and the U.S. S&P 500 index representing the world's major stock markets.

Within this context, our study documents, through the estimation of the MCMS model, the underlying volatility transmission modes across the GCC markets, oil price and the U.S. S&P 500 index. The results should be valuable to traders, investors, portfolio managers and policy makers in the GCC countries and other countries.

To our knowledge, no studies on the GCC markets have explored the three possible mechanisms of spillover, interdependence/independence and comovements, simultaneously and the formulation of portfolio strategies under different regimes chained to previous states. The transmission classification is useful and helpful in several respects including: the description of the transmissions of volatility in financial markets; detection of the data generating processes; prediction of the volatility of a market knowing the kind of link with other markets; the detection of the latitude of influence that a market has on another market; the selection of the "dominant" market whose behavior impact is observed in order to anticipate changes in the behavior of other markets; and the specification of predictive models that help distinguishing the dependence of one market from another. The examination of portfolio strategies under different regimes will also be helpful. This study fills this void and addresses the stated objectives.

2 Data and Descriptive Statistics

We analyze the historical characteristics of the weekly stock market indices of the six GCC markets, oil price and the U.S. S&P 500 index, using weekly data over the period spanning January 5 , 2004 to March 7 , 2011 (363 observations). The weekly data allow us to overcome the problem of different time zones between the markets of the GCC countries, oil and the United States, and to have proper time for regime-switching to occur than the daily data do.

The GCC indices under consideration are the Saudi Arabia Tadawul All Share Index (Saudi Arabia-TASI, hereafter), the Kuwait Stock Exchange Index, (Kuwait-SE), the Dubai General Index (Dubai-DFM), the Abu Dhabi General Index (Abu Dhabi-ADX), the Qatar Doha Securities Market (Qatar-QD), the Oman MSM30 Index (Oman-MSM30), in addition to the oil price and the U.S. S&P 500 index. Within the availability of the data for the GCC markets, the proxy of the volatility is computed weekly as the daily range according to the formula $((\ln(\text{Max}) - \ln(\text{Min})) * (1/4 * \ln(2))^{0.5})$ used in Gallo and Otranto (2008). The choice of a relatively long sample period is motivated by the desire to capture the interactions among the markets over the years that are characterized by an increasing degree of financial and real integrations. As a market becomes more volatile and its shocks are transmitted across other markets, the choice of the weekly frequency of analysis is always crucial in detecting the direction of a temporal relationship

Table 1 (Appendix of tables and figures) shows the main descriptive statistics relative to the volatility of the eight markets for the selected time span. It is evident in the table the presence of asymmetric patters, with very high peaks (apparent by a comparison of the maximum values with the medians and the minimum values) and a clear non-normality of the observations (displayed by the significance of the Jarque-Bera statistic, compared with a critical value of a chi square distribution with 2 degrees of freedom). These facts are consistent with the presence of regimes, as shown in many empirical applications (for a review, see the successive section). These characteristics can be better appreciated by observing the graphs of the volatility dynamics in Figure 1 (Appendix of tables and figures), which show several peaks characterizing the turmoil periods with brief durations, in contrast to larger periods of tranquility (that is, low volatility levels). It is also evident from this figure the presence of a similar pattern for the S&P 500, oil price and Oman market, showing a high volatility period starting in 2009. This is opposite to the behavior of the other GCCs which show different very high volatilities periods in the first three years of the time series.

3 Literature Review

There has been an extensive and steady flow of the literature that generally examines volatility spillover and contagion in many markets since the 1997 Asian crisis. Broadly, the literature pays considerable attention to the structure of interdependence among the stock markets. The studies in this literature are classified by Gallo and Velucchi (2009) and Pericoli and Sbracia (2003) into four groups: The first group includes the MV-GARCH models; the second consists of the Probit/logit models; the third is related to the regime-switching models; and the fourth is the analysis related to the predictive ability of leading indicators linked to economic fundamentals.

There are relatively few studies that examine the movements of stock returns and volatility interdependence in the GCC stock markets. Those studies can be classified into three strands. The first strand focuses on market return interdependence. Assaf (2003), for example, examines the dynamic relationships among the six GCC markets during the weekly period 01/15/1997 to 04/26/2000, using VEC models. He finds strong evidence of interdependence and feedback among these markets. Hammoudeh and Alesia, (2004) and Hammoudeh and Choi (2006), using VEC models for the daily period 02/15/1994 to 12/25/2001, suggest that most of these markets react to the movements of the NYMEX 3-month futures WTI price. In a more recent study, Marashdeh et al. (2010) and Ravichandran and Maloain (2010) find that the GCC stock markets are not integrated with the developed markets as represented by the US and European markets. On the other hand, the empirical evidence according to Ravichandran and Maloain (2010) indicates that the long- and short-run relationships among the GCC markets become more integrated regionally and globally after a crisis than before it.

Within the same strand of the GCC literature on market interdependence, Sbeiti and Alshammari (2010) apply the autoregressive distributed lag (ARDL) approach to the GCC markets and find long-run relationships among the six GCC stock market indices. Hammoudeh and Li (2005), Hammoudah and Al-Gudhea (2006), Hammoudeh et al. (2007/2008) and Hammoudeh and Choi (2007) include within their analysis of stock market interdependence models the most important factor influencing the GCC economies which is the oil price. Hammoudeh et al. (2007/2008) examine the stock markets in three groups of the MENA region: the GCC, the Levant and the North Africa and show that the strongest contemporaneous correlations are in the core GCC markets comprised of Kuwait, Oman, Saudi Arabia and UAE, whereas the lowest are in the Levant region that includes Jordan, Lebanon and Turkey. Abraham et al (2001,) using monthly data for the period 1993-1998, find low correlations of Gulf equity market returns with the U.S. stock market, suggesting that there is a significant diversification benefits for investors from portfolios that include both developed and emerging markets at that time. The second strand of the literature focuses on volatility interdependence across the GCC stock markets and the oil market. This strand is initiated by Malik and Hammoudeh (2004) and Malik and Hammoudeh (2007) using a MV-GARCH (BEKK) model for the period 02/14/1994 to 12/25/2001 to determine the volatility interdependence across the selected GCC markets. They find volatility spillover from oil market to all the GCC stock markets under consideration, but only Saudi Arabia shows a significant feedback volatility spillover with the oil market. In addition, they find an interaction between the US equity market and the global oil market.

The third strand captures both own volatility dependency and volatility interdependence for the GCC markets. Hammoudeh and Li (2008) examine the sudden changes in volatility for five Gulf markets, using the iterated cumulative sums of squares (ICSS) algorithm and analyze their impacts on volatility persistence. They find that most of the GCC Arab stock markets are more sensitive to major global events than to local and regional factors

Within the same strand of the literature on own volatility dependency and volatility interdependence, but at the equity sector level for the service, banking and industrial/or insurance sectors, Hammoudeh et al. (2009) analyze the volatility dependency and the optimal weights and hedge ratios for two-sector portfolio holdings, comprised of combinations of these three sectors for the major individual GCC markets. Their results suggest that past own volatilities matter more than past shocks and there are also moderate volatility spillovers and interdependence between the three equity sectors within the individual countries

Our study is a new attempt to comprehensively document the volatility transmission spectrum, using the MCMS model. In contrast to previous studies, this model enables this study to distinguish between the three different modes of transmission: spillover, interdependence and comovements across the GCC stock markets, the U.S. S&P 500 index and the oil price. It also equips it with tools to examine portfolio strategies under different chained regimes.

4 Research Methodology

We use the MCMS model which was introduced by Otranto (2005) to examine and distinguish between different mechanisms of the volatility transmission dynamics and portfolio strategies in a regime-changing environment. The MCMS-based studies (Otranto, 2005; Gallo and Otranto, 2007 and 2008) insert asymmetries in the model to make the transition probabilities of each market dependent on its own state and those of the other markets in one direction, in addition to allowing mutual relationships between the markets. Their findings also document that the MCMS model has better forecasting performance than the other existing models. Most notably, the MCMS model can distinguish between several inter-market linkages such as spillovers, interdependencies and comovements under different regimes, while others do not.

The volatility spillover is defined as a situation in which a switch in the regime of a dominating market precedes or leads to a change in the regime of the dominated market with a lag. In contrast, interdependence of volatility is seen as a situation in which at the same periods a switch in the regime of one of the markets leads to changes in the regime of other markets, and vice versa in the same period or other periods. The volatility comovement, on the other hand, is a contemporaneous change in regimes across markets. It is important to note that the spillover, interdependence and comovement relationships refer to the full time interval analyzed and not to single periods. For example, if at a certain date a variable seems to have a spillover effect toward another variable, the first variable cannot be classified as a dominant market if this behavior is not regularly repeated in the full span analyzed.

Let us suppose to have the volatility series of n markets in a time interval $[0, T]$ and let $y_{j,t}$ be the variable representing the volatility of market j at time t. We define a two-dimension vector $y_t \equiv (y_{1,t}, y_{2,t})'$, where $y_{1,t}$ and $y_{2,t}$ are two of the n variables, which follows a VAR(p) process, as:

$$y_t = \mu(s_t) + \sum_{m=1}^{p} \Phi_m(s_t) y_{t-m} + \varepsilon_t \tag{4.1}$$

$$\varepsilon_t \sim N(0, \sum(s_t))$$

$$\sum(s_t) = \begin{bmatrix} \sigma_1^2(s_{1,t}, \cdot) & \rho(s_{1,t}, s_{2,t})\sigma_1(s_{1,t}, \cdot)\sigma_2(s) \\ \rho(s_{1,t}, s_{2,t})\sigma_1(s_{1,t}, \cdot)\sigma_2(\cdot, s_{2,t}) & \sigma_2^2(\cdot, s_{2,t}) \end{bmatrix} \tag{4.2}$$

In equation (1), the parameters of the conditional mean, $\mu(s_t)$ and $\Phi_m(s_t), 1 \leq m \leq p$, and in equation (2), the variance-covariance matrix of the error terms ε_t, all depend on the state vector $s_t = (s_{1,t}, s_{2,t})'$ with $s_{j,t}$, assuming values in $[0, 1]$, representing the state of time t. State 0 indicates the tranquility or low volatility state, while state 1 denotes the turmoil or high volatility state). In practice, state s_t is a combination of two latent variables, $s_{1,t}$ and $s_{2,t}$. In the variance-covariance matrix, the variances of each variable (related to the fourth moments of returns which we assume to exist) depend only on the variable's own state. The parameter $\rho(s_{1,t}, s_{2,t})$ refers to the correlation coefficient between the two markets at a certain state $s_t = (s_{1,t}, s_{2,t})'$. This specification implies that volatility is transmitted from one market to another, also causing some changes in the covariance structure, whereas the changes or movements in the variance depend solely on the own state.

The main advantage of the multi-chain Markov-Switching model is that, the variables depend on separate but potentially related state variables. In practice, the state of variable $y_{1,t}$ can be made to depend on the lagged states of the other variable $y_{2,t}$ and vice versa. The transition probability matrix, therefore, captures the volatility transmission mechanism among the variables because the change in the state of one variable can be transmitted to the other variable. More in detail, let us consider a two-asset, two-state and two-lag model $(p = 2)$. The state vector s_t can take at time t one of four possible value pair of the two assets: $(0, 0)', (0, 1)', (1, 0)'$ or $(1, 1)'$ at anytime $0 \leq t \leq T$, where in each cell the first number refers to the state of the first asset and the second number to the state of the second asset. Given this interpretation of the two states, the $s_t = (1, 0)'$, for example, means that, at time t, the first asset is in a high volatility state, whereas the second asset is in the low volatility state.

The transition probability matrix $P = \{Pr[s_t|s_{t-1}]\}$ is a 4×4 matrix and s_t is a vector. We further suppose that conditional on $(s_{1,t-1}, s_{2,t-1})$, the two states $s_{1,t}$ and $s_{2,t}$ are independent.

That is:

$$Pr[s_{1,t}, s_{2,t}|s_{1,t-1}, s_{2,t-1}] = Pr[s_{1,t}|s_{1,t-1}, s_{2,t-1}] \times Pr[s_{2,t}|s_{1,t-1}, s_{2,t-1}] \tag{4.3}$$

We can parameterize the right-hand side of equation (3) with logistic functions where each function explicitly depends on past states [2]:

$$Pr[s_{1,t} = h|s_{1,t-1} = h, s_{2,t-1}] = \frac{exp[\alpha_1(h, \cdot) + \beta_1(h, 1)s_{2,t-1}]}{1 + exp[\alpha_1(h, \cdot) + \beta_1(h, 1)s_{2,t-1}]} \tag{4.4}$$

[2] See Gallo and Otranto (2008) for additional details

$$Pr[s_{2,t} = h | s_{1,t-1}, s_{2,t-1} = h] = \frac{exp[\alpha_2(\cdot, h) + \beta_2(1, h)s_{1,t-1}]}{1 + exp[\alpha_2(\cdot, h) + \beta_2(1, h)s_{1,t-1}]}$$

for $h = (0, 1)$ or low and high volatility regimes, respectively. From the parameterization in equation (4), the parameters $\alpha_1(h, .)$ and $\alpha_2(., h)$ are the constants of the logistic function. We can also note that coefficient $\beta_1(h, 1)$ measures the influence of state of market 2 at time $t-1$ on the probability of market 1 to stay in state h. Similarly, $\beta_2(1, h)$ measures the influence of the state of market 1 at time $t-1$ on the probability of variable 2 to stay in state h. In this way, the estimation of the probabilities in equation (4) shows how the transition probabilities for market 1 change according to the regime of market 2 and vice versa. Thus, the transition probability matrix makes the probability of staying at the same state for asset i conditional on the previous states of both assets.

Since each asset has only two states, the probabilities of switching to another state can be estimated by the following equation:

$$Pr[s_{j,t} = k | s_{j,t-1} = h, s_{i,t-1}] = 1 - Pr[s_{j,t} = h | s_{j,t-1}, s_{i,t-1}] \tag{4.5}$$

for $h, k = 0, 1$ where $h \neq k$ and $i, j = 1, 2, i \neq j$. Thus, the 4×4 transition probability matrix will be as follows:

$$\begin{bmatrix} P(00|00) & P(01|00) & P(10|00) & P(11|00) \\ P(00|01) & P(01|01) & P(10|01) & P(11|01) \\ P(00|10) & P(01|10) & P(10|10) & P(11|10) \\ P(00|11) & P(01|11) & P(10|11) & P(11|11) \end{bmatrix}$$

where, for example, $P(00|00))$ means $Pr(s_{1,t} = 0, s_{2,t} = 0 | s_{1,t-1} = 0, s_{2,t-1} = 0)$. Now we have a system of equations (1) and (2), and also equations (3, 4 and 5) that can be estimated simultaneously in order to investigate the volatility dependence/independence structure, using a battery of tests.

Some estimation problems could arise if some event is never verified in the data analyzed. For example, if there are not events satisfying $(s_{1,t} = 0 | s_{1,t-1} = 0, s_{2,t-1} = 1)$, one of the two parameters in the first equation in (4) is not identified. In this case, it is convenient to put $\alpha_1(1, .)$ identically equal to a very small value (for example, -10) and to estimate only $\beta_1(1, 1)$, so that $P(s_{1,t} = 0 | s_{1,t-1} = 0, s_{2,t-1} = 1) = 0$ and $P(s_{1,t} = 1 | s_{1,t-1} = 0, s_{2,t-1} = 1) = 1$. In this case, we say that the spillover effect from the second variable to the first one does exist and it is deterministic.

The presence of statistical significance of all parameters in equation (4) will provide evidence in favor of the case of interdependence. If the coefficient $\beta_1(h, 1) = 0$ but $\beta_2(1, h)$ is different from zero for each $h = 0, 1$, then the state of market 2 at time $t-1$ does not influence the probability of market 1 to stay in the same regime, but not vice versa. This is evidence in favor of the dominant status of market 1 or a spillover from market 1, and thus shows an asymmetric relationship between the markets. Finally, the non-significance of all the coefficients $\beta_1(h,1)$ and $\beta_2(h,1)$ would show evidence for independence between markets. The statistical significance of $\alpha_1(h,.), \alpha_2(.,h), \beta_1(h,1)$ and $\beta_2(1,h)$ are used jointly to test the comovements (responding to shocks other than the impacts of markets 1 and 2) between the two markets.

More precisely, after estimating the model, we follow the approach developed in Gallo and Otranto (2008) to evaluate the nature of the dependency of the two markets. In particular, we verify the following four null hypotheses, using the classical Wald statistics (see Gallo and Otranto, 2008, for details):

1. $H_0 : \beta_1(0,1) = \beta_1(1,1) = 0$. This hypothesis holds if there is no spillover effect from y_2 to y_1.

2. $H_0 : \beta_2(1,0) = \beta_2(1,1) = 0$. This hypothesis holds if there is no spillover effect from y_1 to y_2.

3. $H_0 : \beta_1(0,1) = \beta_1(1,1) = \beta_2(1,0) = \beta_2(1,1) = 0$. This hypothesis holds if there is no interdependence (no reciprocal spillover) between the two series.

4. $$H_0 : \begin{cases} \alpha_1(0,\cdot) = \alpha_2(\cdot,0), \\ \alpha_1(0,\cdot) + \beta_1(0,1) + \alpha_2(\cdot,1) = 0, \\ \alpha_1(1,\cdot) + \beta_2(1,0) + \alpha_2(\cdot,0) = 0, \text{ and} \\ \alpha_1(1,\cdot) + \beta_1(1,1) = \alpha_2(\cdot,1) + \beta_2(1,1) \end{cases}$$

This fourth hypothesis verifies the presence of a comovement between y_1 and y_2. The ways to obtain this particular form of the fourth hypothesis are explained in the final appendix in Gallo and Otranto (2008). Finally, an important characteristic of the Markov-switching models is the possibility to derive the so-called smoothed probabilities of the states to make inference on the latent bivariate variable $s_t = (s_{1,t}, s_{2,t})'$. Using the Hamilton filtering and smoothing (see, for example Hamilton, 1994), it is possible to estimate for each time t the probability of a certain state $i(i = 0,1)$ conditional on the full data set. In general, if the model has a good fitting, the probabilities are close to 0 or 1, so we can assign each observation to a certain regime or to another. In particular, for the MCMS model, we will obtain the (smoothed) probabilities of each state, $P(s_{1,t} = i, s_{2,t} = j|I_T), (i,j = 0,1)$where (I_T) represents the full information available. To obtain the probabilities of the state of a single variable, it will be sufficient to sum up over all the probability values of the other variable. For example, if we are interested in the smoothed probabilities of the first variable, it will be obtained as $P(s_{1,t} = i|I_T) = P(s_{1,t} = i, s_{2,t} = 0|I_T) + P(s_{1,t} = i, s_{2,t} = 1|I_T)(i = 0,1)$

5 Empirical Results and Economic Applications

In this section, we discuss the relationships between the variables (multiplied by 100), the inferences on regime and the optimal portfolio strategies.

5.1 Empirical results: Relationships between S&P 500, oil and GCC variables

The empirical evidence in Table 2 (Panel A, appendix of tables and figures), indicates the presence of interdependence between the oil price and the U.S. S&P 500 index. Those two major markets represent global benchmarks which are sensitive to the global business cycle and the geopolitical factors. On a distributive time scale, there is a strong interdependence between these two major markets during the selected time period 2004-2011.

However, the relationships of those global variables with the GCC markets vary. In terms of the GCC relationships with the oil price, the panel shows evidence of interdependence between Saudi Arabia and the oil price which is not be surprising because Saudi Arabia is the world's major oil exporter and possesses the largest global oil reserves. Similarly, there is a strong interdependence between Abu Dhabi and the oil price. Abu Dhabi is the second Arab oil exporter and the largest emirate in UAE which is the second largest Arab economy after Saudi Arabia (Figure 2, appendix of tables and figures). On the other hand, there is also a strong spillover from the oil price to Dubai which has built its economy on borrowed dollars and petrodollars during the oil booms. This underscores this emirate's sensitivity to the booms and busts in the oil market. Perhaps, this may explain Dubai's recent debt woes which became apparent after the collapse of the oil price in late 2008.

However, the empirical evidence suggests that there is independence between Qatar and the oil price, perhaps reflecting the importance of non oil factors, such as large revenue proceeds from natural gas exports and large financial endowment, in influencing the Qatari economy. It is also possible that the active role played by the Qatari sovereign wealth fund Qatar Investment Authority (QIA) in the domestic market weakens the relationship between the domestic market and the oil market. There is also independence between Oman and the oil price, and between Kuwait and the oil price. These markets are highly segmented, dominated by inactive stocks and do not always reflect regional or global factors because of government interventions. In Kuwait, the Kuwait Investment Authority (KIA) intervenes in the domestic market.

The second element in the panel captures the relationships between the U.S. S&P 500 index and the selected GCC markets which vary from interdependence to spillover. The results show that there is a strong interdependence between the U.S. S&P 500 index and Saudi Arabia, between the U.S. S&P 500 index, Abu Dhabi, Dubai and Qatar[3].

[3] Ravichandran and Maloain (2010) find a spillover from Saudi Arabia and Abu Dhabi to the German

On the other hand, there is a strong spillover from the U.S. S&P 500 index to Oman and Kuwait, confirming our observation indicated earlier about the varying nature of these markets as it is shown in the same figure.

Several implications can be drawn from the results provided above. The first implication is that global macroeconomic information matters. Our results show more transmissions between each of the U.S. S&P 500 index and the oil prices and each of the GCC markets than was provided in the literature as shown earlier in the literature review section. The relationship between oil and the GCC markets are influenced by common global economic factors (e.g., business cycle phases). This means that if there is a slowdown in the global economy or a financial crisis or a drop in the aggregate demand of the U.S. or major global economies, this will be reflected in a downturn in the U.S. S&P 500 index, a decline in the demand for oil and consequently leading to a negative impact on the GCC economies. This result can be shown in the smoothed probability plot (Figure 3, a appendix of tables and figures.

The second implication is that there is room for diversification gains between the U.S. S&P 500, oil and the GCC markets, which is still consistent with the previous studies despite the increased sensitivity of the GCC markets to global shocks over time (Ravichandran and Maloain, 2010). However the latitude of diversification opportunities differs according to state of the financial market.

Panel B of Table 2 shows the different possibilities of portfolio diversifications between the markets based on their empirical relationships. There is a strong spillover from the fast growing Qatar market to Saudi Arabia, Abu Dhabi and the U.S. S&P 500 index. In addition, there is interdependence between Qatar and these same markets. These results help investors who are keen to diversify their portfolios (if Qatar's index is a main asset) through forcing the investors to include other markets like, Dubai, oil, Oman and Kuwait. With respect to Saudi Arabia as the X or source variable, there is a strong spillover from Saudi Arabia to Kuwait and Abu Dhabi, and as well as interdependence between those markets. Hence there is an opportunity for portfolio diversification with Saudi Arabia (if this country's index is the main asset) through including other markets such as the U.S. S&P 500 index, Oman, Qatar and Abu-Dhabi.

Similarly, in Panel C of Table 2 which shows Dubai as the X or source variable, there is spillover to Oman, and consequently the opportunity of portfolio diversification increases through including the U.S. S&P 500 index, oil, Saudi Arabia, Kuwait, Qatar and Abu Dhabi, which is in addition to including the main index (Dubai) in the portfolio. With respect to Kuwait as the X or the source variable, there is a spillover from Kuwait to Qatar, Saudi Arabia and Abu Dhabi and interdependence between Kuwait and these same markets. As a result, there is a possibility for a portfolio diversification, through including Oman, Dubai, Oil, U.S. S&P 500 in addition to having the main asset (Kuwait) in the portfolio.

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stock market.

Panel D of Table 2 shows evidence of strong spillover from Abu Dhabi to oil, Dubai, Kuwait and Oman. Additionally, there is interdependence between Abu Dhabi, oil, Qatar, Dubai and Kuwait and consequently, the opportunity of portfolio diversification exists through including both Saudi Arabia and U.S. S&P 500 to the main asset (Abu Dhabi). Finally, the same panel shows the interaction between Oman and the selected markets. There is evidence of a spillover from Oman to the U.S. S&P 500 index, Qatar, Saudi Arabia and Kuwait, and consequently including oil and Oman in Oman portfolio will increase the total returns and minimize the portfolio risk of the Oman portfolio.

5.2 Inference on the regimes: the case of Oil and S&P 500

The results of the battery of tests applied to each model provide the general behavior of each pair of series. In this subsection, we illustrate this kind of analysis only for the pair Oil-S&P 500 (variables 1 and 2, respectively).[4]

Figure 3 (Appendix of tables and figures) displays the graphs of the smoothed probabilities for the four combinations of the states of the two variables $(00, 01, 10, 11)$ for the full sample span. In general, these probabilities are close to 0 or 1, so that the inference on the regime is fairly precise. It is evident that the most frequent case is the one in which both variables are in state $(0, 0)$, with an expected duration equal to 9.6 weeks. This duration value is obtained from the transition probability matrix as $1/(1-P(00|00))$, where in general the expected duration of the state (i, j) is obtained as $1/(1 - P(ij|ij)$. This state (state $0, 0$) characterizes a long period from April 2005 until February 2007. The case in which both variables are in the turmoil state (state $1, 1$) is relevant to a period of 27 weeks, ranging from September 2008 to March 2009. This period of high volatility corresponds to the 2008/09 financial crisis that plagued all major global financial markets. It ends in the first week of April 2009 when the S&P 500 switches to the tranquility period, pushing the oil index to the same state at the next week. Putting aside those two relatively long periods, the two series (oil and the S&P 500) are characterized by frequent changing of the regimes

Of particular interest are the cases in which the two variables are in different states $(0, 1)$ or $(1, 0)$. In such cases, the two variables have a very short duration (just one week). Specifically, the case in which the first variable is in state 0 and the second is in state 1 is not frequent much; it happens only four times. The second case (when the first variable is in state 1 and the second variable in state 0) happens 26 times. These cases are a small percentage with respect to the full data set, but they denote a clear interdependence behavior of the two series. This can be observed more clearly in Table 3 (appendix of tables and figures) where the number of events as $(s_{1,t} = h|s_{1,t-1} = i, s_{2,t-1} = j)$ are shown.

[4]The results for the other 27 pairs are available on request.

We can notice that when the first variable is in state 0 and the second one is in state 1 at time $t-1$ (or vice versa), the first variable will change state at time t, by staying four weeks in state 1, compared to zero weeks in state 0. This behavior is a clear evidence of a deterministic spillover effect from the second variable (the S&P 500) to the first one (Oil). On the other hand, the second variable will switch from state 1 to state 0 at time t when the first variable was in state 0 at time $t-1$, but not vice versa. In this case, it seems that the spillover effect of Oil is present only when it is in a tranquility state. Moreover, when the first variable is in state 0 and the second variable is in state 1, the two spillover effects are contemporaneous, in the sense that both variables will change to the opposite states at the same periods.

The other numbers of Table 3 (appendix of tables and figures) confirm the fact that, when both variables are in the same state, this state has a high probability to be confirmed at the next time. All the results are consistent with the estimated transition probability matrix:

$$\begin{bmatrix} P(00|00) & P(01|00) & P(10|00) & P(11|00) \\ P(00|01) & P(01|01) & P(10|01) & P(11|01) \\ P(00|10) & P(01|10) & P(10|10) & P(11|10) \\ P(00|11) & P(01|11) & P(10|11) & P(11|11) \end{bmatrix} = \begin{bmatrix} 0.896 & 0.014 & 0.088 & 0.002 \\ 0.911 & 0.000 & 0.089 & 0.000 \\ 0.963 & 0.037 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.037 & 0.963 \end{bmatrix}$$

It is evident that the states $(0,0)$ and $(1,1)$ are highly persistent with a high probability to stay in the same regime also at the next time. The important difference between them is that from $(0,0)$ it is possible to switch to all the other regimes, whereas from $(1,1)$ the only possibility is to pass through the state $(1,0)$. Moreover, the states $(0,1)$ and $(1,0)$ have probability 0 to stay in the same regime. The most probable situation is a switch to the $(0,0)$ regime, but there is a non zero probability to exchange the state between variables (the case of contemporaneous spillover).

5.3 State implications for portfolio designs and hedging strategies

The study provides several applications of the results by constructing optimal portfolio designs and hedging strategies, using our estimates of MCMS results for the six GCC indices, the oil market and the U.S. S&P 500 index. The results are compared with the same strategies derived from a linear VAR model.

5.3.1 Hedging strategies

The conditional volatility estimates will be used to construct hedge ratios (Kroner and Sultan, 1993). A long position in one market (say market i) can be hedged with a short position in a second market (say market j) at state s_t of four possible cases. Those four cases are: the first one is low state of market i -low state of market j; the second is low state of market i - high state of market j; the third is high state of market i -low state of market j; and the fourth is high state of market i - high state of market j. A hedge ratio between market i and market j will be computed for each state s_t and at time t as well using the following:

$$\beta_{ij,s,t} = \frac{h_{ij,s,t}}{h_{jj,s,t}} \tag{5.1}$$

where $\beta_{ij,s,t}$ is the risk-minimizing hedge ratio for each two markets at state s and time t, $h_{ij,s,t}$ is the conditional covariance between market j and at a state s_t and time t and $h_{jj,s,t}$ is the conditional variance of market j at a state s_t and time t. Moreover it is possible to construct the series of time-varying hedge ratios, by simply calculating for each time t the average of the four hedge ratios weighted with the corresponding smoothed probabilities.

Table 4 (Appendix of tables and figures) demonstrates that the hedging ratios differ from one regime to another, showing varying hedging effectiveness for regimes. For each pair of series, we show also the average of the time-varying hedge ratios with respect to the full period span. Generally speaking, hedging becomes more expensive if both the hedged and hedging assets are in the turmoil state or if the hedged asset in the long position is more volatile. For example, a \$ 1 long position in Qatar can be hedged for 11 cents $(18$ cents) with a short position in the oil market if both of the two markets are at the dual tranquility regime State (00) (dual turmoil State (11)). This ratio will change if the two markets are at different regimes. A \$ 1 long position in Qatar can be hedged for 6 cents with a short position in the oil market if Qatar is at a tranquility regime and oil market is at a turmoil regime (State (01)). Moreover, a \$ 1 long position in Qatar can be hedged for 28 cents with a short position in the oil market if Qatar is at a turmoil regime and the oil market is at a quiet regime (that is, State (01)). The same analysis is applicable to the other pairs. Saudi Arabia is the most expensive among GCC markets in terms of hedging in an oil short position in the case of dual turmoil state (11).

Table 4 also shows significant differences in hedging costs between the VAR model and MCMS models. For example, a \$1 long position in Qatar can be hedged for 9 cents with a short position in the oil market which is underestimated in comparison with the MCMS in the turmoil state. The same is applicable for all the GCC countries in case of hedging in oil. Generally speaking, the hedging ratios estimated using the time-variant MCMS on average are less expensive than those estimated in the VAR model except for few cases. These cases are Qatar-Oil, Saudi Arabia-Oman, Saudi Arabia-Kuwait and Saudi Arabia-Qatar, where in the case of the MCMS-time variant model the hedging costs are 16 cents, 51 cents, 63 cents and 23 cents respectively, while in the case of the VAR model they are 9 cents, 31 cents, 55 cents and 14 cents, respectively (Table 4, the appendix of tables and figures).

Hedging effectiveness for the GCC markets also differs when the short position is in the oil market than in the S&P 500 index. Using MCMS, it seems that hedging GCC markets with the S&P 500 is more expensive than hedging them with oil, probably because GCC economies are major oil-exporting countries and their economies are highly correlated with oil. On the other hand, it appears that the hedging ratios are overestimated for the GCC countries with the S&P 500 if the VAR used instead of the MCMS, except for Qatar. Hedging in this GCC market is the most expensive, as a $1 long position in Qatar should be hedged by 58 cents with a short position in the S&P 500 market at state (10) if the MCMS is used in the estimation, while it is 21 cents if VAR is used

Hedging is also different within the GCC markets at the same state and at different states. The most expansive hedges are: hedging between Saudi Arabia and each of Oman, Kuwait and Qatar at the state $(1, 0)$, and hedging between Kuwait and each of Oman, Abu Dhabi and Dubai at state $(1, 0)$. As indicated above, hedging becomes more expensive if only the hedged market (that is in the long position) is in turmoil. It also appears that hedging is less expensive when both markets are in turmoil than when only the hedged market is in turmoil. All in all, it's generally more expensive to hedge a market that is in turmoil.

Figure 4 (Appendix of tables and figures) displays and compares the dynamic trajectory of hedging ratios for bivariate portfolios for selected pairs calculated from the results of the MCMS model and the constant state VAR model. It can be seen that in the portfolio (the oil and S&P 500 hedging a long position in Oil with a short position in S&P 500 is much more effective under the MCMS than the VAR over time. The same holds for the portfolio that holds the Saudi and Abu Dhabi markets. For the third portfolio that holds the Saudi and oil markets, hedging effectiveness is more mixed over time between the two models where there are days in $2005, 2006, 2008$, and 2009 when the VAR gives better hedging effectiveness than the MCMS. Those are periods of extreme volatility and crashes in the Saudi market.

5.3.2 Portfolio weights

The conditional volatilities from the MCMS model is used to construct optimal portfolio weights (Kroner and Ng, 1998). By considering a portfolio that minimizes risk without lowering the expected returns, in this case, the portfolio weight of two markets holdings is given by:

$$\omega_{ij,s} = \frac{h_{jj,s,t} - h_{ij,s,t}}{h_{ii,s,t} - 2h_{ij,s,t} + h_{jj,s,t}} \tag{5.2}$$

$$\omega_{ij,s,t} = \begin{cases} 0 & \text{if } \omega_{ij,s,t} < 0 \\ \omega_{ij,s,t} & \text{if } 0 \leq \omega_{ij,s,t} \leq 1 \\ 0 & \text{if } \omega_{ij,s,t} \geq 1 \end{cases}$$

In constructing the portfolio weights between two markets, $\omega_{ij,s,t}$ is the weight of the first market in a one dollar portfolio comprised of two markets (market i , market j) at state s_t at time t, $h_{ij,s,t}$ is the conditional covariance between market i and j at state s_t and time t and $h_{jj,s,t}$ is the conditional variance of market j at state s_t and time t. The weight of the second market is $1 - \omega_{ij,s}$. Similarly to the hedge ratios, we can calculate the time-varying weights, using the series of the smoothed probabilities.

5.3.2.1 GCC markets and Oil/ S&P 500 portfolios

Table 4 (the appendix of tables and figures) shows that the optimal weights for pairs of the GCC, the S&P 500 index and oil assets as estimated in both the MCMS and VAR models. It also demonstrates the sensitivity of each pair to the prevailing state of the market for each asset in that pair in the case of the estimates of the state-variant MCMS models. For example, at the tranquility state $(0, 0)$ for the assets in the Saudi Arabia/Oil portfolio, the optimal weight is 0.77 which indicates that for a \$ 1 portfolio 77 cents should be invested in the Saudi stock market, while 23 cents should be invested in the oil market. However, this optimal weight for the same Saudi Arabia/Oil portfolio at the turmoil regime State (11) rises to 0.97. Using the same logic, when the Saudi and oil markets are at different regimes, for example the first market is in the turmoil regime and second market is in the tranquility regime (state1,0), then the optimal weights change significantly, with the Saudi market accounts for 17% of the value of the portfolio, while Oil stands at 83% showing special preference for oil when it is more tranquil than the Saudi market

Generally, the table also shows that at the tranquility state $(0, 0)$, in all of the bivariate portfolios that contain pairs of the GCC indices, the Oil price and the S&P 500 index, the pair of a GCC market and the S&P 500 should have considerably higher weights than Oil, with the exception of Dubai. Thus, in a dual tranquility state investors should place more of their money in a GCC market or the S&P 500 than in the Oil market. Dubai is no longer an important oil producer or exporter since its oil production dropped from $600, 000$ barrels a day in the 1980s to less than $100, 000$ barrels at the present period. Moreover, Dubai's economy has changed from being oil-dependent to an economy that depends on tourism. The situation is different if the bivariate portfolios are for the individual GCC market and the S&P 500 index at the same state $(0, 0)$. Investors should hold at that state more of the S&P 500 than any of the GCC indices, as well as Oil as indicated earlier. Thus in normal times, investors are better off holding in their optimal portfolios more of the S&P 500 index than the GCC equities and Oil.

At the state $(0, 1)$, that is when only the S&P 500 is in turmoil, investors should however hold in their bivariate portfolios) more GCC indices and Oil than the S&P 500 The optimal weight are designed to minimize risk. A similar logic can be used to explain the results for the state $(1, 0)$ when only the GCC equities are in turmoil. Here investors in the Oil/ GCC or S&P 500 portfolios should hold more oil than the GCC equities, except for the S&P 500 and Kuwait which is dominated by momentum traders. At the same state $(1, 0)$, investors should hold more of the S&P 500 than any of the GCC equities, as well as oil.

In the interesting double turmoil state $(1, 1)$, investors should hold more GCC equities and the S&P 500 than Oil, with the exception of Dubai. This result demonstrates that at times of turmoil oil is more risky than the S&P 500 and all of the GCC markets except the risk-ridden Dubai. For portfolios of pairs of the GCC equities and the S&P 500, investors should hold more of only Saudi Arabia and Kuwait than the S&P 500. This is an interesting result at times of turmoil for those two GCC markets.

Other cases are available in Table 4 (the appendix of tables and figures). Overall, the GCC markets are generally more favorable to oil in an optimal portfolio when they are in a tranquility state, regardless of the oil state. They are more favorable to the S&P 500 index particularly when the latter is in the tranquility state. The unconditional weight VAR model gives different and sometimes conflicting results. For some cases, the dominance in the portfolio is reversed.

5.3.2.2 Cross GCC portfolios

The optimal weights for portfolios that hold pairs of GCC stock indices are also highly dependent on the regimes. In a comparison of the Saudi market and other GCC markets (specifically Abu Dhabi, Kuwait, Oman and Qatar) in the dual tranquility state $(0, 0)$, the results generally suggest greater weights should be given to those GCC markets over the Saudi market. At this normal state $(0, 0)$, investors should however hold more assets in the Saudi market only in the cases of portfolios that co-hold Dubai and Qatar indices, which both have high historical volatility. In the interesting double turmoil state $(1, 1)$, the Saudi Arabia and Dubai markets should succumb to Abu Dhabi, Kuwait, Oman and Qatar but not to oil and the S&P 500 index. In this dual high volatility state, investors should also hold in their portfolio more of the other GCC indices than oil but less than the S&P 500 with the exception of Kuwait. Interestingly, Kuwait overwhelmingly dominates oil and the S&P 500 index in this dual highly volatile state.

However, the Saudi market is overwhelmingly more preferred to those GCC markets in the state $(0, 1)$, that is when the Saudi market is calm while the other GCC markets are tumultuous. Dubai dominates Kuwait, Oman and Qatar when it is in the turmoil state while the other GCC markets are in the tranquility state, perhaps because the other GCC markets are more risk-averse than Dubai, and thus risk pays off for Dubai. Interestingly, Abu Dhabi is more preferred to Dubai when the former is in the tranquility state while the latter is in the turmoil state, perhaps because Abu Dhabi is Dubai's big sister and Dubai's extra risk is protected by the sisterhood.

Figure 4 (the appendix of tables and figures) compares over time the optimal portfolio weights for three selected portfolios calculated from the results of the MCMS model and the constant state VAR model. The MCMS model gives the S&P 500 index much more weight over oil than the VAR model over time, with few exceptions including some periods in $2005, 2006$ and 2010. Those are periods that experienced ascending oil prices. The case is much more mixed when it comes to portfolios that hold the Saudi market and oil, and Saudi market and Abu Dhabi.

6 Conclusions

This paper uses the multi chain Markov-switching (MCMS) model to investigate the volatility transmissions: spillover, interdependence, co movements and independence between the oil price, the U.S. S&P 500 index and GCC markets. The selected model enables us to distinguish between these different volatility transmission mechanisms, which is a more preferable approach relative to the standard GARCH family models that do not accommodate all those different relationships. For each pair of series, the MCMS model also enables us to construct the portfolio weights and the hedging ratios at different regimes of the markets. The evidence shows that hedging ratios differ strongly between different markets and from one regime to another. It is more expensive to hedge a market when it is in turmoil than when it is in tranquility.

Hedging between GCC markets and the S&P 500 index is more expensive than hedging with the oil market, perhaps because all GCC markets are oil-based and are highly segmented frontier markets, thus they are less sensitive to global shocks. Interestingly, the results demonstrate that the most expensive hedges are with the world's major oil-exporting country, Saudi Arabia. This is perhaps due to Saudi Arabia playing the role of the swing oil producer within OPEC and having the highest market capitalization intensity in the region. On the other hand, the most expensive GCC market to hedge with the S&P 500 is Kuwait which is dominated by momentum traders and speculators.

As Saudi Arabia and Kuwait are highly expensive markets to hedge with oil and the S&P 500, respectively, they also stand out as relatively more expensive to hedge with other GCC markets; Saudi Arabia particularly with Oman, Kuwait and Qatar and Abu Dhabi, and Kuwait with Dubai and Oman. The MCMS model enables to add to the dynamicity of the hedging ratios and the portfolio weights within a time-variant and state-variant process, in comparison with the time variant single state and VAR model. For example, the hedging ratios between the two states (tranquility and turmoil) estimated by the MCMS model would on average be lower than the hedging cost estimated by time variant single state and the VAR, a result that is of significance for traders and investors in the GCC markets. Consequently, both investors and portfolio managers will benefit from the advantages of the dynamic MCMS in comparison with the constant VAR as signified in the importance of the market states (tranquility and turmoil) in determining the optimal weights of the assets in their portfolios over time. Although the GCC countries are oil-based economies and similar in many other aspects, they offer different opportunities in terms of hedging effectiveness and weights in optimal portfolios. Therefore, the hedging ratios and portfolio weights should be time and state-variant.

References

[1] Abraham, A., Seyyed, F. and Al-Elg, A. (2001). Analysis of Diversification Benefits of Investing in the Emerging Gulf Equity Markets. Journal of Managerial Finance, 27, (10/11).

[2] Alkulaib, Y. A., Najand, M. and Mashayekh, A. (2009). Dynamic Linkages among Equity Markets in the Middle East and North African Countries. Journal of Multinational Financial Management, 19, 43-53.

[3] Almasri, A and Shukur, G. (2003). An Illustration of the Causality Relationship Between Government Spending and Revenue Using Wavelets Analysis on Finnish Data. Journal of Applied Statistics, 30(5), 571-584.

[4] Abraham, A., Seyyed, F. and Al-Elg, A. (2001). Analysis of Diversification Benefits of Investing in the Emerging Gulf Equity Markets. Journal of Managerial Finance, 27, (10/11).

[5] Alkulaib, Y. A., Najand, M. and Mashayekh, A. (2009). Dynamic Linkages among Equity Markets in the Middle East and North African Countries. Journal of Multinational Financial Management, 19, 43-53.

[6] Almasri, A and Shukur, G. (2003). An Illustration of the Causality Relationship Between Government Spending and Revenue Using Wavelets Analysis on Finnish Data. Journal of Applied Statistics, 30(5), 571-584.

[7] Arouri , M. E.-H. and Nguyen, D. K. . (2010). Time-Varying Characteristics of Cross-Market Linkages with Emperical Application to Gulf Stock Markets. Managerial Finance, 36(1), 57-70.

[8] Assaf, A. (2003). Transmission of Stock Price Movements: The Case of GCC Stock Markets. Review of Middle East Economics and Finance, 1(2), 5.

[9] Bertero, E., and Mayer, C . (1990). Structure and Performance: Global Interdependence of Stock Markets around the Crash of October 1987. European Economic Review, 34, 1155-1180.

[10] Bessler, D. A. and Yang, J. (2003). The Structure of Interdependence in International Stock Markets. Journal of International Money and Finance, 22(2), 261-287.

[11] Caramazza, R. and Salgado. L.A. (2000). Trade and Financial Contagion in Currency Crises. IMF working Paper, 55.

[12] Classens, F. (2001). International and Financial Contagion. Kluwer Acadmic Publishers: Boston, MA.

[13] Classens, S. and Forbes, K. (2001). International Financial Contagion: The Theory, Evidence and Policy Implications. . Kluwer Academic Publisher, Boston, MA.

[14] Darrat, A. F., Elkhal, K. and Hakim, S. R. (2000). On the Integration of Emerging Stock Markets in the Middle East. Journal of Economic Development, 25(2), 5.

[15] Draze, A. (1998). Political Contagion in Currency Crisis. University of Maryland Mimeo .

[16] Edwards, S and Susmel R. (2003). Interest Rate Volatility in Emerging Markets. The Review of Economics and Statistics, 85, 328-348.

[17] Edwards, S. (1998). Interest Rate Volatility, Capital Control, and Contagion. NBER Working Paper 6756.

[18] Eichengreen B., A. Rose and C. Wyplosz . (1996). Contagious Currency Crises: Final Test. Scandinavian Journal of Economics, 38, 463-494.

[19] Forbes, K. and Rigobon, R. . (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. Journal of Finance, 5, 2223-2261.

[20] Forbes, K. (2004). The Asian Flu and the Russian Virus: Firm Level Evidence on How Crises are Transmitted Internationally. Journal of International Economics, 63, 59-92.

[21] Fratzscher, M. (2003). On Currency Crises and Contagion. International Journal of Finance and Economics, 8, 109-129.

[22] Gallegati, M. (2005). A Wavelet Analysis of MENA Stock Markets. Working Paper (Universit Politecnica dele Marche).

[23] Gallo, Giampiero M. & Otranto, Edoardo. (2008). Volatility spillovers, interdependence and comovements: A Markov Switching approach. Computational Statistics & Data Analysis, 52(6), 3011-3026.

[24] Gallo, G., and E. Otranto. (2007). Volatility Transmission across Markets: A Markov Switching Approach. Applied Financial Economics, (17), 659-670.

[25] Hamilton, J. D. (1994). Time Series Analysis. Princeton University Press, Princeton, NJ, USA, 677-702.

[26] Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrics, 57(2),357-384..

[27] Hammoudah, S. and Al-Gudhea. S. (2006). Return, Risk and Global Factors in Saudi Equity Sectors. Journal of Emerging Markets, 10 (3), 55-64.

[28] Hammoudeh, S and Li. H. . (2005). Oil Sensitivity and Systematic Risk in Oil-Sensitive Stock Indices. Journal of Economics and Business, 57, 1–21.

[29] Hammoudeh, S, and Choi, K. (2007). Characteristics of Permanent and Transitory Returns in Oil-Sensitive Emerging Stock Markets: The Case of GCC Countries. Journal of International Financial Markets, Institutions& Money, 17 (2), 231–245.

[30] Hammoudeh, S. and Aleisa, E. . (2004). Dynamic Relationship among GCC Stock Markets and NYMEX Oil Futures. Contemporary Economic Policy, 22(April), 250-269.

[31] Hammoudeh, S. and Choi, K. (2006). Behavior of GCC Stock Markets and Impacts of US Oil and Financial Markets. Research of International Business and Finance, 20, 22–44.

[32] Hammoudeh, S. and Huimin Li. (2008). Sudden Changes in Volatility in Emerging Markets: The case of Gulf Arab Stock Markets. International Review of Financial Analysis, 17, 47–63.

[33] Hammoudeh, S. and Yuan, Y. and Smimou, K.. (2008)). Equity Market Diversification in the MENA Regions and Impacts of Oil and Major Global Stock Markets. The Arab Bank R E V I E W, 9(1), 4-19.

[34] Hammoudeh, S. and Yuan, Y., Y. Michael McAleer and Thompson.. M A. (2010). Precious Metals–Exchange Rate Volatility Transmissions and Hedging Strategies. International Review of Economics and Finance, 20, 633-647.

[35] Hammoudeh, S., Yuan, Y.and Smimou, K. . (2010). Equity Market Diversification in the MENA Regions and Impacts of Oil and Major Global Stock Markets. Mimeo, Drexel University, Philadelphia, PA.

[36] Hammoudeh, S., Yuan, Yand McAlee, M. . (2009). Shock and Volatility Spillovers among Equity Sectors of the Gulf Arab Stock Markets. The Quarterly Review of Economics and Finance, 49, 829–842.

[37] Kaminsky G. and Lizondo S, Reinhart C. (1998). Leading Indicators of Currency Crises. IMF Staff papr, 45, 11-48.

[38] Lin, S. and Stevenson, M. . (2001). Wavelet Analysis of the Cost-Carry Model. Studies in Nonlinear Dynamics and Econometrics, 5(1), 87-102.

[39] Malik, F. and Hammoudeh, S. (2007). Shock and Volatility Transmission in the Oil, US and Gulf Equity Markets. International Review of Economics and Finance, 16, 357–368.

[40] Malik, F., Hammoudeh, S. (2004). Shock and volatility transmission in the NYMEX oil, US and Gulf equity markets. In: Paper presented at the Middle East Economic Association Meeting, San Diego, CA .

[41] Marashdeh, H. and Shrestha, M. B. (2010). Stock Market Integration in the GCC Countries. International Research Journal of Finance and Economcis, 37, 102-114.

[42] Masih, R. and Masih, M.M. (2001). Long and Short Term Dynamic Causal Transmission amongst International Stock Markets. Journal of International Money and Finance, 20, 563-587.

[43] Paul, M. (1998). Contagion: Mansonal Effects, Spillovers, and Jumps Between Multiple Equilibria. IMF working Paper 98/142.

[44] Pericoli M. and Sbracia M. (2003). A Primer on Financial Contagion. Journal of Economic Survey, 17(4), 571-608.

[45] Ramsey, J. B., & Lampart, C. . (1998). The Decomposition of Economic Relationships by Time Scale Using Wavelets: Expenditure and Income. Studies in Nonlinear Dynamics and Econometrics, 3(4) , 23-42.

[46] Ramsey, J. B., & Zhang, Z. (1997). The Analysis of Foreign Exchange Rates Using Waveform Dictionaries. Journal of Empirical Finance, 4, 341-372.

[47] Ravichandran , K. and Maloain, Alaa M. (2010). Global Financial Crisis and Stock Market Linkages: Further Evidence on GCC Market. Journal of Money, Investment and Banking, 16, 46-56.

[48] Sbeiti, Wafaa and Alshammari, Turki. (2010). Integration of Stock Markets in the GCC Countries: An Application of the ARDL Bounds Testing Model. European Journal of Economics, Finance and Administrative Science, 20, May.

[49] Valde's, R. (1996). Emerging Market Contagion: Evidence and Theory. MIT Mimeo.

[50] Van Rijckeghem and Weder B. (2001). Sources of Contagion: Is it Finance or Trade? Journal of International Economics, 54, 293-308.

Appendix of Tables and Figures

Table 1: Descriptive statistics of the volatility indices of the selected markets

	SP	OIL	SA	QA	DU	AD	KU	OM
Mean	0.0096	0.0208	0.0136	0.0139	0.0154	0.0112	0.0071	0.0090
Median	0.0072	0.0167	0.0101	0.0096	0.0122	0.00854	0.0058	0.0064
Maximum	0.0673	0.1233	0.0856	0.0735	0.0927	0.7123	0.0328	0.0915
Minimum	0.0007	0.0032	0.0013	0.0003	0.0005	0.0009	0.0001	0.0005
Std. Dev.	0.0083	0.0147	0.0122	0.0123	0.0127	0.0097	0.0052	0.0097
Skewness	3.0706	2.5131	2.4452	1.9142	2.7252	2.5316	1.8752	3.7300
Kurtosis	16.243	12.229	10.639	7.606	14.069	12.064	7.957	24.164
Jarque-Bera	3222.9	1670.4	1244.5	542.5	2302.5	1630.5	584.4	7616.5

Table 2: Hypothesis testing of the null (no spillover, no interdependence and co-movement)

Panel A: Oil ar U.S. (S&P 500) as the x variable							
Market	Oil(x)			Market	U.S. S&P 500 (x)		
	No spillover	No interdependent	Co movement		No spillover	No interdependent	Co movement
S&P 500(y)	47.57(0.000)	12.08(0.0005)	199.00(0.000)	Oil (y)	Deter.*	12.08(0.0005)	199.00(0.000)
Qatar(y)	3.11(0.21)	0.0008(0.97)	77.49(0.000)	Qatar (y)	2.55(0.279)	774.51(0.000)	1825.2(0.000)
Saudi Arabia(y)	1.97(0.373)	3.467(0.063)	106.04(0.0000)	Saudi Arabia (y)	5.29(0.07)	5.195(0.023)	108.04(0.000)
Dubai(y)	1100.4(0.0000)	0.034(0.85)	128.74(0.000)	Dubai (y)	60.238(0.000)	60.24(0.000)	156.35(0.000)
Kuwait(y)	0.0008(0.99)	0.025(0.87)	16.43(0.0024)	Kuwait (y)	110.74(0.000)	111.63(0.000)	271.3(0.000)
Abu Dhabi(y)	Deter.*	126.73(0.000)	352.1(0.000)	Abu Dhabi (y)	15.88(0.00035)	2.393(0.1218)	35.63(0.000)
Oman(y)	1.396(0.49)	0.64(0.42)	68.35(0.000)	Oman (y)	19660.8 (0.000)	0.359(0.548)	33.434(0.000)
Panel B: Qatar, Saudi Arabia as the x variable							
Market	Qatar(x)			Market	Saudi Arabia (x)		
	No spillover	No interdependent	Co movement		No spillover	No interdependent	Co movement
S&P 500(y)	1458.54(0.000)	774.51(0.000)	1825.18(0.000)	S&P 500 (y)	Deter.*	5.195(0.023)	108.04(0.000)
Oil(y)	0.0011(0.99)	0.0008(0.97)	77.49(0.000)	Oil (y)	2.057(0.357)	134.07(0.000)	912.39.18(0.000)
Saudi Arabia(y)	6.82(0.03)	4.67(0.03)	142.75(0.0000)	Qatar (y)	0.6578(0.719)	4.67(0.03)	142.75(0.000)
Dubai(y)	491.78(0.000)	0.045(0.83)	447.35(0.000)	Dubai (y)	2.423(0.29)	0.343(0.55)	17.03(0.002)
Kuwait(y)	0.847(0.65)	0.0034(0.95)	129.82(0.000)	Kuwait (y)	9.083(0.0074)	9.968(0.00159)	60.664(0.000)
Abu Dhabi(y)	6.175(0.045)	4.145(0.041)	17.524(0.0015)	Abu Dhabi (y)	4.7(0.095)	0.69(0.404)	51.6(0.000)
Oman(y)	Deter.*	1.52(0.22)	38.03(0.000)	Oman (y)	1.878 (0.39)	1.505(0.219)	86.12(0.0000)
Panel C: Dubai or Kuwait as the x variable							
Market	Dubai(x)			Market	Kuwait (x)		
	No spillover	No interdependent	Co movement		No spillover	No interdependent	Co movement
S&P 500(y)	Deter.*	60.24(0.000)	156.35(0.000)	S&P 500 (y)	2.26(0.32)	111.63(0.000)	271.3(0.000)
Oil(y)	0.023(0.988)	0.034(0.85)	128.74(0.000)	Oil (y)	0.028(0.98)	0.025(0.87)	16.4(0.0024)
Qatar(y)	2.96(0.23)	0.045(0.83)	447.35(0.0000)	Qatar (y)	12.19(0.0022)	0.0034(0.95)	129.8(0.00)
Saudi Arabia(y)	0.0024(0.99)	0.343(0.55)	17.03(0.002)	Saudi Arabia (y)	5.74(0.056)	9.97(0.00159)	60.664(0.00)
Kuwait(y)	0.0039(0.99)	0.0036(0.95)	72.84(0.000)	Dubai (y)	1.823(0.401)	0.004(0.95)	72.84(0.00)
Abu Dhabi(y)	1.799(0.406)	5.623(0.0177)	13.287(0.009)	Abu Dhabi (y)	2262.09(0.000)	92.87(0.000)	1147.4(0.00)
Oman(y)	2185.3(0.0000)	0.4958(0.481)	36.57(0.000)	Oman (y)	Deter.*	Deter.*	65.79(0.00)
Panel D: Abu Dhabi or Oman as the x variable							
Market	Abu Dhabi (x)			Market	Oman (x)		
	No spillover	No interdependent	Co movement		No spillover	No interdependent	Co movement
S&P 500(y)	Deter*.	2.393(0.1218)	35.63(0.000)	S&P 500 (y)	5.64(0.059)	0.359(0.548)	33.434(0.000)
Oil(y)	7.59(0.006)	126.73(0.000)	352.1(0.000)	Oil (y)	0.025(0.88)	0.64(0.42)	68.35(0.000)
Qatar(y)	3.277(0.19)	4.145(0.041)	17.524(0.0015)	Qatar (y)	5.8(0.055)	1.52(0.22)	38.03(0.000)
Saudi Arabia(y)	3.877(0.144)	0.69(0.404)	51.6(0.000)	Saudi Arabia (y)	7.69(0.021)	1.505(0.219)	86.12(0.0000)
Dubai(y)	6.65(0.035)	5.623(0.0177)	13.287(0.009)	Dubai (y)	3.185(0.203)	0.4958(0.481)	36.57(0.000)
Kuwait(y)	8.538(0.013)	92.87(0.000)	1147.4(0.000)	Kuwait (y)	31.97(0.000)	Deter.	65.79(0.000)
Oman	9.9078(0.0016)	0.00186(0.965)	15.882(0.003)	Abu Dhabi (y)	0.0015 (0.96)	0.00186 (0.965)	15.882(0.003)

*Deter. The coefficient is significant because it is deterministic. The numbers in the parentheses are the p-values (joint hypothesis test).

Table 3: Frequency of the states at time t given a particular combination of states at time $t-1$.

Time t-1	Time t			
	$S_1 = 0$	$S_1 = 1$	$S_2 = 0$	$S_2 = 1$
$S_1 = 0, S_2 = 0$	276	26	298	4
$S_1 = 0, S_2 = 1$	0	4	4	0
$S_1 = 1, S_2 = 0$	26	0	25	1
$S_1 = 1, S_2 = 1$	1	29	2	28

Table 4: Hedging ratios and portfolio weights using MCMS and VAR

	Hedging Ratio-ij-MCMS and time Var.					VAR	Wij-MCMS-State and Time Variant					Wij-VAR
State	00	01	10	11	Time Var.		00	01	10	11	Time Var.	
Saudi A.- Oil	0.00	0.00	0.00	0.50	0.034	0.069	0.766	0.969	0.169	0.974	0.322	0.419
Dubai- Oil	0.00	0.00	0.00	0.00	0	0.096	0.472	0.873	0.062	0.337	0.4878	0.452
A. Dhabi- Oil	0.00	0.00	0.00	0.00	0	0.086	0.698	0.936	0.161	0.546	0.3167	0.299
Oman- Oil	0.00	0.00	0.00	0.16	0.008	0.106	0.815	0.975	0.241	0.817	0.2529	0.276
Kuwait- Oil	0.00	0.01	0.04	0.09	0.008	0.097	0.882	1	0.838	1	0.1043	0.056
Qatar- Oil	0.10	0.06	0.27	0.17	0.159	0.090	0.824	1	0.193	0.787	0.3567	0.420
Oil-S&P 500	0.22	0.00	0.00	0.00	0.077	0.65	0.130	0.781	0.029	0.367	0.8511	0.88
Saudi A.-S&P 500	0.00	0.00	0.00	0.00	0	0.079	0.143	0.749	0.162	0.775	0.7564	0.727
Dubai-S&P 500	0.09	0.00	0.78	0.00	0.169	0.045	0.220	0.783	0.006	0.233	0.7628	0.755
A. Dhabi-S&P 500	0.00	0.00	0.00	0.00	0	0.117	0.448	0.908	0.061	0.441	0.5988	0.64
Oman-S&P 500	0.11	0.00	0.00	0.00	0.093	0.321	0.423	0.876	0.032	0.236	0.5756	0.657
Kuwait-S&P 500	0.00	0.12	0.43	0.00	0.035	0.152	0.463	1	0.0388	0.930	0.5212	0.304
Qatar-S&P 500	0.00	0.58	0.00	0.00	0.050	0.210	0.239	0.344	0.033	0.073	0.7704	0.756
Saudi A.- Dubai	0.07	0.00	0.00	0.00	0.052	0.279	0.564	0.879	0.122	0.442	0.4249	0.445
Saudi A.-A. Dhabi	0.16	0.00	0.00	0.00	0.100	0.378	0.444	0.902	0.079	0.490	0.5344	0.646
Saudi A.-Oman	0.38	0.00	1.60	0.15	0.519	0.308	0.306	0.915	0	0.471	0.6599	0.642
Saudi A.-Kuwait	0.35	0.00	2.77	0.31	0.632	0.558	0.215	0.725	0	0.119	0.7473	0.907
Saudi A.-Qatar	0.07	0.00	1.73	0.00	0.230	0.141	0.516	0.919	0	0.458	0.4587	0.495
A. Dhabi-Dubai	0.65	0.11	0.00	0.50	0.550	0.945	0.174	0.932	0.208	1	0.7447	0.938
Dubai-Oman	0.12	0.00	0.90	0.85	0.243	0.629	0.192	0.880	0.003	0.265	0.8009	0.760
Dubai-Kuwait	0.25	0.64	0.00	1.29	0.381	0.839	0.125	0.623	0.018	0	0.846	0.967
Dubai-Qatar	0.03	0.05	1.61	0.00	0.127	0.136	0.269	0.840	0	0.264	0.5682	0.571
A.Dhabi-Oman	0.21	0.10	0.25	0.67	0.246	0.501	0.309	1	0.044	0.904	0.6404	0.507
A.Dhabi-Kuwait	0.01	0.06	7.53	1.07	0.312	0.736	0.182	0.530	0	0	0.7223	0.906
A.Dhabi-Qatar	0.04	0.00	0.00	0.00	0.032	0.163	0.693	0.835	0.389	0.600	0.3286	0.409
Oman-Kuwait	0.10	0.11	1.91	1.71	0.385	0.539	0.713	0.679	0	0	0.421	0.850
Oman-Qatar	0.00	0.00	0.03	0.36	0.033	0.061	0.898	0.923	0.183	0.184	0.2589	0.405
Kuwait-Qatar	0.00	0.15	0.31	0.06	0.052	0.094	0.891	1	0.458	0.515	0.1751	0.115

Table 5: Estimating parameters of the MCMS model for Kuwait and U.S. S&P 500

Panel A-Switching Coefficients-Constants Term								
Market	S&P 500 Equation				Kuwait Equation			
	μ_1(0,0)	μ_1(0,1)	μ_1(1,0)	μ_1(1,1)	μ_2(0,0)	μ_2(0,1)	μ_2(1,0)	μ_2(1,1)
Coeff.	0.359*	2.23*	0.359*	0.35*	0.305*	1.275*	1.545*	3.01*
S. Error	0.046	0.163	0.046	0.047	0.068	0.135	0.347	0.495
Panel B-Autoregressive Terms								
Market	S&P 500 Equation				Kuwait Equation			
	ϕ_{11}^1	ϕ_{12}^1	ϕ_{11}^2	ϕ_{12}^2	ϕ_{21}^1	ϕ_{22}^1	ϕ_{21}^2	ϕ_{22}^2
Coeff.	0.019	-0.017	0.126*	-0.00007	0.305*	0.126*	0.232*	1.889*
S. Error	0.049	0.048	0.001	0.0004	0.039	0.048	0.075	0.163
Panel C- Switching Coefficients and Correlation Terms								
	Switching Coefficients-Standard Deviation				Switching Coefficients-Correlation Terms			
Market	S&P 500		Kuwait					
	σ_1(0,.)	σ_1(1,.)	σ_2(.,0)	σ_2(.,1)	$\rho(0,0)$	$\rho(0,1)$	$\rho(1,0)$	$\rho(1,1)$
Coeff.	0.368*	0.394*	0.342*	1.433*	0.000	0.488*	0.374**	0.000
S. Error	0.017	0.052	0.044	0.501	0.000	0.083	0.216	0.003
Panel D-Probability Parameters								
Market	S&P 500 Equation				Kuwait Equation			
	α_1(0,.)	β_1(0,1)	α_1(1,.)		β_1(1,1)		α_2(.,0)	α_2(.,1)
Coeff.	2.46*	-2.82*	13.067*		0.2743*		3.856*	0.929*
S. Error	0.559	0.87	1.51		0.04536		0.68	0.052
Panel E- (Transition Probability Matrix (P4×4))								
$S_t \mid S_{t-1}$	(0,0)		(0,1)		(1,0)		(1,1)	
(0,0)	0.902		0.0016		0.077		0.019	
(0,1)	0.298		0.161		0.429		0.112	
(1,0)	0.879		0.000		0.000		0.121	
(1,1)	0.543		0.069		0.184		0.2038	

Notes: Robust standard errors are in parenthesis. * It is significant at 1% significance level and ** It is significant at 5% significance level

Figure 1: Volatility proxy for Oil, U.S. S&P 500 index and the GCC markets.

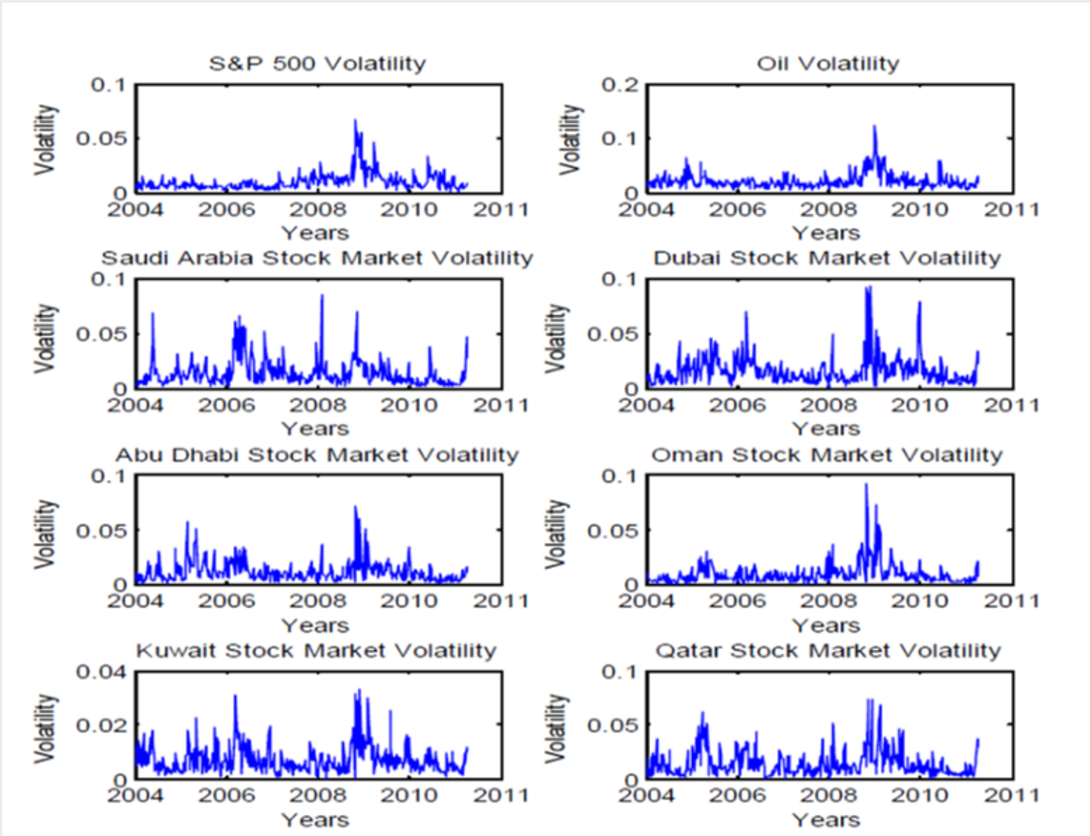
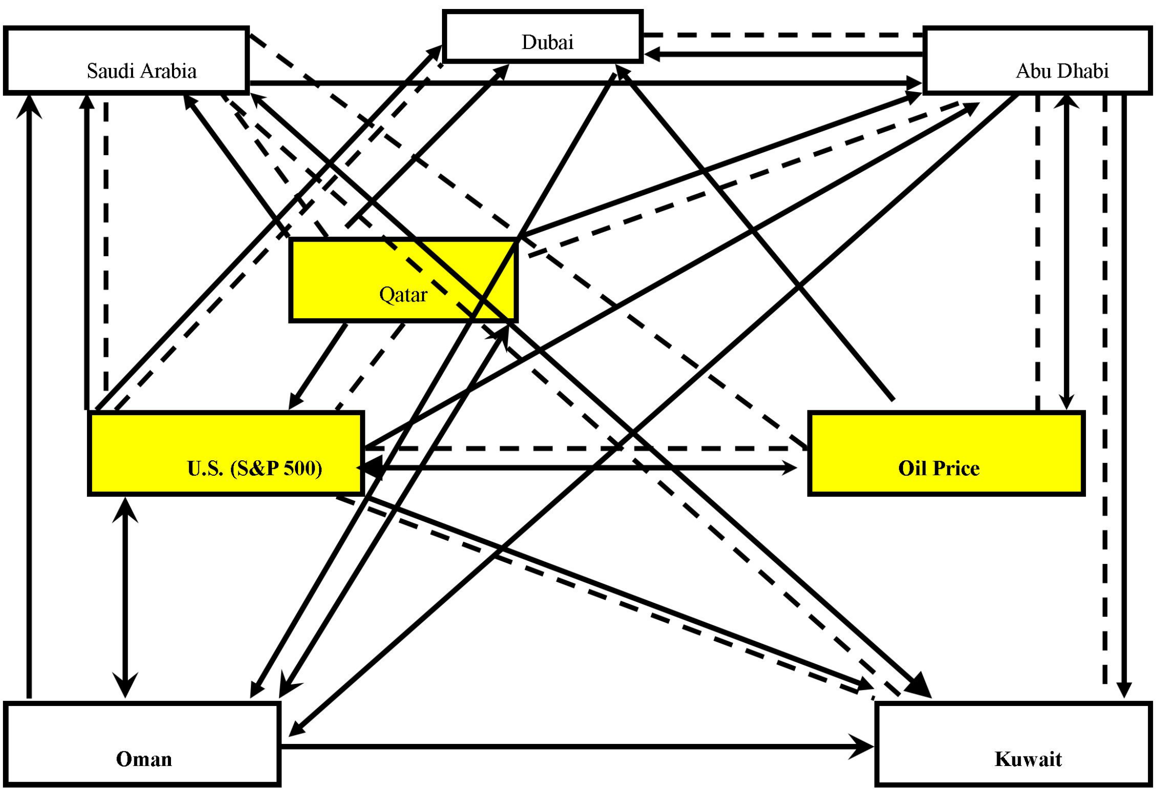


Figure 2: Interdependence and spillovers across Oil, U.S. S&P 500 index and GCC markets



$\longleftrightarrow$ This double arrow line indicates a spillover from the first market to the second market and from the second market to the first market as well.
$\longrightarrow$ The arrow indicates a spillover from the first market to the second market.
$---$ The dot line indicates the interdependence between two markets.

Figure 3: Smoothed probabilities from the bivariate MCMS model for Oil and U.S. S&P 500

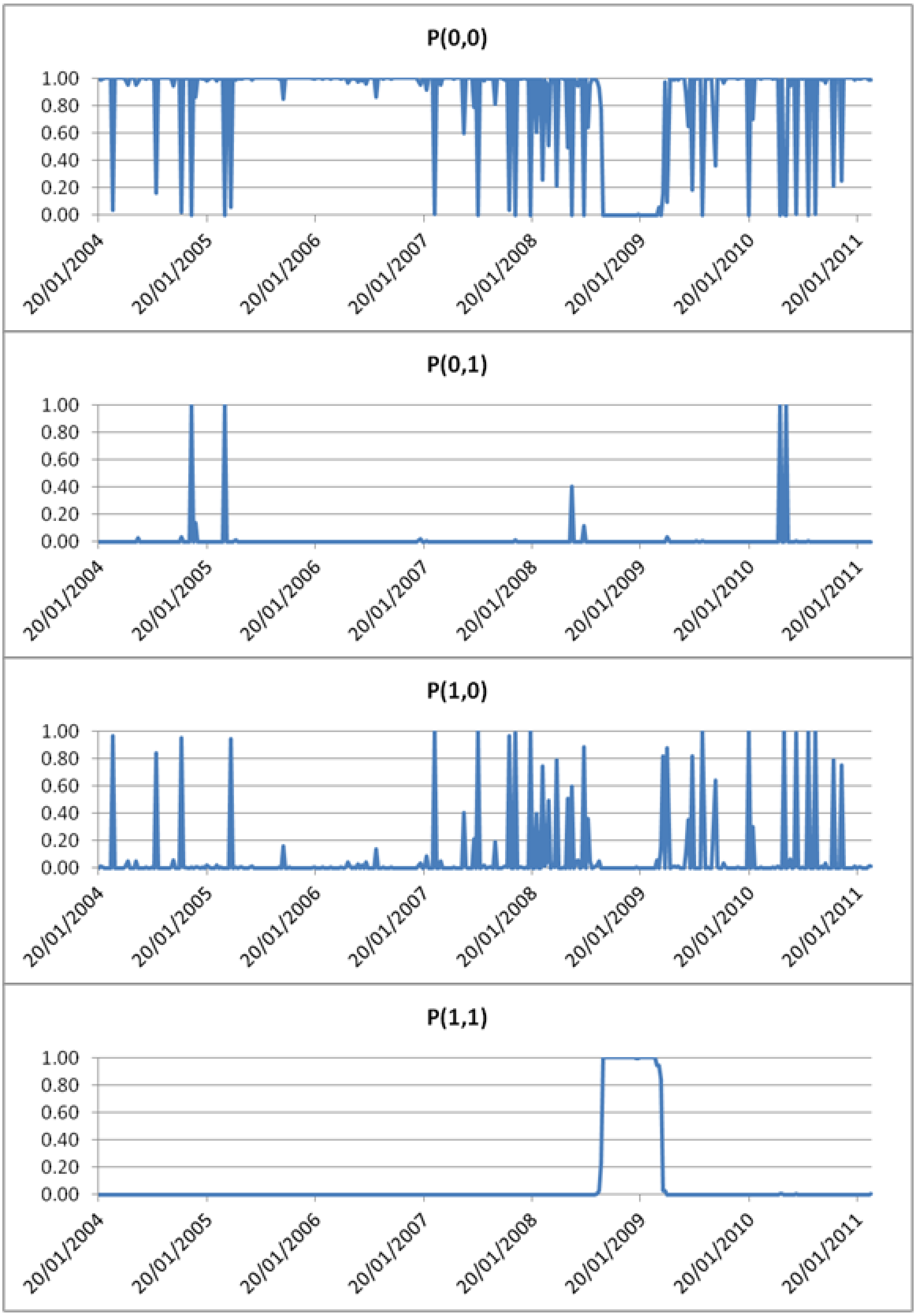
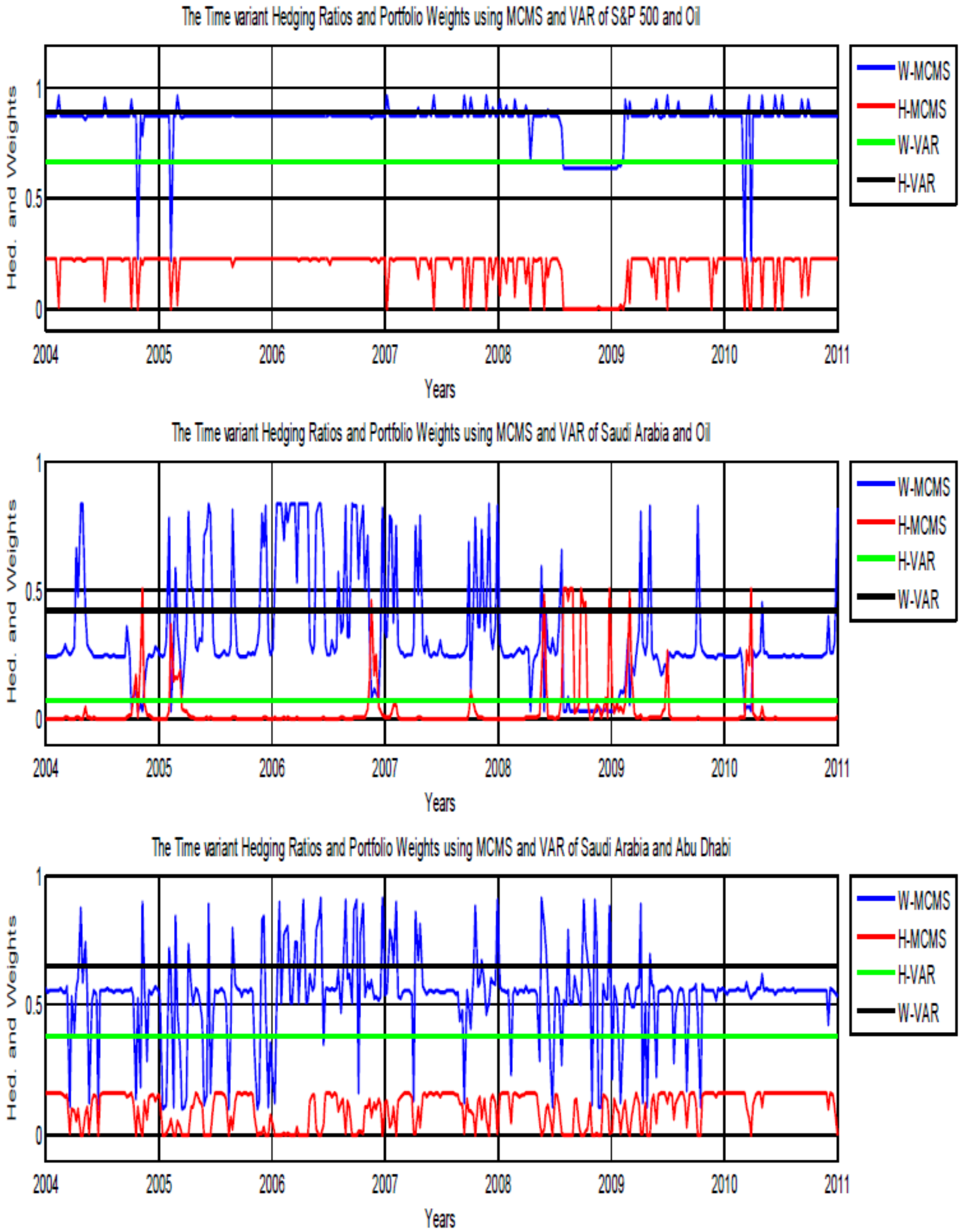


Figure 4: Time-variant hedging ratios and portfolio weights estimated from MCMS and VAR models



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