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Responses of GCC Stock Markets to Oil Price Shocks: Evidence from Markov Switching Vector Error Correction Models

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Executive summary

Stock markets represent an influential instrument of economic activity, suggesting that Gulf Cooperation Council (GCC) economies, as oil-exporting countries, should guard against potential oil price fluctuations to avoid the negative repercussions on various economic sectors, including equity markets, especially in high turbulent periods. It is then pertinent to assess the sensitivity of the stock markets to oil price shocks in the GCC region to provide a clear understanding of the stock-oil nexus to policymakers and investors, allowing them to make suitable decisions. The study is based on a Markov switching setup within the framework of cointegrated relationships for six stock market indexes from five GCC countries, namely Bahrain, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE), over the period from 2005 to 2020.

The results support the instability of the stock-oil nexus for all equity market indexes, as the volatility-switching mechanism of the linkages between stock indexes and oil prices is governed by two regimes, i.e. low- and high-volatility regimes, with more persistence and occurrence for the low-volatility regime. Influential international shocks, such as the collapse of two hedge funds of the Bear Stearns companies in mid-2007, the 2008–2009 stock market crash, the oil price declines from mid-2014 until almost the end of 2015, and the stock prices falls from March to May 2020 caused by the COVID-19 pandemic, affecting the stock markets, are clearly identified. Oil

price is found to be a relevant driver of the stock market indexes, but the responses are not similar across GCC countries over both the low- and high-volatility regimes, thus reflecting the heterogeneity of their oil-dependence degree.

Overall, the results provide important policy recommendations to market participants to help them making rational decisions. Indeed, regulatory authorities should take into consideration the fact that the stock-oil nexus is time-varying to manage better market risks. Investors should take into account the heterogeneity of the responses of the stock markets to oil price shocks across countries and regimes in terms of sign and magnitude when seeking for investment opportunities in the GCC region.

Introduction

Over the last two decades, the linkages between world oil price and stock market indexes have been extensively investigated in the literature. Using various methodologies, prior studies did not come to a consensus on the relationship between stock indexes and oil prices in terms of its nature, sign and magnitude. In this context, early influential empirical works provide evidence of negative links between oil prices and equity index returns (see Jones and Kaul, 1996; Sadorsky, 1999; Nandha and Faff, 2008; Miller and Ratti, 2009; Chen, 2010; Jammazi and Aloui, 2010; and Filis et al., 2011). Other studies support the existence of positive responses of stock indexes to oil price fluctuations (see Hammoudeh and Choi, 2006; Bjornland, 2009; Narayan and Narayan, 2010; Arouri and Rault, 2012; and Salisu and Isah, 2017). It is also found that the net position of the economy in the world oil market and the relevant drivers of oil price shocks play a crucial role in determining how the stock markets react to the fluctuations in oil prices.

There are many motives behind the analysis of the stock-oil nexus for the GCC region. First, GCC countries are among the major suppliers of oil for the global economy, suggesting that oil price movements may influence their equity markets. Second, oil-based commodities undergo higher manufacturing costs following oil price changes, which can influence the expected cash flows of companies, thus affecting stock prices. Third, most of the empirical studies on the stock-oil nexus in the GCC region opt for linear econometric methodologies, but it is now well established that neglecting potential nonlinearity can lead to misleading outcomes (see Balcilar et al., 2015). Fourth, GCC economies are experiencing an economic downturn due to the spread of COVID-19 and the oil price declines, which influence stock prices.

Over the last decade, oil price fluctuations have been prominent. Indeed, after an extremely quiet period from 1986 to 2006, oil prices increased from $60 in 2007 to $145 in 2009. Oil prices lost approximately 75% of their value within some months in 2014 and 2015 due to the booming in US shale oil production. These acute fluctuations in oil prices are accompanied by high volatility in stock markets, thus incentivizing researchers, investors and policymakers to assess the stock-oil nexus based on various methodologies.

In this study, we make use of the two-regime Markov-Switching Vector Error Correction (MS-VEC) model, developed by Balcilar et al. (2015), to assess the stock-oil nexus in five GCC countries within a time-varying framework from January 2, 2005 to August 30, 2020. This robust technical setting allows us to account for some features in the data, such as volatility switching between regimes, cointegrating links between stock indexes and oil prices, and assessment of the expected average durations across regimes to bring out the differences in the volatility switches across equity markets. We also use the model estimates to calculate the regime-dependent impulse response functions to assess the extent of the sensitivity of the stock indexes to oil price shocks across regimes. Therefore, market participants will get reliable information about the market situation, thus leading them to make suitable decisions.

The empirical results reveal that the used methodology allows us to assess the behavior of the stock prices in low- and high-volatility regimes, thus supporting the volatility-switching regime for the considered GCC stock markets and suggesting that these markets are subject to influential shocks. It is worth noting that the low-volatility regime is more persistent and is expected to occur more often than the high-volatility regime for all equity markets. Influential economic and financial crises governing the transition mechanism in the stock-oil nexus for the GCC countries are closely identified, namely the collapse of two hedge funds of the Bear Stearns companies in mid-2007, the 2008–2009 global financial crisis, the oil price declines from mid-2014 until almost the end of 2015, and the stock prices falls from March to May 2020 caused by the COVID-19 pandemic.

The impulse response analysis reveals that the responses of the stock prices to their own shocks behave similarly over each regime and decrease more in the high-volatility regime than the low-volatility regime over time for most stock markets. Regarding the stock-oil nexus, the results show that the responses of stock markets to oil price shocks experience dissimilarity across GCC countries over both regimes, thus reflecting the heterogeneity of their oil-dependence degree. Overall, the results are of great interest for market participants who should take into consideration the time-varying aspect of the responses of GCC stock markets to the fluctuations in oil price before making decisions.

The remainder of the study is structured as follows. Section 1 provides a brief literature review on the stock-oil nexus. Section 2 introduces the model estimation issues to assess the responses of stock markets to the fluctuations in oil prices. Section 3 presents a preliminary data assessment. Section 4 is devoted to the discussion of the empirical results. Concluding remarks and policy recommendations are provided at the end of the study.

1. Literature review

In addition to its effects on macroeconomic variables, such as output and inflation, oil price volatility can also affect stock markets, as evidenced by Kilian and Park (2009) and Kang et al. (2015). Within this context, Jouini (2013) opts for a Vector Autoregressive Generalized Autoregressive Conditional Heteroskedasticity (VAR-GARCH) model to find significant spillovers between stock sectors and oil price for the Saudi economy. Hammoudeh and Choi (2007) reveal that the linkages between the equity markets and oil prices are time-varying for the GCC region by applying the unobserved-component model with Markov switching heteroskedasticity.

Naifar and Al Dohaiman (2013) show that for most GCC markets, the relationship between the stock indexes and oil prices are unstable based on a two-regime MS exponential GARCH model. Jouini and Harrathi (2014) reveal shock and volatility linkages between equity indexes and oil prices for the GCC region based on multivariate GARCH models. Based on similar models, Al-Maadid et al. (2016) reveal comovements between stock indexes and oil prices in the GCC region.

Miller and Ratti (2009) make use of cointegration techniques with structural breaks and find that the stock-oil nexus is unstable for the Organisation for Economic Co-operation and Development (OECD) economies. Balcilar and Ozdemir (2013) show evidence of causal links running from oil price to a sub-grouping of S&P 500 index based on the MS-VAR model. Balcilar et al. (2015) apply the two-regime MS-VEC model to reveal that the US stock-oil nexus is regime-dependent. Lu et al. (2017) apply a time-varying coefficient VAR model based on dynamic lagged correlations and find unstable S&P 500 index-oil nexus. Jammazi et al. (2017) reveal time-varying causality between equity indexes and oil prices for oil-importing countries by combining the wavelet approach and a modified causality test.[1] More recently, Aggarwal and Manish (2020) find that oil price movements significantly and positively affect the Indian stock market index over the long- and short-run based on the

[1] See also Ahmed (2017) and Wei and Guo (2017) for similar outcomes.

Autoregressive Distributed Lag (ARDL) model. Živkov et al. (2020) employ regime-switching conditional volatilities obtained from the two-regime MS-GARCH model to show that central and eastern European stock indexes experience volatility spillover effects from oil prices.

2. Model and estimation issues

In this study, we make use of the MS-VEC model, developed by Balcilar et al. (2015), to investigate the cointegrated linkages between stock and oil prices in a time-varying framework. Practically, the model takes the following form:

$$\Delta Y_t = C_{S_t} + \sum_{k=1}^{p-1} A_{S_t}^k \Delta Y_{t-k} + \alpha_{S_t}\beta' Y_{t-1} + \varepsilon_t \qquad (1)$$

where $\varepsilon_t \big| S_t \to N\left(0,\ H_{S_t}\right)$ with H_{S_t} the variance-covariance matrix; Y_t is a vector consisting of a stock index and oil price that should be integrated of order one and cointegrated; C_{S_t} is a vector of deterministic drifts; $A_{S_t}^k$ is a matrix of short-run coefficients; α_{S_t} is the matrix of adjustment speed to disequilibrium; β is the matrix of cointegrating vectors; p is the lag length of the model whose optimal number is determined by the Bayesian information criterion in the level VAR model; and S_t is a random state variable following a two-regime Markov chain with the matrix of transition probabilities $P = \left[p_{ij}\right]$ with $p_{ij} = Pr[S_t = j | S_{t-1} = i,\ \Im_{t-1}]$ the probability of being in state j at time t given that the economy was in state i at time $(t-1)$, and $\Im_t = \{Y_\tau | \tau = t,\ t-1, \dots, 1-p\}$ an information set.

According to Krolzig et al. (2002), the above two-state MS-VEC model is estimated by the Bayesian Markov-chain Monte Carlo (MCMC) integration method based on Gibbs sampling and using the equilibrium errors computed after determining the cointegrating vectors by the Johansen (1988) approach. By doing so, we can conduct the usual statistical inference, as the obtained estimators are normally distributed asymptotically.

To assess the effects of oil price shocks on the GCC stock markets in a time-varying framework, we make use of the following regime-dependent impulse response functions (see Ehrmann et al., 2003; and Balcilar et al., 2015):

$$\emptyset_{kl,h} = \left.\frac{\partial E_t Y_{t+h}}{\partial u_{k,t}}\right|_{S_t = \cdots = S_{t+h} = l}, \qquad h \geq 0 \tag{2}$$

where $u_{k,t}$ is a structural shock to the k^{th} variable. The structural shocks are identified using the variance-covariance matrix $H_{S_t} = N_{S_t} N_{S_t}^{'}$, implying that $u_t = N_{S_t}^{-1} \varepsilon_t$.

3. Data assessment

The study includes six stock prices from five GCC countries, namely Bahrain (Bahrain All Share), Oman (MSM 30), Qatar (QE General), Saudi Arabia (Tadawul All Share) and the UAE (ADX General for

Abu Dhabi and DFM General for Dubai), and the Brent spot oil price. We consider weekly data over the period from January 2, 2005 to August 30, 2020 (818 observations).[2] The sample period is long enough to examine the dynamic relationship between GCC stock indexes and oil price within a cointegrating framework. In addition, it includes influential economic and financial crises, such as the 2007–2009 global financial crisis, the 2011 instability of the global economy, the fall of oil price from mid-2014 until almost the end of 2015, and the COVID-19 crisis from the end of 2019. All these shocks motivate us to make use of a regime switching framework that allows us to examine the responses of GCC stock prices to the changes in oil prices during turbulent periods. By doing so, the study will be very useful for policymakers and investors to manage the financial effects of oil price shocks in a tangible way.

3.1. Preliminary analysis

Figure 1 displays the evolution patterns of the stock and oil prices. We first observe that the stock and oil markets experience common upward and downward trends during different times of the sample period. The collapse of two hedge funds of the Bear Stearns companies in mid-2007 generates slight falls in the stock prices of

[2] Closing values of the stock prices are gathered from the global financial portal (https://www.investing.com), and data on Brent oil price are collected from the US Energy Information Administration database. The results of the study are based on data converted into natural logarithm.

Abu Dhabi, Dubai, Qatar, and Saudi Arabia. The 2008–2009 stock market crash causes declines in the stock and oil prices. The fall of oil price from mid-2014 until almost the end of 2015 was accompanied by decreases in the stock markets. It is worth noting that the COVID-19 pandemic generates drops in the stock indexes and the oil price notably from March to May 2020 before a gradual recovery was triggered. The oscillation of the stock and oil prices, due to the mentioned influential crises and unrests, is well illustrated in Figure 2 that plots the market price returns.[3] To sum up, the graph analysis reveals that there is a close connection between the stock markets and the oil price, thus suggesting potential cointegration between them within a regime switching framework given the influential shocks that marked the study period.

Table 1 presents descriptive statistics and statistical properties of the logarithmic levels of the stock and oil prices over the period under study. As regards the stock markets, the Qatari market exhibits the greatest average yield (9.119) and least volatility (0.204), as shown by the standard deviation, thus suggesting that this stock market offers good investment opportunities for investors compared to the other GCC stock markets. It is worth noting that the Dubai financial market is considerably more volatile than the other stock markets, thus highlighting the turbulent behavior of this market compared to

[3] The stock market returns are calculated as the first differences of the logarithmic level prices.

the others. The volatility of the Brent oil price is relatively comparable to the volatility of the stock markets.

The Jarque-Bera test results reveal that the GCC stock markets and oil price are not normally distributed, as the test rejects the null hypothesis of normality. In addition, there is also evidence of serial correlation and heteroskedasticity in all stock and oil markets, as the Ljung-Box test rejects the null hypothesis of no autocorrelation in the level prices and the squared level prices, thus highlighting the suitability of the above modeling setup to take into account the serial correlation and heteroskedasticity in the data.

The correlation coefficients between the stock and oil prices indicate that the markets of Bahrain and the UAE are negatively linked to oil price. However, the stock markets of Oman, Qatar and Saudi Arabia are positively connected to oil price. This correlation analysis is not decisive for the linkages between the stock markets and the oil price. Therefore, an in-depth analysis based on the above model and estimation issues is conducted in the next section to draw pertinent conclusions on the reactions of the stock prices to the changes in oil price.

3.2. Unit root and cointegration analysis

We check the unit root properties of the stock indexes and the oil price by applying the Phillips and Perron (PP) (1988) and Elliott (DFGLSu) (1999) tests. The results reported in Table 2 show evidence of non-stationary level prices and stationary returns, suggesting that the variables are integrated of order one, and possible cointegration between them may then exist. For this purpose, we apply the Johansen (1988) approach that involves running the trace and maximum eigenvalue tests to calculate the number of cointegrating vectors in six stock index-based systems. The results presented in Table 3 show evidence of one cointegrating relationship between each stock index and oil price regardless of the test equation. Accordingly, we can opt for the above econometric setup to assess the responses of GCC stock prices to the fluctuations in oil prices.

4. Discussion of the results

We first identify the two states that characterize the linkages between the stock and oil prices. Second, we measure the persistence of the two regimes and examine their properties. Third, we attempt to identify the crises that affect the stock indexes by detecting the occurrence dates of regime shifts through the analysis of the smoothed probabilities. Fourth, we assess the extent of the reactions of stock prices to the fluctuations in oil price over both regimes through the analysis of the state-dependent impulse response functions.

4.1. Regime identification

For all stock index-based systems, the optimal lag length of the two-regime MS-VEC model is equal to two, which is selected by the Bayesian information criterion in the log-level VAR specification. The Bayesian MCMC integration technique with Gibbs sampling is employed to estimate the systems based on 20,000 burn-in draws and 50,000 posterior draws. We first compute the likelihood ratio (LR) test to test the null hypothesis of a linear (single-regime) VEC model against the alternative hypothesis of a two-regime MS-VEC model.[4] The results displayed in Table 4 conclude in favor of a two-regime MS-VEC model to characterize better the relationship between each stock market and oil price, as the LR test rejects the null hypothesis of a linear VEC model.

To interpret economically the two regimes identified by the estimation process of the model, we rely on the variance estimates over the two regimes reported in Table 5. Indeed, the first regime experiences the behavior of the stock prices in the low-volatility phase, whereas the second regime exhibits their behavior in the high-volatility phase, as the variance estimates of the first state are lower than those of the second state. In this context, the variance of the high-volatility state is at least more than five times larger than the variance of the low-volatility state across stock markets, thus

[4] The Davies (1987) upper bound procedure is used to draw pertinent outcomes (see Garcia and Perron, 1996).

supporting the volatility-switching regime for all equity prices and suggesting that the GCC stock markets are subject to influential crises and unrests.

4.2. Persistence and regime properties

The estimates of transition probabilities reported in Table 6 indicate that the regime-shifts are persistent, as $p_{11} \neq p_{12}$ and $p_{22} \neq p_{21}$, and that both regimes are not permanent, as $p_{11} \neq 1$ and $p_{22} \neq 1$. We also see that the transition probability of the low-volatility state p_{11} is greater than that of the high-volatility state p_{22}, pointing out that the low-volatility regime dominates the high-volatility regime for all stock markets. In addition, the low-volatility regime is more persistent than the high-volatility regime for all GCC stock markets, as evidenced by the expected duration in both states (see Table 7), thus showing evidence of asymmetric cycles across states.

It is worth noting that for all stock markets, the persistence differs substantially across states given that the expected duration for the low-volatility state is much longer than that for the high-volatility state, thus implying that shocks over the high-volatility state are shorter than those over the low-volatility regime. In addition, the average durations of the low-volatility state for the stock indexes of Abu Dhabi, Dubai, Bahrain, Oman, Qatar, and Saudi Arabia are 62.5, 50.0, 52.6, 71.4, 38.5, and 31.3 weeks, respectively, thus providing an average of 51.1 weeks. Therefore, the stock markets of Oman and Abu Dhabi, and, to a lesser extent, the stock markets of Bahrain and

Dubai experience the greatest persistence of the low-volatility regime, as evidenced by the plots of smoothed probabilities in Figure 3. The low-volatility state is expected to occur more often than the high-volatility state for the GCC stock markets, as indicated by the long-run average probability of the first state that is higher than that of the second state, thus showing more observations in the first state (see Table 7).[5]

4.3. Smoothed probabilities

Figure 3 reports the estimates of the low-volatility state smoothed probabilities. These probabilities allow us to identify closely the influential economic and financial crises and unrests that govern the transition mechanism in the stock-oil nexus for the GCC region. We observe that the probabilities are equal to or near to one over various periods, thus locating clearly the occurrence dates of regime-shifts. Many simultaneous regime-shifts are spotted across all stock prices, thus pointing to the joint effects of international shocks on all equity prices. It is important to notice that the declines and, thus, the high volatility, recorded by the GCC stock prices (see Figure 2) are clearly illustrated by the periods detected in the high-volatility regime. These periods notably include the collapse of two hedge funds of the Bear Stearns companies in mid-2007, the 2008–2009 global financial

[5] In a similar context, Balcilar et al. (2015) find that for the S&P 500 index-oil price nexus, the low-volatility regime occurs more often than the high-volatility regime over the period from September 1859 to December 2013.

crisis, the oil price drops from mid-2014 until almost the end of 2015, and the stock prices declines from March to May 2020 caused by the COVID-19 pandemic.[6] These periods, in addition to other short-lasting periods, testify the dominance of instability and the transitory mechanism in the stock-oil nexus for the GCC region.

4.4. Impulse response functions

The impulse response functions allow us to assess the responses of GCC equity markets to a one standard deviation shock in oil price within a regime-dependent framework over a 30-week horizon. The impulse response functions reported in Figures 4 and 5 indicate that all stock prices are positively affected by their own innovations in both regimes. The effects are larger over the low-volatility regime compared to the high-volatility regime for the stock markets of Abu Dhabi, Dubai and Bahrain, implying that the low-volatility regime is more influential on the stock prices than the high-volatility regime in terms of the responses of these equity index prices to their own shocks. However, the high-volatility regime is more influential on the equity markets of Oman and Saudi Arabia than the low-volatility regime. It is also found that for the Qatari stock market, the effects of oil price shocks on the stock price are mixed across both regimes. A

[6] These dates are similar to the dates selected by the procedure of Bai and Perron (1998, 2003) (results not reported, but available upon request), thus pointing to the effectiveness of the two-state MS-VEC setup in describing the relationship between the GCC stock markets and the oil price.

feature of substantial importance is that the responses of the stock markets to their own shocks behave similarly over each state, and that the effects decrease more in the high-volatility state than the low-volatility state over time for most of the equity markets throughout the impulse response horizon.

For the low-volatility regime, the responses of the GCC stock markets to a unit standard deviation shock in oil price are displayed in Figure 6. We observe that for the stock markets of Abu Dhabi and Qatar, the responses are mixed. Indeed, there is evidence of a positive effect of oil price during the first 23 weeks for both equity markets. However, the situation is reversed as the impact becomes negative throughout the remaining seven weeks for both markets. Low, stable and positive effects of the oil price shock on the equity price of Bahrain are evidenced throughout the impulse response horizon. For the Omani stock market, increasing positive responses to the oil price shock are observed throughout the 30-week horizon. The stock markets of Dubai and Saudi Arabia show increasing positive responses to oil price shocks over the first four weeks before the responses become decreasing but positive during the remaining horizon. Overall, the impulse response functions reveal that the effects of the oil price shocks experience dissimilarity across the GCC equity markets over the low-volatility state.

Figure 7 plots the impulse responses of equity indexes to a unit standard deviation shock in oil price during the high-volatility state.[7] For the stock markets of Abu Dhabi and Qatar, the impulse responses are still mixed. Indeed, for the market of Abu Dhabi, there is a positive impact of oil price from the second week to the 14th week, and a negative impact for the first week and during the last 16 weeks. For the Qatari market, the impulse responses are positive over the first half of the time horizon and negative over the second half. The stock markets of Dubai and Saudi Arabia behave similarly as for the low-volatility regime, with greater responses over the high-volatility regime for Abu Dhabi and over the low-volatility regime for Saudi Arabia. The stock market of Bahrain shows increasing positive responses to oil price shocks over the first three weeks before the responses become decreasing but positive until the penultimate week and negative for the last week. The Omani stock market experiences increasing positive responses to oil price shocks over the first four weeks before the responses become almost stable over the remaining time horizon.

[7] Balcilar et al. (2015) reveal that the S&P 500 index responds negatively to oil price shocks over the high-volatility regime, but it does not react to the fluctuations in oil price over the low-volatility regime. Kilian and Park (2009) argue that oil production shocks are less significant in explaining the relationship between stock and oil prices.

Conclusion and policy recommendations

The study explores the empirical evidence of the cointegrated relationship between stock markets and oil prices within a time-varying framework based on the Markov switching approach for five GCC countries based on weekly data from 2005 to 2020. The results support the volatility-switching regime for the considered GCC stock markets, as there is evidence of low- and high-volatility regimes in the behaviour of the markets. The low-volatility state is more persistent and is expected to occur more often than the high-volatility state for all stock markets. It is found that some influential economic and financial crises, such as the collapse of two hedge funds of the Bear Stearns companies in mid-2007, the 2008–2009 global financial crisis, the oil price falls from mid-2014 until almost the end of 2015, and the stock prices falls from March to May 2020 caused by the COVID-19 pandemic affect the stock-oil nexus for the GCC economies under study.

The regime-dependent impulse response functions indicate that the responses of the equity markets to their own shocks behave similarly over each state and decrease more in the high-volatility state than the low-volatility state over time for most GCC markets. They also reveal that the reactions of stock markets to oil price shocks are not similar across GCC countries over both regimes, thus reflecting the heterogeneity of their oil-dependence degree.

Overall, our empirical research proves of great interest for market participants to help them handle properly their decisions. Policymakers should take into account the time-varying aspect of the stock-oil nexus to manage better market risks. Investors should be careful when investing in the considered equity markets, as stock indexes react differently to the fluctuations in oil prices across countries and regimes. They also have to manage risks according to the sign and magnitude of the responses of stock indexes to oil price shocks.

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Table 1. Descriptive statistics and statistical properties

	Mean	Std. dev.	JB	Q(12)	$Q^2(12)$	Corr.
Abu Dhabi	8.245	0.266	82.121***	8896.154***	8882.159***	-0.287
Dubai	7.988	0.459	29.363***	9171.011***	9158.912***	-0.162
Bahrain	7.330	0.268	102.694***	9551.399***	9551.342***	-0.003
Oman	8.645	0.231	66.921***	8949.591***	8937.220***	0.560
Qatar	9.119	0.204	36.429***	7945.765***	7965.689***	0.083
Saudi A.	8.970	0.255	237.355***	8469.627***	8482.471***	0.070
Oil price	4.254	0.360	23.254***	7958.491***	8201.858***	-

Notes: JB is the Jarque-Bera test for normality; Q(12) is the Ljung-Box test for serial correlation applied to level series; $Q^2(12)$ is the Ljung-Box test for serial correlation applied to squared level series; and Corr. is the unconditional correlation coefficient between stock and oil prices. *** stands for rejection of the null hypothesis at the 1% level.

Table 2. Unit root test results

	PP		DFGLSu	
	Level	Returns	Level	Returns
Abu Dhabi	-1.863	-25.948***	-2.002	-11.082***
Dubai	-1.541	-23.417***	-1.594	-10.761***
Bahrain	-1.179	-25.700***	-1.499	-8.204***
Oman	-2.907	-27.114***	-2.469	-10.581***
Qatar	-2.862	-27.577***	-2.857	-11.260***
Saudi A.	-2.235	-26.919***	-2.327	-11.375***
Oil price	-2.883	-21.685***	-2.739	-9.729***

Notes: The PP and DFGLSu tests test for unit root under the null hypothesis. We estimate a specification with time trend for the logarithmic level prices and a specification with constant for the returns. *** denotes stationarity at the 1% level.

Table 3. Cointegration test results

	Trace		Max-Eigen	
Null Hypothesis	Model 1	Model 2	Model 1	Model 2
Abu Dhabi				
$r = 0$	27.952***	38.866***	25.271***	32.043***
$r = 1$	1.681	2.824	1.681	2.824
Dubai				
$r = 0$	27.850***	37.469***	25.108***	32.886***
$r = 1$	0.743	1.763	0.743	1.763
Bahrain				
$r = 0$	28.899***	37.223***	26.771***	31.906***
$r = 1$	0.129	1.316	0.129	1.316
Oman				
$r = 0$	28.727***	39.195***	26.299***	31.434***
$r = 1$	1.428	2.760	1.428	2.760
Qatar				
$r = 0$	27.707***	38.429***	25.054***	30.759***
$r = 1$	1.653	2.669	1.653	2.669
Saudi A.				
$r = 0$	28.115***	39.042***	26.648***	30.277***
$r = 1$	1.467	2.764	1.467	2.764

Notes: Model 1: linear deterministic trend, and Model 2: restricted linear deterministic trend. The optimal lag order, which is two for all index-based systems, is determined by the Schwarz information criterion in the log-level VAR specification. r is the number of cointegrating equations. *** stands for rejection of the null hypothesis at the 1% level.

Table 4. Linearity test results

	$log\ L_{VEC}$	$log\ L_{MS-VEC}$	LR
Abu Dhabi	2885.145	3414.494	1058.698 [0.000]
Dubai	2812.738	3879.529	2133.582 [0.000]
Bahrain	2598.153	3154.087	1111.868 [0.000]
Oman	2197.148	3612.092	2829.888 [0.000]
Qatar	2917.037	3287.656	741.238 [0.000]
Saudi A.	2885.145	3277.628	784.966 [0.000]

Notes: $log\ L_{VEC}$ is the log-likelihood value under the null hypothesis of a linear VEC model, $log\ L_{MS-VEC}$ is the log-likelihood value under the alternative hypothesis of a two-state MS-VEC model, and LR is the likelihood ratio test, given by $LR = 2(log\ L_{MS-VEC} - log\ L_{VEC})$. Values in brackets are the *p*-values of the Davies (1987) test.

Table 5. Variance estimates

	State 1	State 2
Abu Dhabi	3.972E-4***	3.693E-3***
	(1.972E-5)	(5.222E-4)
Dubai	7.038E-4***	5.299E-3***
	(3.491E-5)	(5.792E-4)
Bahrain	1.388E-4***	7.626E-4***
	(6.548E-6)	(1.150E-4)
Oman	2.429E-4***	2.625E-3***
	(1.163E-5)	(3.565E-4)
Qatar	4.707E-4***	4.170E-3***
	(2.475E-5)	(4.941E-4)
Saudi A.	4.272E-4***	4.232E-3***
	(2.278E-5)	(4.902E-4)

Notes: The values in parentheses are the standard errors. *** stands for statistical significance at the 1% level.

Table 6. Estimates of transition probabilities

	p_{11}	p_{12}	p_{21}	p_{22}
Abu Dhabi	0.984***	0.118***	0.016***	0.882***
	(0.006)	(0.040)	(0.004)	(0.035)
Dubai	0.980***	0.120***	0.020***	0.880***
	(0.008)	(0.037)	(0.003)	(0.045)
Bahrain	0.981***	0.183***	0.019***	0.817***
	(0.007)	(0.052)	(0.006)	(0.053)
Oman	0.986***	0.100***	0.014***	0.900***
	(0.006)	(0.030)	(0.004)	(0.036)
Qatar	0.974***	0.126***	0.026***	0.874***
	(0.008)	(0.031)	(0.005)	(0.059)
Saudi A.	0.968***	0.138***	0.032***	0.862***
	(0.009)	(0.034)	(0.006)	(0.039)

Notes: p_{ij} $(i, j = 1,2)$ is the probability of being in state j at time t, given that the economy was in state i at time $(t-1)$. The values in parentheses are the standard errors. *** stands for statistical significance at the 1% level.

Table 7. Regime properties

	Probability	Nber of Obs.	Duration (weeks)
Abu Dhabi			
State 1	0.859	701	62.5
State 2	0.141	115	8.5
Dubai			
State 1	0.842	687	50.0
State 2	0.158	129	8.3
Bahrain			
State 1	0.871	711	52.6
State 2	0.129	105	5.5
Oman			
State 1	0.868	708	71.4
State 2	0.132	108	10.0
Qatar			
State 1	0.824	672	38.5
State 2	0.176	144	7.9
Saudi A.			
State 1	0.803	655	31.3
State 2	0.197	161	7.2

Notes: Probability is the long-run average probability of the Markov process; Nber of Obs. is the number of observations of each state based on regime probabilities; and Duration is the expected duration computed as $1/(1 - p_{ii})$ for $i = 1,2$.

Figure 1. Dynamic patterns of the stock and oil prices

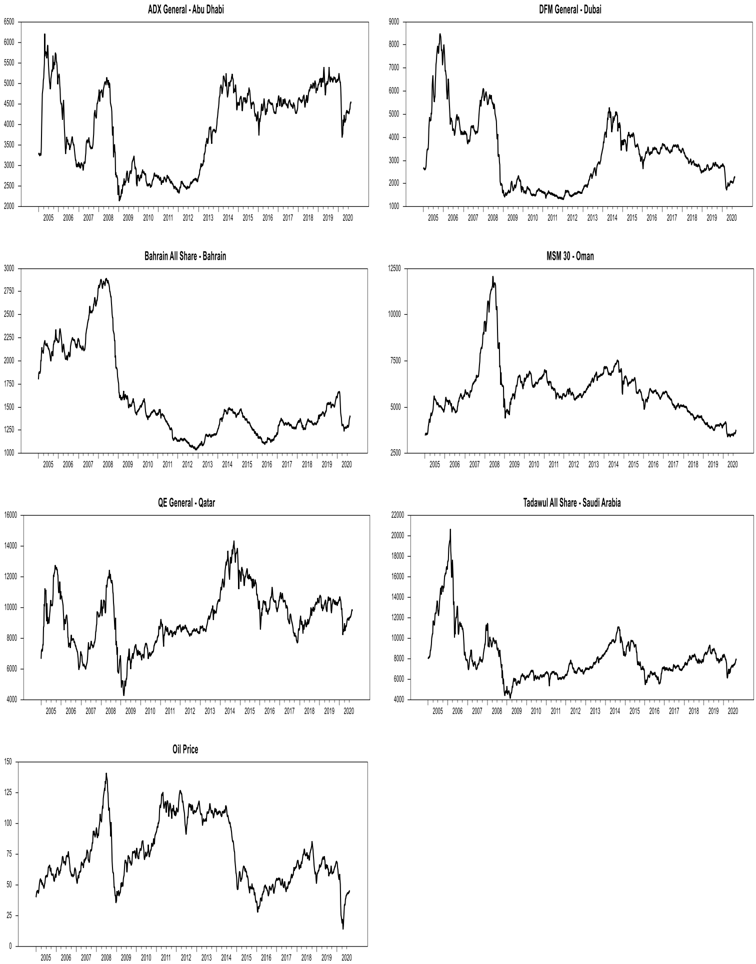


Figure 2. Dynamic patterns of the stock and oil returns

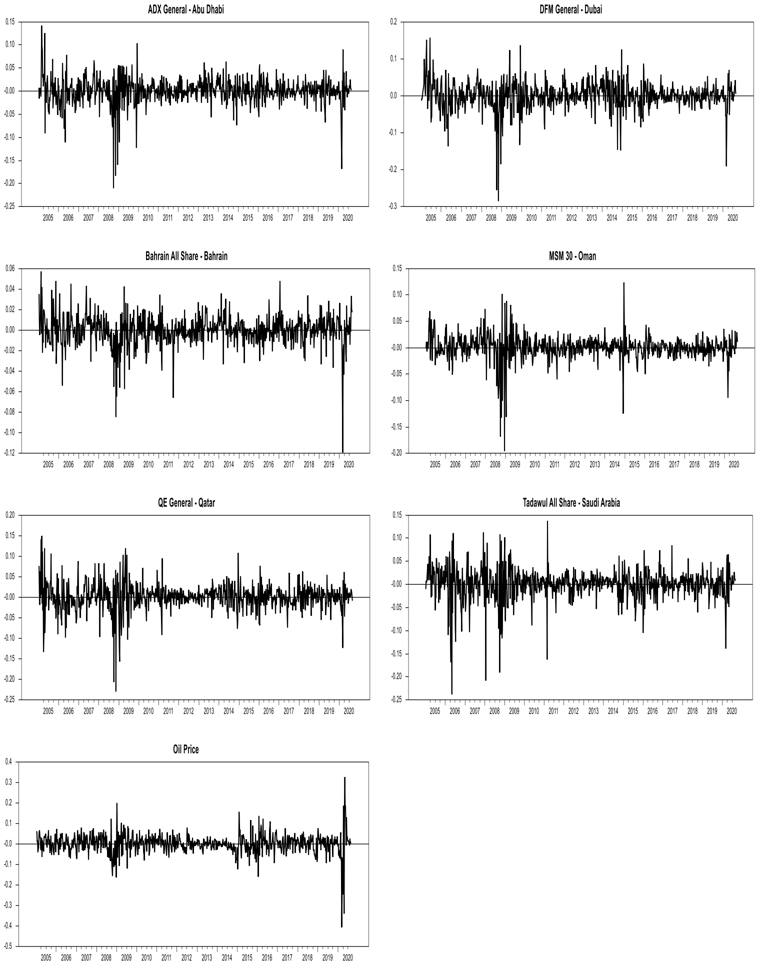


Figure 3. Smoothed probabilities of the low-volatility state

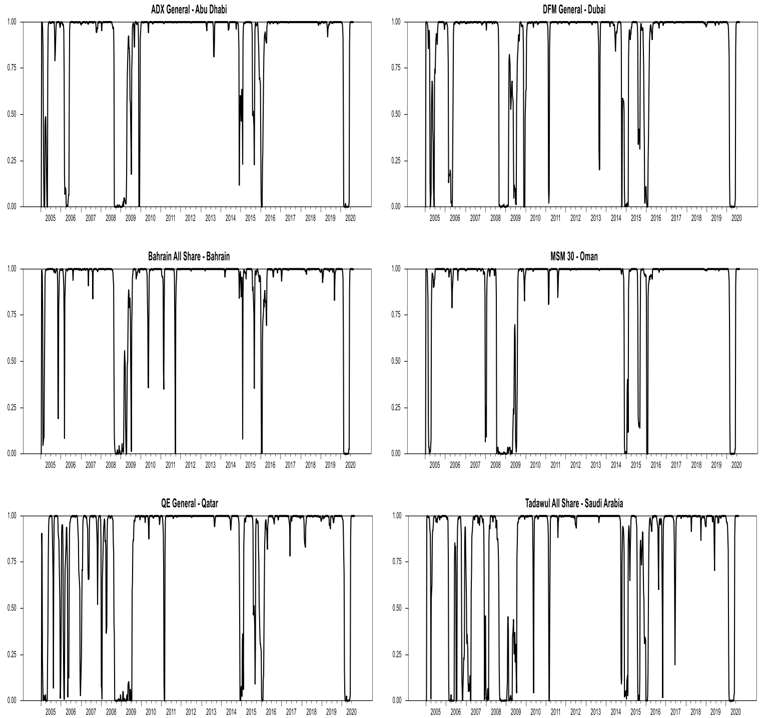


Figure 4. Impulse responses of stock indexes to own shocks in the low-volatility state

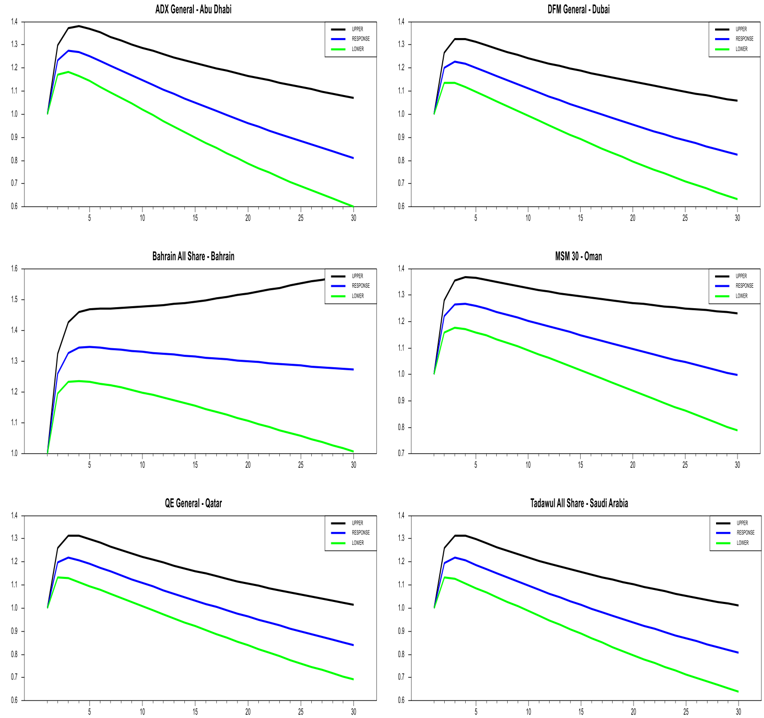


Figure 5. Impulse responses of stock indexes to own shocks in the high-volatility state

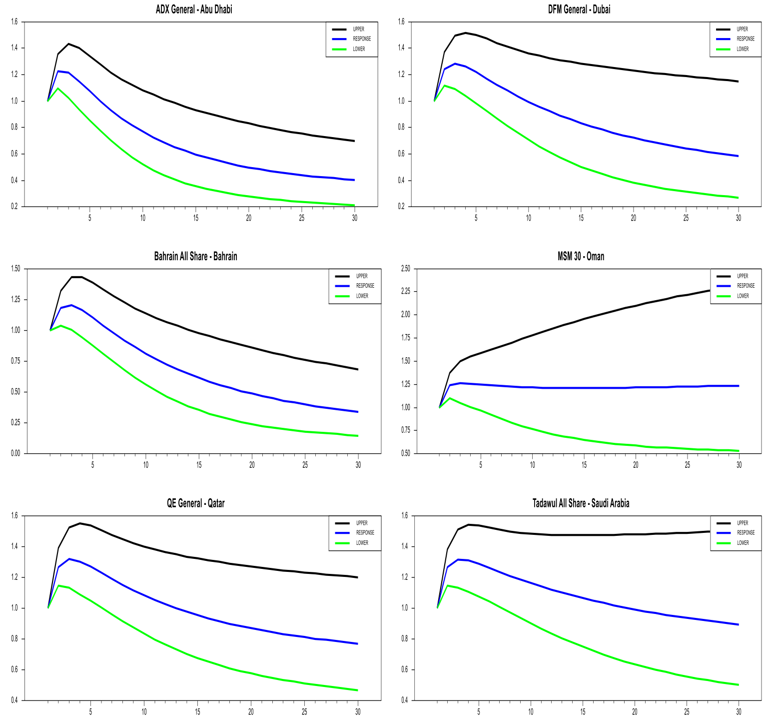


Figure 6. Impulse responses of stock indexes to oil price shocks in the low-volatility state

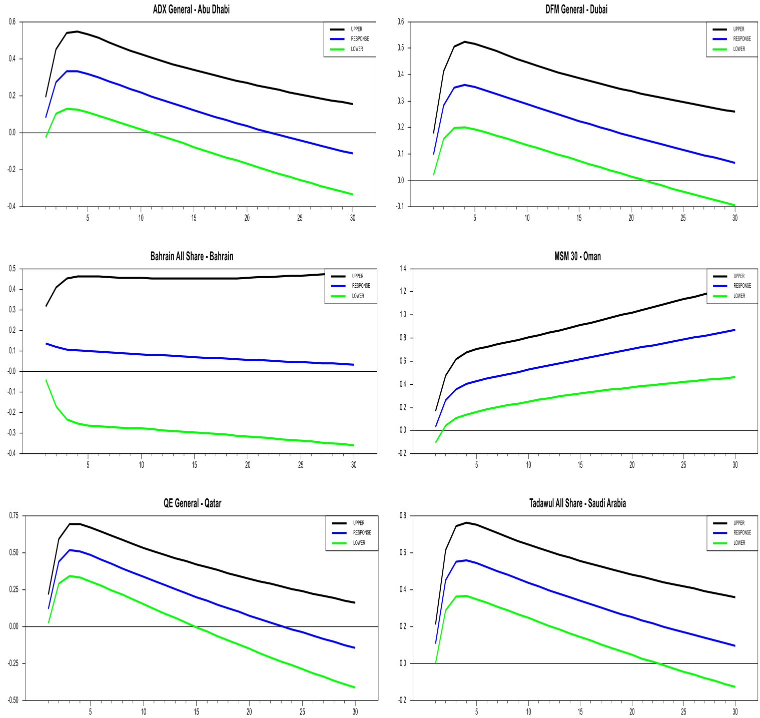
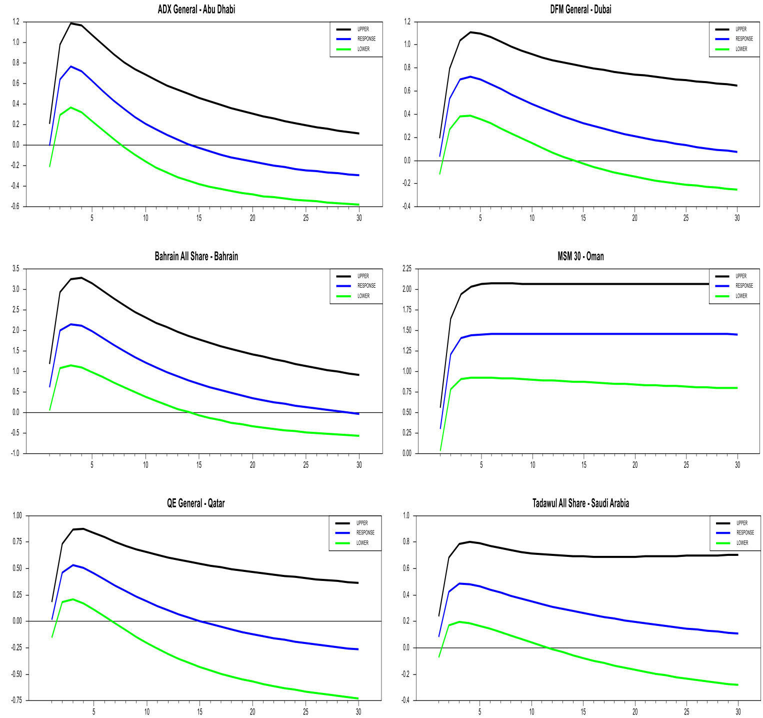


Figure 7. Impulse responses of stock indexes to oil price shocks in the high-volatility state



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